Rolling Bearing Fault Trend Prediction Based on Composite Weighted KELM

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The abilities of different degradation feature types to characterize rolling bearing fault trend are distinctive. And even the characteristic ability of the same degradation feature can change at various times. Thus these feature samples possess heteroscedasticity. However, traditional kernel extreme learning machine (KELM) model assumes that different input samples’ effects on the predicted value are equal, which results in low prediction precision and low computing efficiency. To solve this problem, a novel composite weighted KELM (CWKELM) prediction model, which is fused with explicit weighting and implicit weighting, is proposed. In both feature type scale and sample time scale, the feature samples and the prediction model are weighted according to the prediction error. An adaptive mutation particle swarm optimization (AMPSO) algorithm is applied in optimizing the penalty factor and the kernel parameter in the model. Taking various entropy features as the input samples, the proposed model is adopted to conduct one-step and multi-step prediction for rolling bearing fault trend. Experimental results show that this prediction model has higher prediction accuracy and computing efficiency compared with the traditional KELM model.

1. INTRODUCTION

Rolling bearing is one of the key components that are widely used and affect the health status of rotating machinery. In order to prevent bearings and equipment from failure or damage, it’s of great safety significance and economic value to carry out rolling bearing fault trend prediction. The key of rolling bearing fault trend prediction is to extract accurate degradation characteristics and establish a good predictive model.

On the one hand, as the input sample of the prediction model, the degradation characteristics need to be sensitive and robust to the degradation state of the rolling bearings in the whole life cycle. The nonlinear complexity characteristics based on the information entropy theory can measure the probability distribution difference of variable bearing vibration signals in different degradation stages from multiple perspectives. And these degradation characteristics can reveal the developing trend of the ball bearing degradation state in essence. Therefore, entropy characteristics, including multiscale entropy, energy spectrum entropy, singular spectrum entropy and spatial information entropy etc. have been widely utilized in rotating machinery fault diagnosis and prediction. These characteristics are combined with time-frequency analysis methods and perform well in fault diagnosis and degradation state identification. Zhang et al proposed a novel hybrid bearing fault classification method based on permutation entropy (PE) and ensemble empirical mode decomposition (EEMD) which can calculate the multi-scale intrinsic characteristics as the fault classification features. In order to extract accurate fault features from vibration signals, Li et al employed multi-scale permutation entropy (MPE) to characterize the complexity of the product function (PF) components which are computed by local mean decomposition (LMD). Zheng et al put forward a new and effective bearing fault diagnosis methodology based on fuzzy entropy (FuzzyEn) and a self-adaptive time-frequency analysis method named local characteristic-scale decomposition (LCD) which deals with rolling bearing vibration signals. In summary, the information entropy features are mostly applied in rolling bearing fault classification and diagnosis, and the effect is significant. However, there are few applications of entropy features in the characterization and prediction of the whole degradation life of rolling bearings. This is mainly due to the degradation state of rolling bearings changing at every moment in their full life cycles. Bearing vibration signals have a large amount of non-stationary and unbalanced data that are difficult to process. When dealing with degradation data during the bearings’ whole life cycles, there are wide performance variations of different single entropy features on both type scale and time scale and it can very likely result in a large prediction error. Therefore, it’s better to carry out an effective weighted fusion pro-