Mechanical Wear Life Prediction Based on Abrasive Debris Generation

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***Abstract*—Assessment and prediction of mechanical wear life are imperative for ensuring the effective application, reducing maintenance cost and minimizing material waste, especially for the machines whose main failure modes are related to wear. For an assembled product, the prediction of wear life is difficult because there is no an appropriate method for direct measurement. The direct product of wear is believed to contain key information of the wear status of the contact surfaces and has been suggested as an indicator for mechanical failures. Currently, several online oil debris monitoring methods are proposed with high precision for accurate debris detection, but there is still a lack of a model to describe the relationship between the wear status and the debris. This paper presents a physics-based model to predict the generation of abrasive debris of contact pairs with a certain roughness, so as to predict the wear life of mechanical components. The probabilistic model is given in a numerical way, based on the boundary element method and atomic attrition mechanism. The proposed method is able to provide predictive features of wear debris including the amount, the distribution of sizes and morphological information. Combining the online oil debris detection approaches, the method is applied to the prediction of an aviation hydraulic pump. The experimental result indicates that the method is effective in predicting the remaining useful life of mechanical components.**

Keywords—remaining useful life, life prediction, mechanical prognosis, oil debris detection

I. Introduction

The relative motion of contact pairs which are commonly used for power transmission in mechanical systems inevitably brings about material loss, which is recognized as the wear process. Wear, working as a primary failure mode of mechanical systems, may lead to catastrophic result if not being paid enough attention. An accurate prediction of wear life will not only guarantee the effective application of the components, but also meet the requirement of condition based maintenance (CBM) as well [1].

Many efforts have been made on estimating the remaining useful life (RUL) of mechanical components. Generally, the methods can be divided into two categories [2]: model-based methods and data-driven methods. For model-based methods, to build a trustworthy model may be expensive but accurate [3]. To reduce the cost, the models used in model-based methods may also be empirical models with uncertainties. To eliminate the uncertainties of the models, filter-based methods are also employed. Li et al. proposed an improved exponential model to predict the life of bearings [4]. Wang et al. [5] proposed an enhanced particle-filter method combined with the tool wear rate model to estimate the life of the tool wear. Grey model is used combining with an adaptive-order particle filter to predict the RUL of aviation piston pumps [6]. As for the data-driven methods, artificial neural networks play important roles in the research of recent years for their capability of modeling non-linear functions [7-9]. Alternative solutions of artificial intelligence are also used for the prediction such as echo state networks [10] and recurrent neural networks [11]. Ren et al. [12] used a deep learning approach for multi-bearing remaining life collaborative prediction, which can effectively represent multi-bearing degradation. With adequate data, data-driven methods may take advantages in modeling complex systems which are not feasible to develop physics-based models.

Sometimes, we need to learn the exact wear status of a key component in a system like a pair of the cylinder block and valve plate in an aviation piston pump, while for an assembled product, it is nearly impossible to detect wear status by conducting directly detecting methods like profilometry and microscope. Instead, vibration signals, pressures and flow rates are usually used. However, data-driven methods using these indicators seldom provide effective wear status, let alone an accurate prediction of remaining wear life.

Concerning model-based methods, Archard's model [13] is commonly used, which states that the wear volume is

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proportional to the normal force and sliding distance. The wear coefficient is usually confirmed by experiment. The uncertainty of the model makes it an empirical model and may be failed in some conditions [14]. Meng and Ludema [15] stated that there was actually not a general equation to predict wear under different work conditions with different materials after analyzing over 180 wear equations and over 100 related variables. With the help of advanced technologies such as atomic force microscopy (AFM) and transmission electron microscopy (TEM), the deformed asperities which were abraded atom by atom gradually were observed in nanoscale [16, 17]. A similar phenomenon was found in Diamond [18], Diamond-like carbon which is widely used coating material [19], and metallic materials [20, 21]. Later, Jacobs proposed an atomic attrition mechanism [14, 16], which makes it possible to give out a predictive result of wear from microscale.

As the direct product of wear, abrasive debris is deemed to contain key information of the wear status of the contact surfaces and have been suggested as an indicator for mechanical failures [22]. Several online oil debris monitoring methods have been proposed [23], and the information of debris can be obtained. However, there is still a lack of an effective method for predicting the generation of wear debris with given rough surfaces. Aiming at providing a predictive solution for wear life based on the information of abrasive debris generation, a numerical model is proposed in this work. Two metallic entities with rough surfaces are supposed to contact under an applied load. The numerical single-loop conjugate gradient method is firstly used to get static contact stress. A discretized solution of subsurface stress based on half-space theory is then used to obtain Von Mises stress at each potential wear unit. The wear debris generation model is based on the atomic attrition mechanism. Then, a predictive model is established for wear debris generation based on the simulative results. The proposed model is tested by using the return oil flow of a certain type of aviation piston pump. The rest of the paper is organized as follows: Section 2 introduces the modeling approaches including the static contact model, subsurface stress distribution model and the wear debris generation model. In section 3, a Monte Carlo simulation is conducted and the simulation results are used for predicting wear life of aviation pumps. Conclusions are drawn in section 4.

II. Modeling approaches

Analysis of wear debris generation depends on an understanding of the contact behavior of two separated surfaces whether under lubrication or not. Different from a macroscale interpretation of contact pressure distribution, wear debris whose sizes are usually in the range of nanometers to micrometers, form depending on the microscale contact mechanism of rough surfaces. Supposing that there are two contact components with rough surfaces as is shown in Fig. 1, z direction is perpendicular to the x-y plane and an externally applied load P_0 is conducted. Each small sphere in the figure stands for a discrete removable unit (DRU) of the surfaces according to the atomic attrition mechanism. The load balance can be expressed as

$$P_0 = \int_{\Gamma_c} p_{i,j} \mathrm{d}\Gamma \tag{1}$$

where Γ_c is the real contact area and $p_{i,j}$ is the contact pressure at node (i, j). Node (i, j) denotes the DRU at row i and column j of the grid.

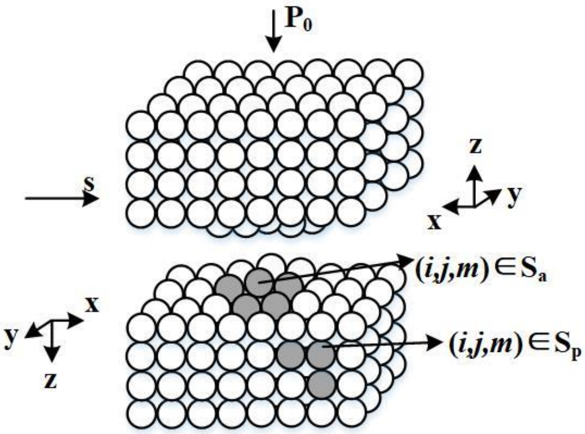

Fig. 1 Coordinate system of two contact components

The deformation of each DRU under the given applied load can be calculated by

$$u_{i,j} = \sum_{k=0}^{M_x-1} \sum_{l=0}^{M_y-1} K_{i-k,j-l} p_{k,l}, 0 \le i < M_x, 0 \le j < M_y \tag{2}$$

where M_x and M_y are the number of rows and columns of the grid and $K_{i-k,j-l}$ is the contact coefficient of the DRU at (k,l) on the DRU at (i, j), which can be calculated as

$$K_{i-k,j-l} = \frac{1}{\pi E^*} \int_{x_k-\frac{1}{2}a_x}^{x_k+\frac{1}{2}a_x} \int_{y_l-\frac{1}{2}a_y}^{y_l+\frac{1}{2}a_y} \frac{dxdy}{\sqrt{(x_i - x_k)^2 + (y_i - y_k)^2}} \tag{3}$$

a_x and a_y are the grid spaces of rows and columns. The E^* is the composite Young's Modulus. Based on the boundary element method, the real applied load on each DRU can be calculated by solving the set of inequalities using conjugate gradient method:

$$\begin{cases} h_{i,j} = u_0 + u_{i,j}, (i, j) \in \Gamma_c \\ p_{i,j} > 0, (i, j) \in \Gamma_c \\ h_{i,j} \le u_0 + u_{i,j}, (i, j) \notin \Gamma_c \\ p_{i,j} = 0, (i, j) \notin \Gamma_c \\ P_0 = a_x a_y \sum_{i=0}^{M_x-1} \sum_{j=0}^{M_y-1} p_{i,j} \end{cases} \tag{4}$$

where u_0 is the surface deflection and $h_{i,j}$ is the separation at node (i, j) of the two surfaces when there is no load applied.

When the applied load of each DRU of the contact surfaces is obtained, the stress of the underlying DRU can be calculated if an elastic half-space is assumed. By solving Boussinesq's equation, the stress of a DRU at (i, j, m) can be obtained by

$$\sigma_{qr}(x_i, y_j, z_m) = \sum_{k=0}^{M_x-1}\sum_{l=0}^{M_y-1}(p_{k,l}D_{qr}^{N}(x_i - x_k, y_j - y_l, z_m) + s_{k,l}D_{qr}^{S}(x_i - x_k, y_j - y_l, z_m)), \quad q, r = x, y, \text{or } z \tag{5}$$

where (x_i, y_j, z_m) denotes the position of DRU at (i, j, m), $p_{k,l}$ is the normal pressure which can be calculated by (4) and $s_{k,l}$ is the shear traction at node $(k, l, 0)$. $D_{qr}^{N}(x_i - x_k, y_j - y_l, z_m)$ and $D_{qr}^{S}(x_i - x_k, y_j - y_l, z_m)$ are the influence coefficients of normal pressure and shear traction, which share the similar formation with the contact coefficient. Then the Von Mises stress of each DRU can be calculated.

$$\sigma_{VM} = \frac{1}{\sqrt{2}}\sqrt{(\sigma_{xx}-\sigma_{yy})^2 + (\sigma_{xx}-\sigma_{yy})^2 + (\sigma_{xx}-\sigma_{yy})^2 + 6(\sigma_{xy}^2 + \sigma_{yz}^2 + \sigma_{xz}^2)} \tag{6}$$

Supposing that a shear traction s is conducted on the contact component as is shown in Fig. 1, the equivalent stress of each DRU may exceeds the yield stress σ_{yield}:

$$S_p(t) = \{(i, j, m) \mid \sigma_{VM}(x_i, y_j, z_m) > \sigma_{yield}\} \tag{7}$$

where $S_p(t)$ is the potential removal set. Actually, not all of the DRU in the potential set will be removed during the wear process. Those that spatially concatenate the superficial DRUs may be removed if the superficial DRUs are also included by $S_p(t)$ and they consist the actual removal set $S_a(t)$ which can be written as

$$S_a(t) = \{(i, j, m) \mid (i, j, m) \in S_p(t), (i, j, m-1) \in S_a(t), m > 0\} \cup \{(i, j, 0) \mid (i, j, 0) \in S_p(t)\} \tag{8}$$

The adjacent DRUs in the actual removal set will be recognized as one debris particle. So several wear debris particles might be generated in one simulation step and the equivalent size of the debris particle can be estimated by

$$D_i = \sqrt[3]{\frac{6V_i}{\pi}} \tag{9}$$

where V_i is the size of a wear particle. The debris particles are collected and the rough surfaces of the two contact components will be updated by subtracting the actual removal DRUs. The flowchart of the numerical modeling method for abrasive debris generation is shown in Fig. 2. The method has been validated currently by Li [24].

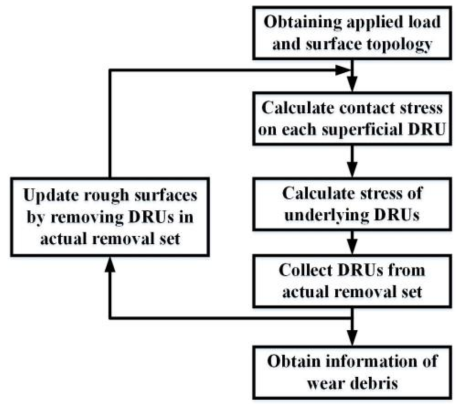

Fig. 2 Flowchart of the modeling method for abrasive debris generation

III. NUMERICAL SIMULATION AND AN APPLICATION ON AVIATION PISTON PUMP

A. Numerical simulation

In an engineering application, the profile of a certain rough surface can be obtained by profilometry techniques such as atomic force microscopy and white light interferometry. Then, the roughness of the surface can be calculated by

$$R_a = \frac{1}{n}\sum_{i=1}^{n}|y_i| \tag{10}$$

where n is the total number of nodes on the surface and y_i is the vertical distance from the mean line to the i^{th} data point.

To conduct the proposed model on an engineering case, two artificial surfaces are firstly generated by a Fourier based digital filter with Gaussian height distribution as is shown in Fig. 3. The roughness of the surfaces is 80 μm.

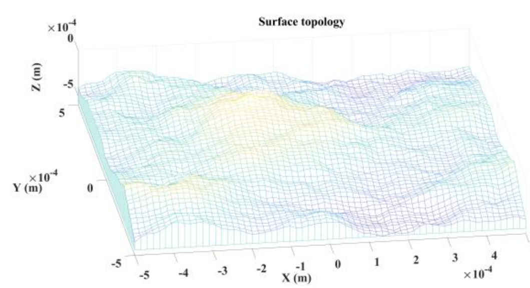

Fig. 3 Surface topology of a contact component

According to the statistical results [25], most debris sizes generated by engineering machinery range from 50 μm to 500 μm. So the area of the researched surfaces are set to be 1 mm^2 to cover all the possible debris sizes. Within the area, 128×128 data points are set, so the size of each DRU is approximate $1.19e^{-4}\mu m^3$, which is also the resolution of the wear debris in the simulation. Other parameters for the simulation are listed in TABLE I.

TABLE I VALUES OF PARAMETERS FOR SIMULATION

Parameter	Meaning	Value
μ_c	Dry friction coefficient	0.3
v_1	Poisson's ratios of upper surface	0.3
v_2	Poisson's ratios of lower surface	0.3
E_1	Young's Modulus of upper surface	210GPa
E_2	Young's Modulus of lower surface	210GPa
L_x	Length of simulation space in x direction	1mm
L_y	Length of simulation space in y direction	1mm
R_z	Resolution in z direction	7.8125 μm
σ_{yield}	Yield stress of composite surface	355MPa
F_0	Initial normal force	50N

The applied force on the contact component is set to be 50N. By using the proposed contact model, the stress on each DRU can be calculated. The equivalent stress distribution of the superficial DRUs is displayed in Fig. 4. For steel, the yield stress is approximate 355 MPa and obviously, the equivalent stress of some DRUs exceed the yield stress. The displacement of one contact component is displayed in Fig. 5.

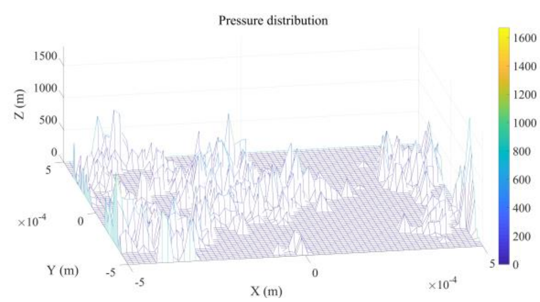

Fig. 4 Pressure distribution

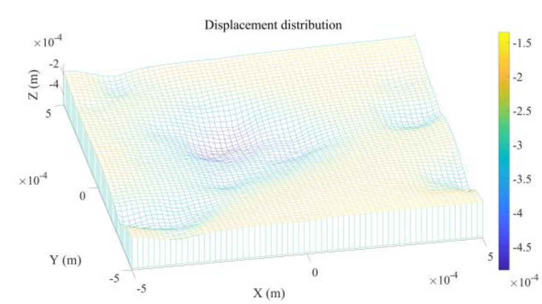

Fig. 5 Displacement distribution

For each simulation step, the DRUs in actual removal set are collected. The adjacent DRUs in the actual removal set will be recognized as one debris particle as is shown in Fig. 6. The size of a certain debris particle is the summation of the sizes of the DRUs which constitute the debris. The wear volume of each simulation step can be obtained by summing all the debris' sizes. We can see from the figure that the proposed method can also provide morphological information of the debris such as length, diameter and ratio of length to diameter. In addition, amount of the particles can also be obtained.

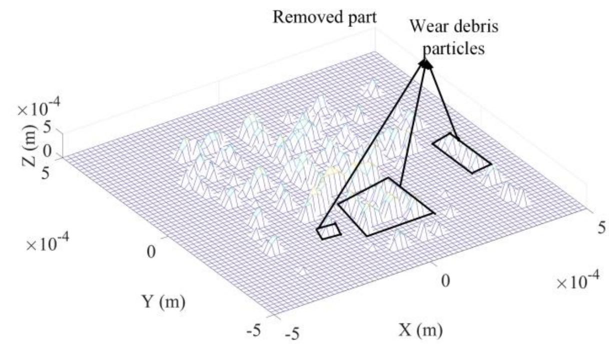

Fig. 6 Simulation of wear debris particles

However, the simulation on single contact pair may present individual characteristics. To get statistic results, a Monte Carlo simulation is carried out. 100 contact pairs are generated stochastically with same roughness 80 μm. All simulations are conducted with the parameters listed in TABLE I. The wear volumes of all the contact pairs are displayed in Fig. 7, from which we can find that the numerical simulation provides us a probabilistic model instead of a deterministic model which means that we may obtain a more accurate predicting result.

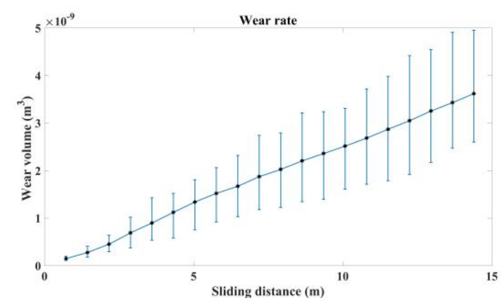

Fig. 7 Wear volumes

B. An application on aviation piston pump

Aircraft hydraulic power supply system provides high pressure fluid for actuation system, braking system, landing gear system and other sub-function systems. As the power source of the aircraft hydraulic system, aviation piston pump's performance influences the flight safety directly. The debris generation model is used to predict the remaining wear life of a key friction pair: pair of valve plate and cylinder block in an aviation piston pump. Because the main degradation mode of the pair is abrasive wear and for the case, it is assumed that there are no other mechanisms leading to the failure of this component, the remaining wear life approximately equal to the RUL which is used to denote the result in this case.

The debris generation model provides information of debris on a small area, but the research object is obviously larger than that. If the model is used to predict the RUL of the component, an integral should be done, as is shown in Fig. 8, and the aforementioned simulation is an example of the green element shown in the figure. For each small element, the applied load is changing with the rotation of the valve plate. The structural parameters for the valve plate for this case can be found in [26]. The result of the partial lubrication model is used as the pressure distribution in this case and the assumption is that for each element the load is applied uniformly. Then, a probabilistic model can be obtained by integrating the information of abrasive debris generation on each element.

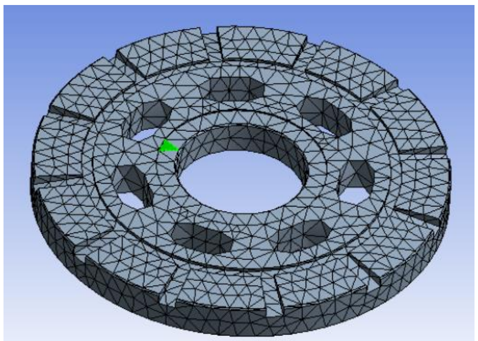

Fig. 8 cylinder block of piston pump

Wear of the pump will result in leakage and the outlet flow rate and pressure will decrease. Assuming that the cylinder block and the valve plate are wedge-shaped, the total leakage of the component can be calculated by

$$Q_{cv} = \frac{\alpha_0 (P_s - P_0)}{60\mu}\left[4(h_2 - h_1)^3 + 5h_1^3\right]\left[\frac{1}{\ln(r_2 / r_1)} + \frac{1}{\ln(r_4 / r_3)}\right] \quad (11)$$

where α_0 is the distribution angle of the pistons, h_1 and h_2 are the maximum and minimum displacements between the cylinder block and the valve plate, P_s is the outlet pressure, P_0 is the inlet pressure, μ is the dynamic viscosity of fluid, r_1 and r_2 are the inner and outer radii of the internal sealing zone, r_3 and r_4 are the inner and outer radii of the external oil sealing zone. The original leakage flow of the pump is 1.774 L/min and the failure threshold is 2.8 L/min. So we can estimate the original interval of the cylinder block and the valve plate is approximate 14.4222 μm and the average failure interval is approximate 16.7919 μm.

The remaining wear life of the component can be expressed as

$$RUL = (I_{AF} - I_C) / R_{wd} \quad (12)$$

where I_{AF} denotes the average interval when the component meet the failure threshold, I_C denotes the current interval between the cylinder block and the valve plate and R_{wd} is the wear rate alone the direction of interval which can be obtained by

$$R_{wd} = R_w / A \quad (13)$$

where R_w is obtained by the debris generation model and A is the average contact area.

The result of the prediction is shown in Fig. 9. We can find that the upper and lower boundaries cover the experiment result well.

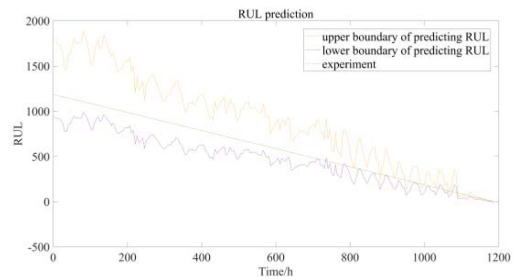

Fig. 9 Upper and lower boundaries of RUL prediction

IV. Conclusion

This paper proposes a wear debris generation model for predicting the wear life of mechanical components. For some mechanical components whose main failure mode is wearing, the remaining useful life equals the remaining wear life.

By using the proposed model, features of abrasive debris generated by two contact components with rough surfaces can be obtained including the amount, the distribution of sizes and morphological information like aspect ratio. All thess characteristics may provide a potential relation between the debris and the components' wear status. Further research is need concerning there is not a doubtless equation explaining the exact degradation performance of debris particles on certain wear status.

An application on an aviation piston pump to validate the effectiveness of the model and experiment result indicates that the proposed wear debris generation model fits the results well.

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References

[1] WangXingjian, LinSiru, WangShaoping, HeZhaomin, and ZhangChao, "Remaining useful life prediction based on the Wiener process for an aviation axial piston pump," Chinese Journal of Aeronautics, vol. 29, pp. 779-788, 2016.

[2] S. Jian, H. Li, and B. Xu, "Prognostic for hydraulic pump based upon DCT-composite spectrum and the modified echo state network," Springerplus, vol. 5, p. 1293, 2016.

[3] A. Mosallam, K. Medjaher, and N. Zerhouni, Data-driven prognostic method based on Bayesian approaches for direct remaining useful life prediction, 2016.

[4] N. Li, Y. Lei, L. Jing, and S. X. Ding, "An Improved Exponential Model for Predicting Remaining Useful Life of Rolling Element Bearings," IEEE Transactions on Industrial Electronics, vol. 62, pp. 7762-7773, 2015.

[5] J. Wang, W. Peng, and R. X. Gao, "Enhanced particle filter for tool wear prediction," Journal of Manufacturing Systems, vol. 36, pp. 35-45, 2015.

[6] L. I. Tongyang, S. Wang, J. Shi, and M. A. Zhonghai, "An adaptive-order particle filter for remaining useful life prediction of aviation piston pumps," Chinese Journal of Aeronautics, vol. 31, pp. 941-948, 2018.

[7] X. Min, L. Teng, S. Tongxin, W. Jiafu, s. C. W. De, and W. Zhongren, "A Two-Stage Approach for the Remaining Useful Life Prediction of Bearings using Deep Neural Networks," IEEE Transactions on Industrial Informatics, 2018.

[8] J. B. Ali, B. Chebel-Morello, L. Saidi, S. Malinowski, and F. Fnaiech, "Accurate bearing remaining useful life prediction based on Weibull distribution and artificial neural network," Mechanical Systems & Signal Processing, vol. 56-57, pp. 150-172, 2015.

[9] Y. Zhe, P. Baraldi, and E. Zio, "A comparison between extreme learning machine and artificial neural network for remaining useful life prediction," in Prognostics & System Health Management Conference, 2017.

[10] M. Rigamonti, P. Baraldi, E. Zio, I. Roychoudhury, K. Goebel, and S. Poll, "Ensemble of optimized echo state networks for remaining useful life prediction," Neurocomputing, vol. 281, pp. 121-138, 2018.

[11] G. Liang, N. Li, J. Feng, Y. Lei, and L. Jing, "A recurrent neural network based health indicator for remaining useful life prediction of bearings," Neurocomputing, vol. 240, pp. 98-109, 2017.

[12] L. Ren, J. Cui, Y. Sun, and X. Cheng, "Multi-bearing remaining useful life collaborative prediction: A deep learning approach," Journal of Manufacturing Systems, vol. 43, pp. 248-256, 2017.

[13] J. F. Archard, "Contact and Rubbing of Flat Surfaces," Journal of Applied Physics, vol. 24, pp. 981-988, 1953.

[14] A. Schirmeisen, "Wear: One atom after the other," Nature Nanotechnology, vol. 8, p. 81, 2013.

[15] H. C. Meng and K. C. Ludema, "Wear models and predictive equations: their form and content," Wear, vol. 181, pp. 443-457, 1995.

[16] T. D. Jacobs and R. W. Carpick, "Nanoscale wear as a stress-assisted chemical reaction," Nature Nanotechnology, vol. 8, pp. 108-112, 2013.

[17] B. Gotsmann and M. A. Lantz, "Atomistic Wear in a Single Asperity Sliding Contact," Phys.rev.lett, vol. 101, p. 125501, 2008.

[18] L. Pastewka, S. Moser, P. Gumbsch, and M. Moseler, "Anisotropic mechanical amorphization drives wear in diamond," Nature Materials, vol. 10, pp. 34-8, 2011.

[19] T. D. B. Jacobs, B. Gotsmann, M. A. Lantz, and R. W. Carpick, "On the Application of Transition State Theory to Atomic-Scale Wear," Tribology Letters, vol. 39, pp. 257-271, 2010.

[20] J. Zhong, R. Shakiba, and J. B. Adams, "Molecular dynamics simulation of severe adhesive wear on a rough aluminum substrate," Journal of Physics D Applied Physics, vol. 46, p. 055307, 2013.

[21] M. R. So/Rensen, K. W. Jacobsen, and P. Stoltze, "Simulations of atomic-scale sliding friction," Physical Review B Condensed Matter, vol. 53, p. 2101, 1996.

[22] W. Hong, S. Wang, M. M. Tomovic, H. Liu, J. Shi, and X. Wang, "A Novel Indicator for Mechanical Failure and Life Prediction Based on Debris Monitoring," IEEE Transactions on Reliability, vol. PP, pp. 1-9, 2017.

[23] T. Li, S. Wang, E. Zio, J. Shi, and W. Hong, "Aliasing Signal Separation of Superimposed Abrasive Debris Based on Degenerate Unmixing Estimation Technique," Sensors, vol. 18, p. 866, 2018.

[24] T. Li, J. Shi, S. Wang, E. Zio, and Z. Ma, "Mesoscale Numerical Modeling for Predicting Wear Debris Generation," Tribology Letters, vol. 67, p. 38, 2019.

[25] W. Hong, S. Wang, M. Tomovic, L. Han, and J. Shi, "Radial inductive debris detection sensor and performance analysis," Measurement Science & Technology, vol. 24, p. 5103, 2013.

[26] L. Han, S. Wang, and C. Zhang, "A partial lubrication model between valve plate and cylinder block in axial piston pumps," Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science, vol. 229, pp. 3201-3217, 2015.