

Bearing Fault Diagnosis using Multi-sensor Fusion based on weighted D-S Evidence Theory

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Abstract—This paper has presented a novel method for bearing fault diagnosis using a multi-sensor fusion approach based on an improved weighted Dempster-Shafer (D-S) evidence theory combined with Genetic Algorithm (GA). Vibration measurements are collected from an industrial multi-stage centrifugal air compressor using three wireless acceleration sensors. Fine-to-Coarse Multiscale Permutation Entropy (F2CMPE) is applied to extract the complexity changes of vibration data sets. Then, the extracted feature vectors produced by F2CMPE via multiple scales are fed into Back Propagation Neural Network (BPNN) for fault classification. The normalized probability outputs of BPNN are considered now as inputs of the proposed weighted D-S evidence theory for multi-sensor information fusion. The measurements collected from real industrial equipment are analyzed using the proposed diagnosis method, and the experimental validation has demonstrated its efficiency to identify rolling bearing conditions, the results of which have also shown higher accuracy compared to those using individual sensor signal analysis.

Keywords—Fault Diagnosis, Multi-sensor Fusion, Fine-to-Coarse Multiscale Permutation Entropy, Back Propagation Neural Network, Weighted D-S Evidence Theory.

I. INTRODUCTION

Rolling bearing plays a vital role in industrial rotating machinery, such as aerospace, mechanical and petrochemical plants. In the industrial manufacturing process, higher demands on the safety and reliability of industrial systems are increasingly needed to avoid unexpected downtime and potential personnel injury [1], [2]. Fault detection and diagnosis of rolling bearing are vital to pinpoint the incipient failures and isolate faults as early as possible, which is critical to condition-based maintenance [3]–[5]. For monitoring the real-time working states of bearings, sensors are normally mounted on places that are close to rolling bearing and

used to measure various signals, such as vibration, acoustic emission, and current signals. Typically, the use of a single sensor is generally enough to collect signals from rolling bearing; however, the premise is that the sensor itself must be healthy and precise. In the complex environment, after a long time work, the sensor may also have failures; hence, this may not accurately reflect the intrinsic characteristics of bearing signals. Moreover, when the only sensor fails, the whole monitoring and analytic system cannot offer reliable diagnosis services, which leads to deteriorating performance of detecting failures and ensuring high reliability in industrial mechanical systems.

Multi-sensor system can give diverse observations of rolling bearing by deploying several wired or wireless sensors in different places to provide comprehensive and redundant monitoring information. The redundant information is especially useful when one of those monitoring sensors has faults or cannot work properly, by this time the others would still offer reliable monitoring information; hence, the reliability and robustness of the whole system can be greatly improved [6]. Multi-sensor data fusion is needed to make full use of multiple sensor data sources to achieve consistent interpretation and description of bearing conditions [7]. Dempster-Shafer (D-S) evidence theory is one of the most common and useful methods for fusing multi-source information [8]. It can be considered as a generalization to the Bayesian theory that deals with probability mass functions and gives useful combination rules to fuse information. In the past decades, it has been widely applied for fault diagnosis of rotating machinery. In [9], Yang and Kim proposed an induction motor diagnosis method by fusing vibration and current signals using D-S evidence theory. They applied Neural Networks (NN) to classify different conditions of motors, the output results of which are then fused using D-S fusion method. Khazaei et al. [10] developed a classifier fusion method for gearbox fault diagnosis based on vibration and acoustic signals. D-S evidence theory was applied to fuse fault diagnosis accuracy rates obtained by Neural Network (NN). Xiong et al. [11] applied D-S evidence theory to deal with the uncertainty of the information through the

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k -nearest neighbor and dimensionless indicators to improve the reliability of bearing fault diagnosis. It should be noticed that, in the case of multiple sensors, differences usually exist in various sensors, such as the deployment places and the acquisition precision because of the manufacturing process. Not all the usefulness and quality of data collected from these sensors are the same. Hence, there is a strong need to assign important factor, namely the concept of evidence weight, to various sensors to maximize the usefulness of redundant information measured from these sensors so that the efficiency of both monitoring and the analytic system can be guaranteed and enhanced to the most extent. Recently, an improved D-S evidence theory method was proposed in [12], where weights were proactively assigned to each evidence source by the authors' experience. Nevertheless, human's practical experiences may be not limited which may not be in line with the real situations due to the complex industrial equipment and environments. Besides, it is more convenient and credible to appropriately acquire evidence weights from experimental data sets rather than empirical decisions according to various application scenarios.

In this paper, a new weighted D-S evidence theory is proposed with the combination of Genetic Algorithm (GA), where GA is used to self-adaptively locate the optimized weights of sensors. Through the optimization, the sensors that can give accurate and reliable results are given more trust and a larger important factor. The procedure of the proposed method is presented in Fig. 1. Vibration measurements are collected from an industrial system using three wireless acceleration sensors, and the Fine-to-Coarse Multiscale Permutation Entropy (F2CMPE) measure is applied to extract entropy features from vibration signals. After that, entropy feature vectors are fed into Back Propagation Neural Network (BPNN) for fault classification, and the output results are normalized and then considered as input into the weighted D-S evidence theory for decision fusion. The main contributions in this paper are concluded as follows:

- An improved multi-sensor data fusion method, namely a weighted D-S evidence theory, is proposed with the combination of GA for optimizing weights through the analysis of bearing vibration data sets.
- A new rolling bearing fault diagnosis is developed based on F2CMPE, BPNN, and the proposed D-S evidence theory by fusing three wireless sensors's evidences, the efficiency of which has been verified through the analysis of experimental vibration signals collected from an industrial experimental test rig.

The rest of this paper is organized as follows: Section II presents the principles of F2CMPE, original and weighted D-S evidence theory. Section III introduces the proposed bearing fault diagnosis method based on F2CMPE, BPNN, and proposed weighted D-S evidence theory. Section IV shows the experimental results through investigating the proposed method for analyzing bearing vibration signals. Finally, conclusions are drawn in Section V.

II. BACKGROUND OF F2CMPE MEASURE AND THE PROPOSED WEIGHTED D-S METHOD

This section briefly introduces the principles of F2CMPE measure for feature extraction, D-S evidence theory and the

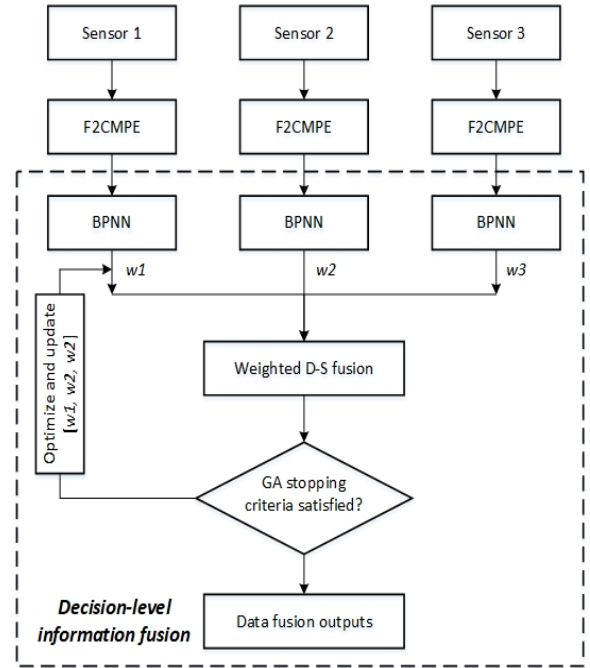


Fig. 1: Framework of the proposed bearing fault diagnosis method based on the F2CMPE, BPNN, and weighted D-S evidence theory.

proposed weighted D-S evidence theory for data fusion.

A. F2CMPE

F2CMPE is a newly proposed multiple-scale entropy method for estimating the complexity and irregularity of time series based on the analysis of fine-grained and coarse-grained time-frequency signals using Permutation Entropy (PE) via multiple scales [13]. Given a signal $\{x(i), 1 \leq i \leq N\}$, the calculation of F2CMPE mainly includes three steps:

- 1) Generate reconstructed signals: apply wavelet packet decomposition to decompose the signal $x(i)$ to the first decomposition level, then select the approximate coefficient and continue to decompose the approximate coefficient to a j -th level. Reconstruct wavelet coefficients in the j -th level to the signals with data length N ; hence, 2^j reconstructed signals, $R_{j,n} (0 \leq n \leq 2^j - 1)$, are obtained.
- 2) F2C procedure: construct F2C signals by successively removing the reconstructed signals having high-frequency bands, starting from the accumulation of all reconstructed signals in the j^{th} level:

$$F2C(\tau) = \sum_{i=0}^{2^j - \tau} R_{j,i}, 0 \leq i \leq 2^j - 1, 1 \leq \tau \leq 2^j \quad (1)$$

- 3) Perform PE measure: estimate the complexity of F2C signals ($F2C(\tau), 1 \leq \tau \leq 2^j$) over different scales using PE, where τ is the scale factor.

$$PE = -\ln(k!)^{-1} \sum_{j=1}^{k!} p(\pi_j) \ln(p(\pi_j)) \quad (2)$$

where for each permutation, π_j , the relative frequency can be determined by:

$$p(\pi_j) = \frac{\text{Number}\{X_i^k\}}{N - (k-1)\lambda} \quad (3)$$

where $\text{Number}\{X_i^k\}$ represents the number of X_i^k which is consistent with the type π , k is the embedding dimension, and λ is the time delay in the calculation of PE. For brevity, more details can be found in [14].

B. BPNN

Artificial Neural Network (ANN) is a kind of network system that imitates the human brain information processing mechanism [15]. Multi-layer feed-forward neural network and error Back Propagation (BP) arithmetic are most widely used networks in the field of fault diagnosis. Multi-layer BPNN can realize the arbitrary nonlinear mapping between the input and output of network, which could be used for the function approximation, pattern recognition, and so on. In a BPNN, a single sample has r inputs and n outputs, and there are several hidden layers between the input and output layers. For a mechanical system, the relationships between fault types and fault characteristics are normally non-linear; hence, BPNN could be used to identify and classify fault patterns based on the input of intrinsic fault features obtained from rotating machinery. A three-level BPNN is used, and we set the transfer function to Tan-sigmoid and training function to trainlm in this study. The outputs of BPNN are then normalized between zero and one, which are considered as input into D-S evidence theory for multi-sensor decision fusion.

C. Classic D-S Evidence Theory

D-S evidence theory is a multi-source information fusion theory that is concerned with the questions of belief in a proposition and systems of propositions [8]. Let $\Theta = \{\theta_1, \theta_2, \dots, \theta_N\}$ be a finite nonempty set of N elements that are mutually exclusive and exhaustive. $P(\Theta)$ is assumed that constitute the set Θ of their subsets. For any proposition Θ , the mass function m is defined as a mapping of the $P(\Theta)$ to a number between 0 and 1, which satisfies the following conditions:

$$m(\emptyset) = 0, \quad \sum_{A \subseteq P(\Theta)} m(A) = 1 \quad (4)$$

where \emptyset denotes an empty set, A denotes non-empty focal element of power sets, and m is also called Basic Probability Assignment (BPA) on the hypothesis space.

Suppose m_1 and m_2 are two BPAs obtained from two evidence sources in the same frame of discernment, the fusion algorithm of the classic D-S evidence theory is defined as:

$$m(\emptyset) = 0 \quad (5)$$

$$m(A) = m_1 \oplus m_2(A) = \frac{1}{1-K} \sum_{B \cap C = A} m_1(B)m_2(C) \quad (6)$$

where K represents the amount of conflict between the two data sources and is given by

$$K = \sum_{B \cap C = \emptyset} m_1(B)m_2(C) \quad (7)$$

The larger K is, the more conflicting the data sources are and the less informative their combination is.

D. Weighted D-S Evidence Theory

In D-S evidence theory, K is a conflict coefficient to measure the conflicting degree between evidences, and $1-K$ is a normalization factor. This factor strongly implies the agreement between multiple sources and ignores the conflict between them. Yager improved D-S evidence theory by classifying conflicting evidence into set Ω [16]. In Yager's rule, Ω and $q(A)$ for two pieces of evidence can be presented by following equations [16], [17]:

$$\Omega_i = 1 - \alpha_i \quad (8)$$

$$q(A)_{12} = \sum_{B \cap C = A} m_1(B)m_2(C) + \sum_{B \cap C = A} m_1(B) \times \Omega_2 + \sum_{B \cap C = A} m_2(C) \times \Omega_1 \quad (9)$$

where α_i is the weight of evidence or importance factor of evidence, and $q(A)$ is ground probability assignment. In Yager's formulation, he circumvents normalization by allowing the ground probability mass assignment of the null set to be greater than 0 to alleviate the evidence conflict issue: $q(\emptyset) \geq 0$. The new combination rule for two evidence is presented as

$$m_{12}(A) = m_1 \oplus m_2(A) = \frac{q(A)_{12}}{1 - q(\emptyset)} \quad (10)$$

Based on two evidence fusion using Yager's rule, we extend it to three pieces of evidence when three sensors are independently used for bearing fault diagnosis. Assume w_i is the importance factor of the evidence acquired using the i -th sensor, which subjects to

$$0 \leq w_i \leq 1 \quad (11)$$

$$\sum_{i=1}^n w_i = 1 \quad (12)$$

where n is the number of sensors applied in the data acquisition. Therefore, for three evidence data fusion, the rule can be followed by:

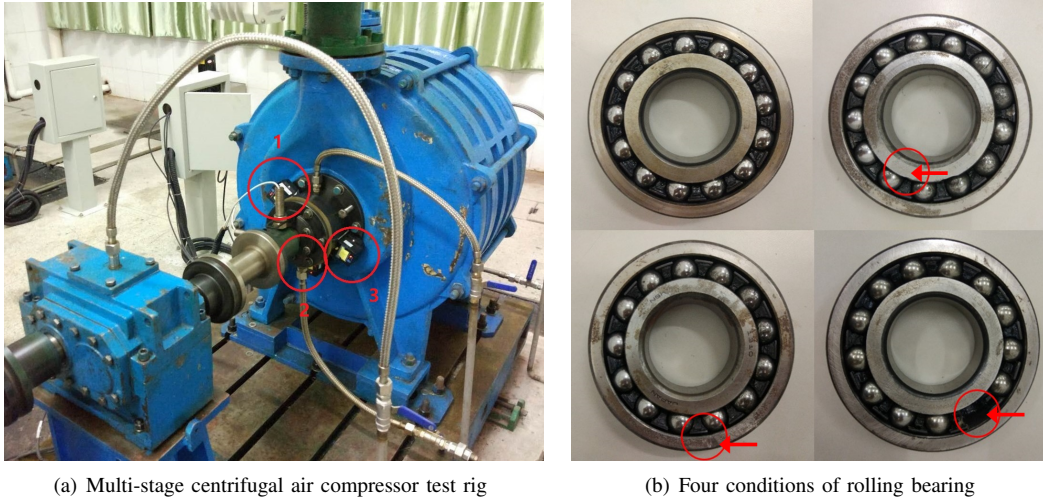
$$\Omega_i = 1 - w_i, \quad 0 \leq w_i \leq 1, \quad 1 \leq i \leq 3 \quad (13)$$

$$q(A)_{123} = \sum_{B \cap C = A} m_{12}(B)m_3(C) + \sum_{B \cap C = A} m_{12}(B) \times \Omega_3 + \sum_{B \cap C = A} m_3(C) \times \Omega_{12} \quad (14)$$

where $m_{12}(B)$ is obtained by using Eq. (9) and Eq. (10) to combine two BPAs m_1 and m_2 , and in this study we assume the important factor of the $m_{12}(B)$ as the average of w_1 and w_2 ; hence, $\Omega_{12} = 1 - (w_1 + w_2)/2$. The new combination rule for three evidence, m_1, m_2, m_3 , is defined as following

$$m(A)_{123} = (m_1 \oplus m_2) \oplus m_3(A) = \frac{q(A)_{123}}{1 - q(\emptyset)} \quad (15)$$

To self-adaptively obtain the appropriate important factor w_i of each sensor through experimental analysis rather than



(a) Multi-stage centrifugal air compressor test rig

(b) Four conditions of rolling bearing

Fig. 2: Experimental test rig and four conditions of rolling bearings (normal condition, and damages on inner race and outer race, ball lacked conditions).

the empirical assignment manner with human's prior knowledge, GA is applied to acquire the appropriate weights by optimizing the fitness function that could achieve the highest classification accuracy rate for bearing fault identification. The fitness function is given as follows:

$$fit = \left(\frac{N_f}{N_t + N_f} \right) \times 100\% \quad (16)$$

where N_t and N_f are the number of true and false classification outputs. In this study, a population size is set to 10 and the individuals are initialized with randomly generated genomes. The maximum number of generations were set 100 as the termination criterion for searching optimum solutions. The crossover probability is set 0.8, and the mutation probability is set 0.1 respectively.

III. PROPOSED MULTI-SENSOR DATA FUSION METHOD FOR BEARING FAULT DIAGNOSIS

In this section, the proposed bearing fault diagnosis method is introduced by using the F2CMPE, BPNN, and weighted D-S evidence theory. The procedure of the proposed method is presented in Fig. 1. The detail steps are described as follows:

- Step 1: synchronous data acquisition using three wireless vibration sensors which are mounted on three different places near to rolling bearing.
- Step 2: perform F2CMPE estimation to extract entropy features from original vibration signals to produce feature vectors. In the calculation of F2CMPE features, the decomposition level 4 is selected, and in total 16 F2C signals are generated. The embedding dimension k and the time delay λ are set to 5 and 3 respectively for computing PE measure.
- Step 3: apply BPNN to classify training samples with different conditions of rolling bearing. Then, the normalization results of the BPNN outputs is considered the BPAs as input into weighted D-S evidence theory for multi-sensor evidence fusion.

$$BPA_i = P_i / \sum_{i=1}^n P_i, \quad 1 \leq i \leq n \quad (17)$$

where P_i is the probability of the i -th condition of rolling bearing obtained from BPNN, and n is the number of conditions to be classified. Herein, $n = 4$.

- Step 4: assign a weight w_i ($1 \leq i \leq 3$) to three sensors and use GA to locate the the best solutions that satisfy stopping criteria or achieve the smallest error rate based on the proposed weighted D-S evidence theory.
- Step 5: based on the obtained optimized weights (important factors), apply the weighted D-S diagnosis model to analyze testing samples and verify its efficiency for bearing fault diagnosis with the use of F2CMPE and BPNN for feature extraction and fault classification respectively.

IV. EXPERIMENTAL STUDY

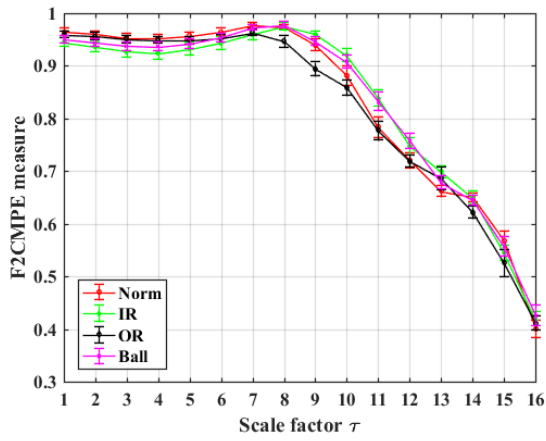
This section introduces the experimental test rig and results by analyzing vibrations signals measured from this large-scale rotating equipment.

A. Experiment Setup

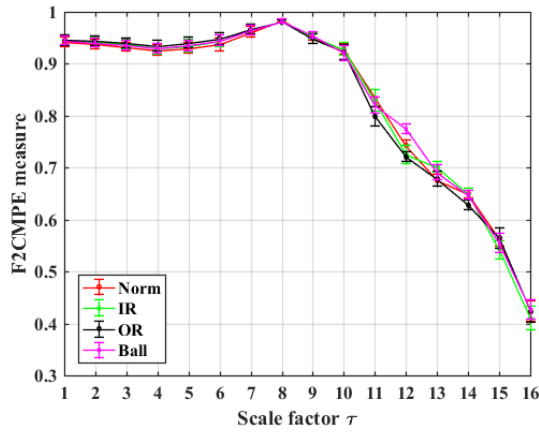
In the experiments, a multi-stage centrifugal air compressor equipment is used, and four conditions of rolling bearing are applied. The Fig. 2 (a) shows the applied experimental test rig, which consists of an inverter motor, multi-stage centrifugal fan, and gearbox. Fig. 2 (b) shows four conditions of rolling bearing, namely Normal bearing (Norm), Inner Race (IR) fault bearing, Outer Race (OR) fault bearing, and Ball (Ball) lacked bearing. Three wireless vibration sensors and one wireless gateway (designed by Beijing BeeTech Inc.) were applied to collect vibration signals from this equipment. Three wireless sensors are mounted on different places that are close to the rolling bearing. Sensors are connected to a data acquisition system using a wireless gateway via USB port. The rotating speed is 800 r/min, and the sampling rate is 1024Hz.

B. Results and Discussion

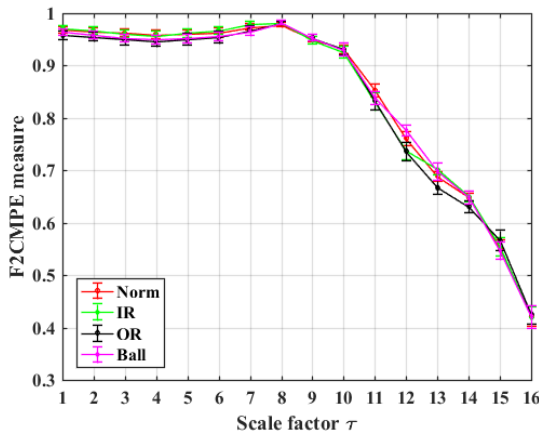
Vibration signals measured by three wireless sensors are analyzed using the proposed multi-sensor data fusion method. After data acquisition, in total 200 samples were



(a) Mean and SD values from Sensor 1



(b) Mean and SD values from Sensor 2



(c) Mean and SD values from Sensor 3

Fig. 3: Mean and SD values of the F2CMPE measure over 16 scales using sensor 1, sensor 2, and sensor 3 respectively.

collected for each condition; therefore, there are 2400 samples are obtained for four conditions and three sensors. In each condition, 100 samples are used for training, and the left 100 samples are selected for testing. The F2CMPE measure is then applied for extracting the complexity change of vibration signals. In this case, the level 4 is selected, and 16 F2C signals and scales are obtained. That is, 16 F2CMPE features are produced from each sample and are applied to construct entropy feature vectors for classifying bearing conditions. The mean and Standard Deviation (SD) values

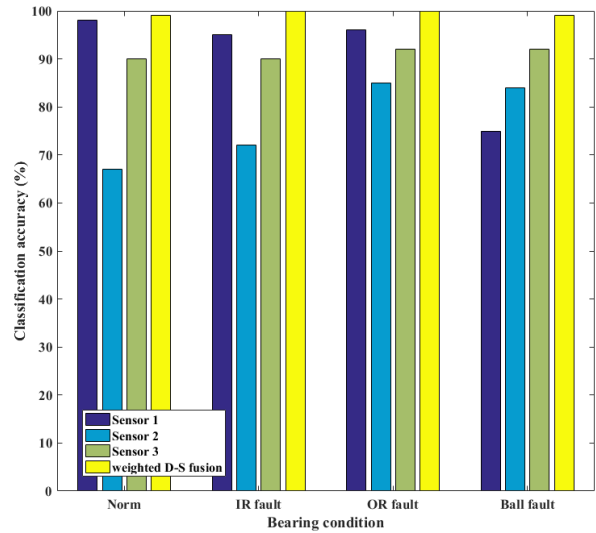


Fig. 4: Comparative classification accuracy by using individual sensor and three sensors based on the proposed weighted D-S evidence theory.

of the F2CMPE features for four conditions are illustrated in Fig. 3. It shows that both F2CMPE feature curves obtained from three sensors initially keep steady until the 8-th scale, then gradually decrease with an increasing scale. This can be explained that high-frequency components are consecutively removed from the previous F2C signals in the calculation of F2CMPE; hence, F2C signals at high scales become more and more smooth, as a result of which PE values obtained from such signals become smaller. Moreover, the F2CMPE measure has a small deviation which shows the stability when applied for characterizing the complexity of signals. Besides, Fig. 3 shows that starting from 8-th scale, an obvious distinction of four bearing conditions can be seen. Especially, in Fig. (3) (a), sensor 1 has more prominent features that can discriminate between four conditions of rolling bearing.

Comparative studies were carried out to verify the efficiency of the proposed data fusion method using three sensors (sensor 1 & 2 & 3) and the approaches using an individual sensor (sensor 1 or sensor 2 or sensor 3) for bearing diagnosis. For this study, F2CMPE and BPNN were applied as feature extraction and classification methods respectively. Comparative accuracy results are presented in Fig. 4. As can be seen, sensor 1 (dark blue) could achieve the highest classification accuracy rate in contrast with sensor 2 (light blue) and sensor 3 (green), the reason of which might due to the monitoring places and hidden noises that finally make the differences. From Fig. 4, it can be observed that the proposed diagnosis method (yellow) by fusing multi-sensor information can greatly improve bearing classification accuracy for identifying single condition, which achieves an average 99.5% for discriminating four conditions of rolling bearing. After searching the desired important factor using GA, the obtained weights assigned to sensor 1, sensor 2, and sensor 3 are 0.61, 0.26, and 0.13 respectively. Besides, for each single bearing condition, the accuracy rate of the proposed fusion method is higher than any of the approaches

where a single sensor is applied for bearing diagnosis. The experimental results have demonstrated the efficiency and reliability of the proposed multi-sensor decision fusion method for rolling bearing fault diagnosis in an industrial rotating machinery.

V. CONCLUSIONS

In this paper, an improved weighted D-S evidence theory was proposed with the combination of GA to self-adaptively optimize the weights of each evidence given by individual sensor. A new bearing fault diagnosis method is presented by using F2CMPE, BPNN, and weighted D-S evidence theory. F2CMPE features extracted from vibration signals that are collected from each sensor are fed into BPNN individually for fault classification. Then, the probability outputs of BPNN are normalized and considered as BPAs that are then fused using weighted D-S evidence theory for decision fusion. In this study, the experimental results have demonstrated the superiority of the proposed multi-sensor decision fusion method for bearing diagnosis. The use of three sensors can achieve higher classification accuracy rate compared to those applying individual sensor based on data-driven diagnosis approach where the F2CMPE and BPNN are used as feature extraction and classifiers respectively.

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ABBREVIATIONS

α_i	Importance factor
fit	Fitness function
Ω_i	Conflicting of evidence
π_j	Permutation type
τ	Time delay
j	Decomposition level
K	Conflict coefficient
k	Embedding dimension
m_i	BPA for the i -th evidence
N	Data length
P_i	Probability output from BPNN
$R_{j,n}$	Wavelet reconstructed signal
w_i	Weight of the i -th sensor's evidence
BPA	Basic Probability Assignment
BPNN	Back Propagation Neural Networks
D-S	Dempster-Shafer
F2CMPE	Fine-to-Coarse Multiscale Permutation Entropy
GA	Genetic Algorithm
PE	Permutation entropy
SD	Standard Deviation