**Appendix**

The definitions of the sixty time domain features of the vibration signals are presented in Table 1. In this study, these sixty feasible features are explored for RUL prediction of bearings. These features are the bearing condition indicators that quantify vibration signals to aid in RUL prediction process. The RReliefF algorithm is used to develop effective features that accomplish RUL prediction through the quantification of vibration signals. The condition indicators can be developed from the raw signal or after a signal processing technique. In this study, sixty different compute equations are introduced to extract features from the time domain signals. Once the time domain vibration signal is obtained and features computed, the RUL prediction of bearings can be accomplished. The hybrid prediction model is facilitated by examining the feature selection results for the time domain vibration signals to predict the RUL of bearings. If the features can acquire the characterize of the operating bearing effectively, predicting of the RUL for bearings is accomplished.

**Table 1**: Description of input features used in this study

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| No. | Variable name and formula | Ref. | No. | Variable name and formula | Ref. |
| 1 | Maximum signal voltage: *F*1 = max(*xi*) | [1] | 31 |  | [11] |
| 2 | Minimum signal voltage: *F*2 = min(*xi*) | [1] | 32 | Most frequent values in array: | [12] |
| 3 | Mean: | [1] | 33 |  | [13] |
| 4 | Standard deviation: | [1] | 34 | Mean absolute value: | [13] |
| 5 | Root Mean Square: | [1] | 35 |  | [13] |
| 6 | Peak: | [1] | 36 |  | [13] |
| 7 | Kurtosis: | [1] | 37 | Median value: | [13] |
| 8 | Kurtosis factor: | [1] | 38 |  | [2] |
| 9 | Crest factor: | [1] | 39 |  | [2] |
| 10 | Peak to peak: | [2] | 40 | Waveform factor: | [2] |
| 11 | Impulse factor: | [3] | 41 |  | [2] |
| 12 | CRIS (a combined effect of **C**rest factor, **R**oot mean square value, **I**mpulse factor and **S**tandard deviation): | [4] | 42 | Sum: | [6] |
| 13 | Coefficient of variation: | [1] | 43 | Impact-factor: | [14] |
| 14 | Inverse coefficient of variation: | [5] | 44 | Shannon’s entropy: | [9] |
| 15 | Energy: | [1] | 45 | Log entropy: | [9] |
| 16 | K factor: | [1] | 46 |  | [15] |
| 17 | 5th moment: | [6] | 47 |  | [15] |
| 18 | 6th moment: | [6] | 48 | Absolute value of the summation of square root: | [16] |
| 19 | Square-mean-root: | [2] | 49 | Mean value of the square root: | [16] |
| 20 | Skewness: | [1] | 50 | Zero crossings: F50 = count (if {*xi* > 0 and *xi*+1 < 0} or {*xi* < 0 and *xi*+1 > 0}) | [17] |
| 21 | Skewness factor: | [1] | 51 | Slope sign changes: *F*51= count (if {*xi*> *xi*-1 and *xi* > *xi*+1} or {*xi* < *xi*-1 and *xi* < *xi*+1}) | [17] |
| 22 | Shape factor: | [1] | 52 | Waveform length: | [7] |
| 23 | Mean absolute deviation: | [7] | 53 | Logarithmic mean absolute value: *F*53 = log(*F*34) | [18] |
| 24 | Variance: | [7] | 54 | Logarithmic root mean square: *F*54 = log(*F*5) | [18] |
| 25 | Margin factor: | [2] | 55 | Logarithmic waveform length: *F*55 = log(*F*52) | [18] |
| 26 |  | [8] | 56 | Logarithmic standard deviation value: *F*56 = log(*F*4) | [18] |
| 27 | Histogram upper bound: | [9] | 57 | Waveform length ratio: | [19] |
| 28 | Histogram lower bound: | [9] | 58 | Mobility:  *F*4ʹ is the standard deviation of the first derivative of the vibration signal | [20] |
| 29 | Clearance factor: | [10] | 59 | Complexity:  *F*4ʺ is the standard deviation of the second derivative of the vibration signal | [20] |
| 30 | Log-log ratio: | [8] | 60 | Willison amplitude: | [7] |

References

1. Motahari-Nezhad M, Jafari SM. Bearing remaining useful life prediction under starved lubricating condition using time domain acoustic emission signal processing. Expert Syst Appl. 2021; 168: 114391.
2. Yang YZ, Jiang DX. Casing vibration fault diagnosis based on variational mode decomposition, local linear embedding, and support vector machine. Shock Vib. 2017; 5963239.
3. Wang X, Zheng Y, Zhao ZZ, Wang JP. Bearing fault diagnosis based on statistical locally linear embedding. Sensors. 2017; 15(7): 16225–16247.
4. Paliwal D, Choudhury A, Tingarikar G. Wavelet and scalar indicator based fault assessment approach for rolling element bearings. In: The 2014 International Conference on Advancess in Manufacturing and Materials Engineering. Jakarta, Indonesia. Procedia Materials Science. p. 2347–2355.
5. Niknam SA, Songmene V, Au YHJ. Proposing a new acoustic emission parameter for bearing condition monitoring in rotating machines. T Can Soc Mech Eng. 2013; 37(4):1105–1114.
6. Bagheri B, Ahmadi H, Labbafi R. Application of data mining and feature extraction on intelligent fault diagnosis by Artificial Neural Network and k-nearest neighbor. In: IEEE 2010 XIX International Conference on Electrical Machines. Rome, Italy, 2010 Sep 6-8, IEEE Press, p.1–7.
7. Altin C, Er O. Comparison of different time and frequency domain feature extraction methods on elbow gesture's EMG. Eur J Interdis Stu Art. 2016;5(1):35–44.
8. Kumar HS, Pai SP, Sriram NS, Vijay GS. Rolling element bearing fault diagnostics: Development of health index. Pro IMechE Part C: J Mech Eng Sc. 2016; 1–17.
9. Heche BEV. Development of novel acoustic based methodology and tools for bearing fault diagnostics (Ph.D. Thesis). University of Illinoise: USA; 2015.
10. Ratnam C, Jasmin NM, Rao VV, Rao KV. A comparative experimental study on fault diagnosis of rolling element bearing using acoustic emission and soft computing techniques. Trib Indus. 2018; 40(3):501–513.
11. Sharma A, Jigyasu R, Mathew L, Chatterji S. Bearing fault diagnosis using weighted K-nearest neighbor. In: Proceedings of 2nd international conference on trends in electronics and informatics. Tirunelveli, India. 2018 May 11–12. IEEE Press. p. 1132-1137.
12. Kavsaoğlu AR, Polat K, Bozkurt MR. An innovative peak detection algorithm for photoplethysmography signals: an adaptive segmentation method. Turk J Electr Eng Co. 2016; 24(3): 1782–1796.
13. Farooq M, Fontana JM, Boateng AF, McCrory MA, Sazonov E. A comparative study of food intake detection using artificial neural network and support vector machine. In: Proceedings of 12th International Conference on Machine Learning & Applications, Miami, USA, 2013 Dec 4–7. IEEE Computer Society, p.153–157.
14. Wang Y, Peng YZ, Zi YY, Jin XH, Tsui KL. A two-stage data-driven-based prognostic approach for bearing degradation problem.IEEE T Ind Inform. 2016; 12(3):924–932.
15. Chen JJ, Xu B, Zhang X. A vibration feature extraction method based on time-domain dimensional parameters and mahalanobis distance. Math Probl Eng. 2021; 2498178:1–12.
16. Samuel OW, Zhou H, Li XX, Wang H, Zhang HS, Sangaiah AK, et al. Pattern recognition of electromyography signals based on novel time domain features for amputees' limb motion classification. Comput Electr Eng. 2018; 67:646–655.
17. Englehart K, Hudgins B. A robust, real-time control scheme for multifunction myoelectric control. IEEE T Bio-med Eng. 2003; 50(7):848–854.
18. AL-Quraishi MS, Ishak AJ, Ahmad SA, Hasan MK, Al-Qurishi M, Ghapanchizadeh H, et al. Classification of ankle joint movements based on surface electromyography signals for rehabilitation robot applications. Med Biol Eng Comput. 2017; 55:747–758.
19. Nayana BR, Geethanjali P. Improved identification of various conditions of induction motor bearing faults. IEEE T Instrum Meas. 2020; 69(5):1908–1919.
20. Caesarendra W. Vibration and acoustic emission-based condition monitoring and prognostic methods for very low speed slew bearing (Ph.D. Thesis). University of Wollongong: Australia; 2015.