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REVIEW

# Comprehensive Overview on Computational Intelligence Techniques for Machinery Condition Monitoring and Fault Diagnosis

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**Abstract** Computational intelligence is one of the most powerful data processing tools to solve complex nonlinear problems, and thus plays a significant role in intelligent fault diagnosis and prediction. However, only few comprehensive reviews have summarized the ongoing efforts of computational intelligence in machinery condition monitoring and fault diagnosis. The recent research and development of computational intelligence techniques in fault diagnosis, prediction and optimal sensor placement are reviewed. The advantages and limitations of computational intelligence techniques in practical applications are discussed. The characteristics of different algorithms are compared, and application situations of these methods are summarized. Computational intelligence methods need to be further studied in deep understanding algorithm mechanism, improving algorithm efficiency and enhancing engineering application. This review may be considered as a useful guidance for researchers in selecting a suitable method for a specific situation and pointing out potential research directions.

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## 1 Introduction

With the rapid development of science and technology in modern society, the developmental law of machinery and equipment has become considerably large scale, complex, and automated. Machinery condition monitoring and fault diagnosis are critical for modern industrial manufacturing. Effective condition monitoring enables the early detection of faults, with the consideration of downtime, maintenance cost, operation reliability, and production efficiency. Research on machinery condition monitoring and fault diagnosis are practically significant [1, 2].

The purposes of machinery condition monitoring and fault diagnosis are to determine the cause of abnormality and conduct necessary countermeasures by capturing the past and present condition data of equipment, such as vibration, noise, temperature, and lubrication state. A comprehensive condition monitoring program consists of three phases, namely, feature extraction, fault diagnosis, and prediction [3]. Feature extraction and fault diagnosis are usually used in detecting the abnormal state, determining the fault location, and predicting the failure extent [4]. Prognostic techniques relate to the remaining useful life (RUL) prediction, which is used in planning an effective maintenance strategy that can improve system reliability [5]. The realization of the importance of optimal sensor placement in condition monitoring system and optimal sensor placement methods are also investigated.

Several methods have been proposed for machinery condition monitoring and fault diagnosis in the last decades. These methods can be categorized into model-based, statistical, and artificial intelligence methods [1]. A model-based method is based on the physical characteristics of monitored machine for the establishment of an explicit mathematical model. Various model-based diagnostic methods have been widely used in gearboxes [6–8] and bearings [9]. However, the model-based method is difficult to use when the system model is complex, because such systems are often difficult to describe with a precise mathematical model. A statistical model assumes that historical data can be used to represent the future mechanism of mechanical failure. However, failure mechanism changes with respect to failure evolution. Therefore, statistical methods cannot fully represent the wear process, especially in the case of wear evolution stages [10]. Artificial intelligence techniques are suitable for addressing the complex and large-scale nonlinear problems without any statistical assumptions about the data [11].

Computational intelligence is a branch of artificial intelligence and extensively used in scientific research and engineering practice given the continuous increasing of computational resources and size decreasing of computing architectures. Examples of applications are quality control [12], robot control [13], medical and biological [14], and environmental [15]. Computational intelligence mimics nature and human beings by using computer science and technology; thus, it can also be called intelligent optimization method. Computational intelligence can be categorized into three main groups, namely, neural computation, evolutionary algorithms (EAs), and fuzzy computing. In the last decades, increased attention has been given to computational intelligence methods [16]. While considerable achievements have been acquired, several new computational intelligence techniques, such as fuzzy neural network [17], deep learning network [18], and extreme learning machine (ELM), have been proposed to solve the practical problem [19].

In existing literature, computational intelligence techniques have been investigated in the field of wave energy [20], financial market [21], and power quality disturbance [22, 23]. However, the published review articles about condition monitoring and fault diagnosis have a limited scope, by focusing either on fault feature extraction and classification [24], or on rotating machinery prediction techniques [5, 25]. However, few comprehensive reviews have summarized the ongoing of computational intelligence. Therefore, this paper attempts to review computational intelligence techniques and their applications for fault diagnosis, prognosis, and optimal sensor placement after 2009. This survey not only reviews the main primary studies but also discusses characteristics of the methods, which may be considered as a valuable guide for researchers in selecting a suitable method for a specific situation. Finally, some challenges in applying computational intelligence are discussed to draw some conclusions from the current research and main work to focus in future research.

The remainder of this paper is organized as follows. Section 2 reviews the application of computational intelligence in fault diagnosis. Section 3 presents the application of computational intelligence in prognosis. Section 4 investigates the application of computational intelligence method in optimal sensor placement. Section 5 presents a discussion on the application situations. Section 6 describes challenges and prospects in this area. Finally, Section 7 concludes the research.

## 2 Fault Diagnosis Using Computational Intelligence

Fault diagnosis combining fault mechanism and detection techniques; it is a subject based on the theory of signal processing and pattern recognition. Various algorithms based on computational intelligence for fault diagnosis are presented in this section. Fig. 1 shows the taxonomy of the computational intelligence techniques used as classifiers for machinery fault diagnosis.

### 2.1 Artificial Neural Network (ANN)

ANN is a special case of neural computation, which is inspired by the human brain. This neural network is a mathematical model that can achieve distributed parallel information processing. ANN can adjust the interconnections among internal nodes to achieve information processing of a complex system.

Diagnostic inference can be interpreted as a solution of a problem based on the specific mapping relationship between fault symptoms and fault causes. For complex mechanical systems, the mapping relationship is generally nonlinear. Therefore, ANN has been widely used in fault diagnosis because it can effectively approximate various mapping relations. At present, most of fault classification

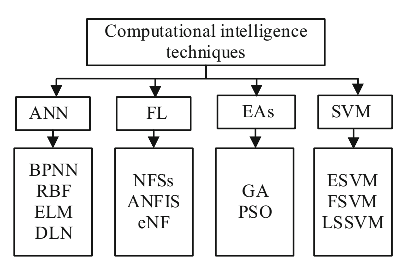


**Fig. 1** Taxonomy of computational intelligence

methods utilize time-frequency analysis methods as the early feature extraction, and ANN or its optimized forms are then employed for fault classification. Fig. 2 shows the flowchart of fault diagnosis based on ANN. In Ref. [26], wavelet packet transform (WPT) and ANN were integrated to diagnose fault in internal combustion engine, in which WPT was used to extract the fault characteristics, and generalized recurrent neural network (RNN) was proposed to classify various fault conditions. Lei, et al [27], proposed an intelligent diagnosis method based on ensemble empirical mode decomposition (EEMD) and wavelet neural network. EEMD was used to extract the characteristics of time and frequency domains from the sensitive intrinsic mode functions (IMFs). Wavelet neural network was adopted to complete the pattern recognition. WPT and empirical mode decomposition (EMD) were utilized to preprocess and extract features, and ANN was used to diagnose early fault in rotating machinery [28]. Cui, et al [29], proposed a new backpropagation neural network (BPNN) based on the coefficient entropy of wavelet packet decomposition to realize quantitative diagnosis of fault severity trend of rolling bearings. Saravanan, et al [30], presented a new hybrid method based on discrete wavelet transform (DWT) and ANN to diagnose various faults of spur bevel gearbox. Zhao, et al [31], utilized BPNN and improved shuffled frog-leaping algorithm (SFLA) to perform fault classification. The accurate selection of suitable features that reflect the running status of equipment in practical application of fault diagnosis is the key point of research. Therefore, fault feature selection based on ANN is an important research direction.

Fault diagnosis of mechanical system based on ANN has some limitations. First, extraction and selection of features depend largely on the prior knowledge of signal-processing technique and diagnosis experience, and generalization is weak. Second, ANN adopts a shallow structure, which also limits ANN to learn complex nonlinear structures in fault

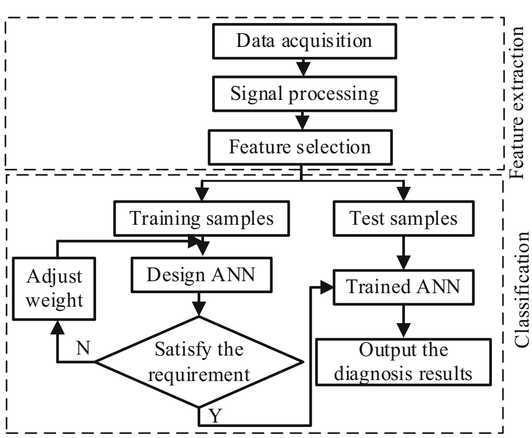


**Fig. 2** Flowchart of fault diagnosis based on ANN

diagnosis [32]. Deep neural network (DNN) is developed based on deep learning theory, which can enhance the accuracy of big data classification [33] and effectively overcome the preceding shortcomings. Deep learning was first introduced into the field of fault diagnosis by Tran, et al [34], who applied deep belief network (DBN) based on Teager energy operator to achieve fault diagnosis of reciprocating compressor valves. A multisensor health diagnosis method based on the DBN was presented in Ref. [35], which classified the sensor signals collected from a damaged structure. Guo, et al [36], developed a hierarchical adaptive deep convolutional neural network for bearing fault diagnosis. Jia, et al [32], used DNN for intelligence fault diagnosis in rotating machinery, especially in the case when the vibration data were massive. ELM has been extensively applied and popularized in the fault diagnosis of mechanical system in recent years. Yang, et al [37], proposed a multilayer ELM based on representational learning for fault diagnosis. The effectiveness of this method was successfully verified by applying a wind turbine system. Wei, et al [38], proposed a method based on local mean decomposition to identify the different fault types of gearbox, combining permutation entropy and ELM. More references on the applications of ELM in machine fault diagnostics were provided in Refs. [39–42].

## 2.2 Fuzzy Logic and Neuro-Fuzzy Systems (NFSs)

Fuzzy theory is the process of imitating the way that people logically think in dealing with fuzzy information, which is suitable for the qualitative analysis of complex large-scale systems. The relationship between fault and symptom is difficult to describe using an accurate mathematical model due to the complexity of engineering practice. Therefore, the application based on fuzzy logic theory in fault diagnostics is closer to human thinking habits and language expression. Fuzzy logic is an effective pattern recognition method, which has been successfully used in power [43], transmission line [44], transportation [45], and industrial production [46]. Fuzzy logic mainly imitates human's logical thinking and thus has strong capability of expressing knowledge. ANN imitates the function of human brain neuron, which has the strong capability of self-learning and direct processing of data. Adaptive neuro-fuzzy inference system (ANFIS) comprises both merits of neural network and fuzzy logic. Zheng, et al [47], proposed a fault diagnosis method based on local characteristic-scale decomposition (LCD) and fuzzy entropy (FuzzyEn) for fault diagnosis of rolling bearings. A series of intrinsic scale components (ISCs) was first obtained using LCD, and the FuzzyEns of the first few ISCs that contained the main failure information were then extracted. Finally, the FuzzyEns were used as the input of the ANFIS, which achieved the accurate classification of bearing fault types. Zhang, et al [48], proposed an early fault diagnosis method based on multiscale entropy and ANFIS. Tran, et al [49], combined ANFIS with decision tree to achieve fault diagnosis. Result indicated that the proposed method could effectively diagnose the fault of induction motors. Wu, et al [50], combined DWT with ANFIS to identify gear faults. DWT was used to extract the energy spectrum feature vector, which was regarded as ANFIS input.

### 2.3 EAs

Neural computation is the process of imitating the physiological structure and information processing of the human brain, whereas EA is the process of imitating the biological evolution and group intelligence. EAs provide a new way to address complex optimization problems, which have the advantages of simple principle and convenient implementation, especially in the case of solving large-scale dynamic optimization problems.

The present review of EAs used for fault diagnosis can be broadly divided into two sections, as shown in Fig. 3.

#### 2.3.1 *Fault Feature Extraction Using EAs*

The main function of EAs in fault feature extraction is to optimize signal-processing methods. For example, EAs are used in optimizing filtering parameters or wavelet basis function to better extract fault features. At present, genetic algorithm(GA) and particle swarm optimization(PSO) are widely used in fault feature extraction. Li, et al [51], presented an adaptive cascaded stochastic resonance method to detect the weak impulsive features submerged in noise; the multi-parameters of this method were optimized by GA synchronously, and results showed that the proposed method was suitable for extracting the weak impact features of a gearbox. Lu, et al [52], applied GA to search the optimal multi-wavelets from an adaptive multi-wavelet library. Combination of optimal Morlet wavelet and autocorrelation analysis was used to extract the early stage fault of rolling bearings, and GA was employed to optimize the filtering parameters of the Morlet wavelet [53]. Some related research was conducted in the author's laboratory.

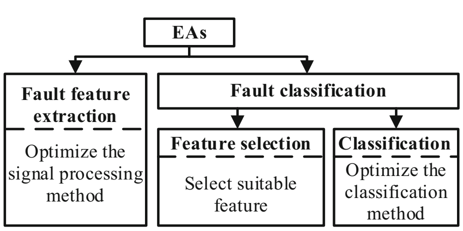


**Fig. 3** EAs used for fault diagnosis

For example, Yan, et al [54], employed PSO to optimize the structural element scale of the combined morphological hat transformation and improved the accuracy of the mathematical morphology operator in processing vibration signals. The experimental results showed that the proposed method could effectively identify the wear fault on the high shaft of a wind turbine gearbox. Zhang, et al [55], utilized SFLA to optimize the parameters of the Morlet wavelet and used information entropy as the fitness function. The optimized Morlet wavelet had superior capability in extracting the early fault feature of rolling bearings. Yan, et al [56] combined the optimal variational mode decomposition (VMD) and 1.5 envelope spectrum analysis to separate compound faults. In this current research, GA is used to select the decomposition parameters of VMD adaptively.

#### 2.3.2 *Fault Classification Using EAs*

EAs can simultaneously search multiple regions of the solution space, and include the computing mechanism of parallel processing and the characteristics of self-organization and self-learning, without any other auxiliary information. EAs are presently applied to fault diagnosis by combining with other algorithms. EAs are used to optimize the structural parameters of machine learning algorithm. Ciancio, et al [57], discussed the optimization of the structural parameters of ANN by GA, such as the number of hidden layers, the activation function of hidden and output layers, the number of neurons in the hidden layer, and the training algorithm. Unal, et al [58], applied GA to optimize ANN in fault diagnosis of rolling bearings. Shao, et al [59], utilized PSO to determine the DBN structure and employed the optimized DBN in the fault diagnosis of rolling bearings. More published literature of structural parameter optimization of ANN or support vector machine (SVM) based on EAs can be found in Refs. [60–64]. Conversely, feature selection based on EAs combining with classification method is used for fault diagnosis. Therefore, a feature selection process is indeed needed before fault classification. Considerable research has been conducted on this issue. For example, Sadegh, et al [65], utilized ANN to classify lubrication condition and employed GA to search for an optimal feature space. Saxena, et al [66], used GA to select an optimal feature set, which was used as the input of ANN for mechanical fault classification. GA could successfully determine the desired number of good features in a large search space. The superiority of the GA-ANN method was manifested in training accuracy and classification success rate. Ahmed, et al [67], integrated GA and ANN to select effective fault features in reciprocating compressors. Cerrada, et al [68], selected the optimal features of different stages based on

GA and then combined them with ANN for gearbox fault diagnosis to select the optimal characteristic parameters in the time, frequency, and time-frequency domains. More examples of EAs in feature selection are presented in Refs. [69, 70].

### 2.4 SVM

Broadly, neural computation includes kernel methods, such as SVM. However, SVM does not belong to ANN [20], and it is a new machine-learning method based on statistical theory.

SVM solves the optimal classification hyperplane by using the structural risk minimization principle, overcomes the dimensionality disaster and local minimum problem, and has a small demand for the samples. Therefore, SVM is particularly suitable for establishing a fault diagnosis model. SVM, which was first introduced into the field of fault diagnosis by Jack and Nandi [71], was used to achieve rolling bearing fault classification. SVM has been widely used in mechanical system fault diagnosis in recent years. Konar, et al [72], used wavelet transform and SVM to detect bearing faults in induction motors. Li, et al [73], proposed a fault diagnosis method based on redundant second-generation wavelet transform to achieve fault diagnosis, which was combined with neighborhood rough set and SVM. Cheng, et al [74], proposed singular value decomposition and SVM based on EMD to perform fault diagnosis of rolling bearings and gear. In this method, feature vector matrix was the singular value of the sensitive IMF component decomposed by EMD, which was regarded as SVM input for intelligent fault diagnosis. Zhang, et al [75], proposed a hybrid model based on permutation entropy, EEMD, and SVM for motor bearing fault diagnosis. The vibration signal was initially decomposed into a set of IMF components by EEMD. Then, the permutation entropy feature vector of the first few IMFs was obtained, which was regarded as the input of the optimized SVM for achieving fault-type classification. Some improved SVM has been proposed, such as ensemble SVM (ESVM) and fuzzy SVM (FSVM), to solve the problem of multiple fault classification. The ensemble classifier not only solves the multi-fault classification problem but also significantly improves the classification performance compared with the single SVM [76, 77]. Zheng, et al [78], proposed composite multiscale FuzzyEn and ESVM for rolling bearing fault diagnosis. FSVM was also used to solve multi-classification problems [79]. Hang, et al [80], employed EEMD to extract fault feature vectors, and FSVM was adopted to solve multi-classification problems in fan fault diagnosis. Comparison of FSVM classification results with back-propagation and standard SVM indicated that FSVM had higher classification accuracy. More recent references of SVM in fault diagnosis can be found in Refs. [81–88].

Although SVM has made some achievements in the research of machinery fault diagnosis, some issues need to be further studied, such as the following: (1) selection of the appropriate kernel function and its parameters; (2) selection of the appropriate multi-classification algorithm to meet the needs of a multi-fault classifier; (3) improvement of training speed to satisfy the real-time requirement of fault diagnosis; and (4) combination of other knowledge-based fault diagnosis methods, such as fuzzy logic and neural network, with SVM for fault diagnosis.

## 3 Prognostics Using Computational Intelligence

Prognostic plays a vital role in predicting RUL and optimizing machine usage in engineering practice [5]. Effective prognosis can avoid machine downtime that results in significant losses and reduce the risk of severe accidents [89]. The effective improvement of the performance of degradation assessment has been a subject undergoing intense study in academia and industry. Prognostic methods are divided into three categories, namely, physical model-based, data-driven, and hybrid prediction methods [25, 90]. The methods based on physical model describe the failure model of the system by using mathematical theory. The failure models have such ways as crack growth and peeling growth. However, describing a more stochastic and complex practical system model is difficult using these methods. In general, these models are only suitable for a specific fault type, and their universality is weak. Data-driven methods are used to analyze and predict the current and future health status of the mechanical system by using the condition monitoring data. These methods are applied to nonlinear reliability prediction when compared with physical model methods, which mainly include computational intelligence methods, statistical methods, and state space methods. Hybrid prediction methods combine physical model-based and data-driven methods. These methods can obtain more accurate and reliable prediction results. However, they are difficult to implement in practical application because of their large computation.

A large number of prediction methods have been proposed in recent years, however, establishing an efficient prediction method remains a problem that needs to be addressed. Compared with physical model-based methods, data-driven methods are a good choice in describing the complex and nonlinear degradation process. This section focuses on the application of computational intelligence approaches for fault prediction.

### 3.1 ANN

ANN implements RUL estimation and prediction of future health conditions by including direct or indirect observation data, independent from the failure process of a physical model. Various types of data can be used as the input of ANN, such as some process variables, monitoring data (vibration signals), evaluation characteristics (age and stop time), and some historical features. The output of ANN is RUL prediction or performance degradation assessment, which is used for conducting effective maintenance strategies. ANNs widely used in fault prediction include BPNN [91–95], radial basis function network (RBFN), and RNN [96]. Ahmadzadeh, et al [94], proposed a three-layer feedforward BPNN for RUL estimation of grinding mill liners, which considered degeneration and condition monitoring data as the inputs of ANN, and used RUL as the output of ANN. Rodriguez, et al [95], presented ANN (six input layers, three hidden layers, and one output layer) to predict and simulate the behavior of life-cycle assessment in blades of steam turbines. In view of the shortcomings of traditional incremental training methods in long-term prediction, Malhi, et al [96], proposed an RNN based on competitive learning method to improve the accuracy in long-term prediction of rolling bearings. Mahamad, et al [97], used feedforward neural network and the Levenberg-Marquardt training algorithm to predict the RUL of rolling bearings. Considering the complexity and nonlinearity of the pitch system, and the difficulty of describing with precise mathematical model, Chen, et al [98], proposed ANFIS based on a prior knowledge, which was used to predict wind turbine pitch faults. Existing ANN methods predict the RUL by using failure history data, but suspended historical data are rarely utilized. Hong, et al [99], used a self-organizing map, which combined wavelet packet and EMD for feature extraction, to estimate bearing performance degradation. Javed, et al [100], used ELM and fuzzy clustering to predict the degradation state and the RUL of complex nonlinear systems. Compared with ANN, ELM improved the algorithm efficiency by randomly selecting hidden layer parameters. Zhang, et al [101], proposed a multi-objective DBN ensemble method for RUL estimation.

### 3.2 Fuzzy Logic

The main purpose of introducing fuzzy logic is to overcome uncertainty and inaccuracy, and fuzzy logic has obvious superiority in dealing with large time delay, time variation, and nonlinear processing. This method is based on fuzzy mathematics theory, including the appropriate membership and fuzzy rules; then, fuzzy inference is continued to implement fuzzy prediction. Baban, et al [102], acquired the vibration and temperature signals of the textile machine, evaluated the machine status-based fuzzy logic, and implemented preventive maintenance. Stetter, et al [103], used fuzzy logic to monitor the health status of the pump system in an engine. Ishibashi, et al [104], combined decision tree, fuzzy logic, and GA for RUL prediction of aeroengine, and acquired the historical data from the sensor on the aeroengine. Tian, et al [105], proposed a fuzzy-adaptive unscented Kalman filter to improve the prediction accuracy of nonlinear processes. Zio, et al [106], proposed a method based on fuzzy similarity analysis to estimate system RUL. This method is subjective to manually select membership function of fuzzy logic. Therefore, this method is generally used in conjunction with fault tree, expert system, and neural network.

### 3.3 NFSs

Neural network and fuzzy logic are important methods in computational intelligence. The advantages of neural network are its parallel processing capability, strong fault-tolerant capability, self-learning, and self-adaptability. However, the neural network is similar to a black box, which lacks transparency. Expressive knowledge of weights in the network is not easy to understand, and ANN cannot utilize the language knowledge of experts. Fuzzy logic make the inference process understand easily, which can use expert knowledge directly, with lower requirements on the samples. Nevertheless, the disadvantages of fuzzy logic are slow inference speed and low precision. Adaptive learning is difficult to implement. Thus, the two above mentioned methods are integrated to form NFSs, which have the merits of both methods. NFSs have been widely used in machinery performance prediction in recent years. Zhang, et al [107], used neuro-fuzzy network to predict tool wear and RUL, considering that tool condition monitoring is critical to the manufacturing industry. Gokulachandran, et al [108], used neuro-fuzzy and support vector regression to evaluate RUL of cutting tools. The experimental results showed that the neuro-fuzzy method could obtain a more accurate prediction. Ali, et al [109], combined fuzzy neural network and Weibull distribution to predict RUL of rolling bearings. Chen, et al [110], employed ANFIS using a prior-knowledge-based method to predict wind turbine pitch fault. Zhao, et al [111], used neuro-fuzzy method to predict the health condition of bearings. Compared with the RBFN, the proposed method is superior with respect to reliability and robustness. Chen, et al [112], proposed a method based on NFSs and Bayesian algorithms to predict the health status of helicopter gearboxes and bearings. The results showed that the proposed algorithm was superior to RNN and NFSs in prediction accuracy. Ramasso, et al [113], proposed a method combining NFSs and belief function theory to evaluate the RUL of a turbofan engine. Wang, et al [114], proposed an evolutionary neuro-fuzzy (eNF) predictor on time-varying dynamic systems. A newly enhanced least squares estimator was used to train the linear parameters of the eNF predictor. Experiments showed that the proposed method could be successfully applied to mechanical condition monitoring. The existing literature shows that the NFSs are superior to other nonlinear prediction methods (that is, RNN and RBFN). Recent development of NFSs based on fault diagnosis can be found in Refs. [17, 115–122]. Nevertheless, several issues still need to be considered. For example, the number of nodes in the hidden layer is still difficult to be determined, and the selection of fuzzy parameters requires human intervention, all of which affect the prediction results of NFSs.

### 3.4 SVM

The establishment of a suitable model under the limited monitoring data is the key problem to estimate RUL and an urgent need for industrial production. SVM is a machine-learning algorithm based on Vapnik-Chervonenkis theory, which is used to solve the problems of classification and prediction when the sample size is small [123]. At present, SVM research mainly focuses on algorithm solution and model establishment. The purpose of algorithm solution is to address a constrained optimization problem by adopting the appropriate algorithm. The problem of model establishment includes optimization of model parameters, kernel function selection, feature vector extraction, and unbalanced sample. The aforementioned factors directly affect the model accuracy. Lu, et al [124], considered the difficulty of obtaining ideal prediction results under a small sample size. Thus, they proposed a least squares SVM (LSSVM) to estimate the degradation trend of slewing bearings and used PSO to optimize LSSVM parameters. Compared with the RBFN, the LSSVM model was demonstrated to be more accurate and effective. Dong, et al [125], used principal component analysis (PCA) to fuse the original features and reduce the dimension. Then, they used the LSSVM model to predict the bearing degradation process. Chen, et al [126], proposed an RUL prediction method based on relative feature and multivariate SVM (MSVM). In contrast to univariate SVM, MSVM overcame the shortcomings of insufficient condition monitoring information and mined potential, and useful information from small sample size. Caesarendra, et al [127], combined Cox proportional hazard model and SVM for failure degradation prediction of bearings. Widodo, et al [128], proposed a prediction method based on survival analysis and SVM. Kaplan-Meier and probability density function estimators were used to generate survival probability, and the kurtosis of measured data and survival probability were used as input and output of the SVM, respectively. The trained SVM successfully predicted machine failure time. Tran, et al [129], combined auto-regressive and moving average (ARMA) model, Cox proportional hazard model, and SVM for RUL prediction. Loutas, et al [130], used wavelet packet nodal energies and Wiener entropy as the feature vector, and proposed ε-support vector regression method in predicting the RUL of rolling bearings. He, et al [131], proposed a hidden Markov-SVM to predict surface roughness in hard turning. More published literature of applying SVM in RUL estimation of mechanical systems can be found in Refs. [132–137]. SVM has been successfully developed rapidly in recent years, with an increasing number of studies focusing on SVM. However, SVM still has some problems to be solved, such as feature selection and large-scale training sample problem.

## 4 Optimal Sensor Placement Using Computational Intelligence

Appropriate measurement strategy should be adopted and sensor placement should be optimized to obtain sufficient and effective measurement information, and improve the diagnostic capability of a machinery system. Practical experience shows that although sensor redundancy can effectively reduce the loss of information, the mass of data transmission will greatly increase the cost of data analysis and processing, especially in long-distance transmission network. The optimal sensor placement plays an important role in structural model updating and structural health monitoring. The existing literature indicates that sensor optimization placement has been effectively applied to various engineering systems, such as bridges [138, 139], trusses [140–142], beams [143], plates [144], gearbox systems [145], and manufacturing processes [146, 147].

The optimal sensor placement problem generally consists of two aspects, as presented in Fig. 4. A multi-objective combinatorial optimization problem is built due to the complexity of the actual engineering structure. This problem is an NP-hard problem, and computational intelligence plays an important role in solving such a problem, among which GA is widely applied and studied [148, 149]. Rao, et al [139], treated

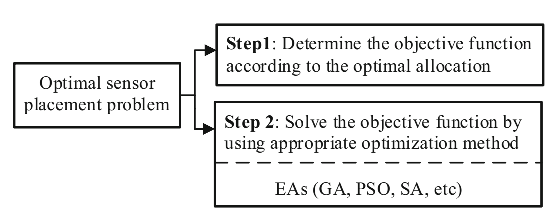


**Fig. 4** Process of solving the optimal sensor placement problem

an optimal sensor placement problem as a combinatorial optimization problem, which was solved by using a hybrid PSO, and this method was successfully applied to a slab bridge. Guo, et al [141], proposed an improved GA to solve the optimization objective function and applied this method to search for the optimal sensor position of the truss structure. Mahdavi, et al [142], proposed a wavelet-based GA to search the optimal sensor location of a 2D steel and pin-jointed truss structure. Dutta, et al [143], combined the artificial bee colony algorithm with the glowworm swarm optimization algorithm to determine the optimal position of actuators and sensors in cantilever beams. Pan, et al [145], solved an optimal sensor placement problem using adaptive-speed PSO. Ren, et al [146], presented a data-mining-guided evolutionary method to address the optimal sensor location problem in a multi-station assembly process. Based on the finite element modeling and modal analysis of gearbox, a feature-based approach for determining the optimal sensor position in a multi-station assembly project was proposed [147], and GA was employed to solve this optimization problem. Lian, et al [150], proposed a fitness function of near-neighborhood index, and adopted improved PSO and clonal selection algorithm to solve the proposed fitness function. Chow, et al [151], proposed a hybrid method integrating GA with entropy-based method to solve the sensor location problem of transmission towers. Some research in this field has been performed in the author's laboratory. For example, a new improved SFLA was proposed in Ref. [152] and was applied to the multi-type sensor network optimization problem of gearboxes. He, et al [153], proposed an adaptive EA based on GA to optimize the sensor placement for cutting process condition monitoring. In Ref. [154], an improved SFLA based on quantitative causal graphs was applied to address the optimal sensor placement in a single-station multistep manufacturing process.

Optimal sensor placement is a key step in the rationality, accuracy, long term, and economy of structural health monitoring. Although some great progress has recently been made in the theory of sensor optimization, it still faces some problems, such as determining how to use the optimal sensor placement theory directly as a guide in engineering practice. Several researchers have focused on improving the efficiency of the optimization algorithm and reducing the number of iterations. The fusion of different methods can form a new hybrid algorithm, which includes the merit of different methods. The above mentioned aspects should be given more focus in future research.

## 5 Discussion

In previous section, we have summarized several computational intelligence methods and their applications in condition monitoring and fault diagnosis. The application scope is decided, considering that different computational intelligence methods have different characteristics. This section discusses the selection of a suitable method for special problems instead of choosing randomly.

ANN: On the basis of the literature review, ANN is one of the most commonly used classifiers in intelligent fault diagnosis methods, which has the capabilities of high learning and generalizing performances. The accuracy of ANN depends heavily on the training sample. In the case of a limited number of sample size, ANN often shows poor generalization capability, namely, the over-fitting problem. Therefore, ANN is usually applied in the case of a sufficient training sample size.

SVM: By contrast, SVM is based on the principle of structural risk minimization, with an outstanding generalization performance. SVM is introduced into machinery fault diagnosis and prediction according to its high accuracy and good generalization for a small sample size, because a sufficient fault sample size is difficult to obtain in practice. However, SVM comprises a few disadvantages. For example, SVM is for binary-class classification; thus, many SVMs need to be combined specifically for a multiclass classification problem. SVM learning is also time consuming in dealing with large-scale data. Several improved methods based on SVM are proposed to overcome the aforementioned problems. The performance of such methods is better than that of a single SVM.

DNN: ANN adopts a shallow structure, which limits its learning of some complex nonlinear structure in fault diagnosis and prediction. The accuracy of ANN and SVM also depends largely on feature selection based on the prior knowledge of signal-processing techniques. The selected features may be suitable for special problems but not for other problems. DNN can adaptively mine representative information from the original data without the need for prior knowledge because of the depth structure. Therefore, DNN can be used for fault feature mining and intelligent fault diagnosis. When the fault feature is difficult to determine, DNN can be used for fault diagnosis. However, DNN needs more training time compared with ANN due to the depth structure. With the development of hardware technology, DNN can be built more rapidly in the future.

Fuzzy logic: The fuzzy rule base is the key point and bottleneck in developing fuzzy logic, which is based on expert knowledge and experience. With the lack of self-learning and self-adaptability, fuzzy logic is often combined with other algorithms, such as neural network, fault tree, and expert system, to achieve fault classification and prognosis.

EAs: GA and PSO are the most widely used in fault diagnosis. EAs have been applied to (1) extract a fault feature by combining with other signal-processing methods, such as wavelet transform, EMD, and stochastic resonance; (2) optimize the structural parameters of classification algorithms (such as ANN, SVM, etc.); (3) select a suitable feature space combining with machine-learning methods to achieve fault classification; (4) address the objective function that is established according to the optimal allocation criterion in the problem of optimal sensor placement.

## 6 Challenges and Prospects

With the rapid development of the modern industry, the processing approaches of condition monitoring and fault diagnosis would be integrated with two or more intelligent methods for enhancing the diagnosis performance, given each computational intelligence method has its own specialty. For example, NFSs are a combination of neural network and fuzzy logic, which has the merit of both methods. Considering the difficulty of determining the structural parameters of neural network, EAs are used to optimize the neural network parameters for fault classification and prediction. The development of computational intelligence faces the following challenges:

(1) Computational intelligence techniques lack a robust mathematical foundation. Although neural network has a relatively perfect theoretical basis, EAs have not yet perfected mathematical foundation. Theoretical studies of instance, stability, efficiency, and convergence remain in the early research stage. Therefore, computational intelligence can be applied to condition monitoring and fault diagnosis appropriately rather than instinctively if researchers have a deep understanding of the algorithm mechanism.

(2) Further simulated or tested signals are used to verify the effectiveness of computational intelligence methods that are difficult to be applied in engineering practice. Computational intelligence techniques should be further explored and improved to develop robust and practical methods for condition monitoring and fault diagnosis.

(3) Considering that computational intelligence and its improved methods are based on iterative process, these algorithms are correspondingly time consuming. Hence, the development of fast online condition monitoring and fault diagnosis systems based on computational intelligence should be the focus in future research.

With the development of industrial big data, the Internet of Things, and intelligent manufacturing, new technique based on computational intelligence is an important way to implement a zero-fault and predicable production system. The collected data are aggregated to a large data platform, which can realize real-time monitoring, perform fault alarm, fault prediction, asset management, intelligent service, auxiliary research, and development, and meet some individual requirements, thereby ultimately creating a more practical value.

## 7 Conclusion Remark

(1) Recent developments and applications of computational intelligence to condition monitoring and fault diagnosis are reviewed, following the categories of fault diagnosis, prognosis, and optimal sensor placement. A comprehensive references are provided for researchers who are interested in this topic.

(2) A comparative analysis of the characteristics of computational intelligence methods is performed, which may be considered as a valuable guide for researchers and practitioners in selecting a suitable method for a specific situation.

(3) Based on the survey and summary of recent research on actual application of mechanical engineering, challenges and prospects of computational intelligence in condition monitoring and fault diagnosis are discussed with emphasis on theoretical foundation, algorithm efficiency, and engineering practice, so as to show the potential researches in the further.



## References

1. A K S Jardine, D M Lin, D Banjevic. A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical Systems and Signal Processing*, 2006, 20(7): 1483–1510.
2. Z W Gao, C Cecati, S X Ding. A Survey of Fault Diagnosis and Fault-Tolerant Techniques Part I: Fault Diagnosis with Model-Based and Signal-Based Approaches. *IEEE Transactions on Industrial Electronics*, 2015, 62(6): 3757–3767.
3. R B Randall. *Vibration-based condition monitoring: industrial, aerospace and automotive applications*. Chichester: John Wiley & Sons, Ltd., 2011.
4. J Z Sikorska, M Hodkiewicz, L Ma. Prognostic modelling options for remaining useful life estimation by industry. *Mechanical Systems and Signal Processing*, 2011, 25(5): 1803–1836.
5. A W Heng, S Zhang, A C C Tan, et al. Rotating machinery prognostics: State of the art, challenges and opportunities. *Mechanical Systems and Signal Processing*, 2009, 23(3): 724–739.

6. Y Gui, Q K Han, F L Chu. A vibration model for fault diagnosis of planetary gearboxes with localized planet bearing defects. *Journal of Mechanical Science and Technology*, 2016, 30(9): 4109–4119.
7. S Xue, I Howard. Dynamic modelling of flexibly supported gears using iterative convergence of tooth mesh stiffness. *Mechanical Systems and Signal Processing*, 2016, 80: 460–481.
8. O D Mohammed, M Rantatalo. Dynamic response and time-frequency analysis for gear tooth crack detection. *Mechanical Systems and Signal Processing*, 2016, 66–67: 612–624.
9. I El-Thalji, E Jantunen. Dynamic modelling of wear evolution in rolling bearings. *Tribology International*, 2015, 84: 90–99.
10. I El-Thalji, E Jantunen. A summary of fault modelling and predictive health monitoring of rolling element bearings. *Mechanical Systems and Signal Processing*, 2015, 60–61: 252–272.
11. M Eremia, C C Liu, A Edris. *Advanced Solutions in Power Systems: HVDC, FACTS, and Artificial Intelligence*. Hoboken: John Wiley & Sons, Inc., 2016.
12. V Piuri, F Scotti, M Roveri. Computational Intelligence in Industrial Quality Control// *Proceedings of the IEEE 2005 International Workshop on Intelligent Signal Processing*, Faro, Portugal, September 1–3, 2005: 4–9.
13. X Y Wang, Y M Ding. Adaptive Real-time Predictive Compensation Control for 6-DOF Serial Arc Welding Manipulator. *Chinese Journal of Mechanical Engineering*, 2010, 23(3): 361–366.
14. Q K Al-Shayea. Artificial neural networks in medical diagnosis. *International Journal of Computer Science Issues*, 2011, 8(2): 150–154.
15. R D Labati, A Genovese, E Muñoz, et al. Computational intelligence for industrial and environmental applications// *Proceedings of the IEEE 8th International Conference on Intelligent Systems*, Sofia, Bulgaria, September 4–6, 2016: 8–14.
16. P K Kankar, S C Sharma, S P Harsha. Fault diagnosis of ball bearings using machine learning methods. *Expert Systems with Applications*, 2011, 38(3): 1876–1886.
17. S Kar, S Das, P K Ghosh. Applications of neuro fuzzy systems: A brief review and future outline. *Applied Soft Computing*, 2014, 15: 243–259.
18. J Schmidhuber. Deep learning in neural networks: An overview. *Neural Networks*, 2015, 61: 85–117.
19. G B Huang, Q Y Zhu, C Siew. Extreme learning machine: Theory and applications. *Neurocomputing*, 2006, 70(1): 489–501.
20. L Cuadra, S Salcedo-Sanz, J C Nieto-Borge, et al. Computational intelligence in wave energy: Comprehensive review and case study. *Renewable and Sustainable Energy Reviews*, 2016, 58: 1223–1246.
21. R C Cavalcante, R C Brasileiro, V L F Souza, et al. Computational Intelligence and Financial Markets: A Survey and Future Directions. *Expert Systems with Applications*, 2016, 55: 194–211.
22. O P Mahela, A G Shaik, N Gupta. A critical review of detection and classification of power quality events. *Renewable and Sustainable Energy Reviews*, 2015, 41: 495–505.
23. S Khokhar, A A B Mohd Zin, A S B Mokhtar, et al. A comprehensive overview on signal processing and artificial intelligence techniques applications in classification of power quality disturbances. *Renewable and Sustainable Energy Reviews*, 2015, 51: 1650–1663.
24. P Henriquez, J B Alonso, M A Ferrer, et al. Review of Automatic Fault Diagnosis Systems Using Audio and Vibration Signals. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 2014, 44(5): 642–652.
25. M S Kan, A C C Tan, J Mathew. A review on prognostic techniques for non-stationary and non-linear rotating systems. *Mechanical Systems and Signal Processing*, 2015, 62–63: 1–20.
26. J D Wu, C H Liu. An expert system for fault diagnosis in internal combustion engines using wavelet packet transform and neural network. *Expert Systems with Applications*, 2009, 36(3): 4278–4286.
27. Y G Lei, Z J He, Y Y Zi. EEMD method and WNN for fault diagnosis of locomotive roller bearings. *Expert Systems with Applications*, 2011, 38(6): 7334–7341.
28. G F Bin, J J Gao, X J Li, et al. Early fault diagnosis of rotating machinery based on wavelet packets—Empirical mode decomposition feature extraction and neural network. *Mechanical Systems and Signal Processing*, 2012, 27: 696–711.
29. L L Cui, C Q Ma, F B Zhang, et al. Quantitative diagnosis of fault severity trend of rolling element bearings. *Chinese Journal of Mechanical Engineering*, 2015, 28(6): 1254–1260.
30. N Saravanan, K I Ramachandran. Incipient gear box fault diagnosis using discrete wavelet transform (DWT) for feature extraction and classification using artificial neural network (ANN). *Expert Systems with Applications*, 2010, 37(6): 4168–4181.
31. Z Zhao, Q S Xu, M P Jia. Improved shuffled frog leaping algorithm-based BP neural network and its application in bearing early fault diagnosis. *Neural Computing and Applications*, 2016, 27(2): 375–385.
32. F Jia, Y G Lei, J Lin, et al. Deep neural networks: A promising tool for fault characteristic mining and intelligent diagnosis of rotating machinery with massive data. *Mechanical Systems and Signal Processing*, 2016, 72–73: 303–315.
33. G E Hinton, R R Salakhutdinov. Reducing the Dimensionality of Data with Neural Networks. *Science*, 2006, 313(5786): 504–507.
34. V T Tran, F AlThobiani, A Ball. An approach to fault diagnosis of reciprocating compressor valves using Teager–Kaiser energy operator and deep belief networks. *Expert Systems with Applications*, 2014, 41(9): 4113–4122.
35. P Tamilselvan, P F Wang. Failure diagnosis using deep belief learning based health state classification. *Reliability Engineering & System Safety*, 2013, 115: 124–135.
36. X J Guo, L Chen, C Q Shen. Hierarchical adaptive deep convolution neural network and its application to bearing fault diagnosis. *Measurement*, 2016, 93: 490–502.
37. Z X Yang, X B Wang, J H Zhong. Representational Learning for Fault Diagnosis of Wind Turbine Equipment: A Multi-Layered Extreme Learning Machines Approach. *Energies*, 2016, 9(6): 379.
38. Y Wei, X Minqiang, L Yongbo, et al. 1983. Gearbox fault diagnosis based on local mean decomposition, permutation entropy and extreme learning machine. *Journal of Vibroengineering*, 2016, 18(3): 1459–1473.
39. P K Wong, Z Yang, C M Vong, et al. Real-time fault diagnosis for gas turbine generator systems using extreme learning machine. *Neurocomputing*, 2014, 128: 249–257.
40. Y Tian, J Ma, C Lu, et al. Rolling bearing fault diagnosis under variable conditions using LMD-SVD and extreme learning machine. *Mechanism and Machine Theory*, 2015, 90: 175–186.
41. M Mishra, M Sahani, P K Rout. An Islanding Detection Method Based on Wavelet Packet Transform and Extreme Learning Machine. *International Journal of Renewable Energy Research (IJRER)*, 2016, 6(3): 856–865.
42. S Li, G Wu, B Gao, et al. Interpretation of DGA for Transformer Fault Diagnosis with Complementary SaE-ELM and Arctangent Transform. *IEEE Transactions on Dielectrics and Electrical Insulation*, 2016, 23(1): 586–595.

43. M A El-Gamal, M Abdulghafour. Fault isolation in analog circuits using a fuzzy inference system. *Computers & Electrical Engineering*, 2003, 29(1): 213–229.
44. H Eristi. Fault diagnosis system for series compensated transmission line based on wavelet transform and adaptive neuro-fuzzy inference system. *Measurement*, 2013, 46(1): 393–401.
45. J Chen, C Roberts, P Weston. Fault detection and diagnosis for railway track circuits using neuro-fuzzy systems. *Control Engineering Practice*, 2008, 16(5): 585–596.
46. S M El-Shal, A S Morris. A fuzzy expert system for fault detection in statistical process control of industrial processes. *IEEE Transactions on Systems, Man and Cybernetics-Part C: Applications and Reviews*, 2000, 30(2): 281–289.
47. J Zheng, J Cheng, Y Yang. A rolling bearing fault diagnosis approach based on LCD and fuzzy entropy. *Mechanism and Machine Theory*, 2013, 70: 441–453.
48. L Zhang, G Xiong, H Liu, et al. Bearing fault diagnosis using multi-scale entropy and adaptive neuro-fuzzy inference. *Expert Systems with Applications*, 2010, 37(8): 6077–6085.
49. V T Tran, B Yang, M Oh, et al. Fault diagnosis of induction motor based on decision trees and adaptive neuro-fuzzy inference. *Expert Systems with Applications*, 2009, 36(2): 1840–1849.
50. J Wu, C Hsu, G Wu. Fault gear identification and classification using discrete wavelet transform and adaptive neuro-fuzzy inference. *Expert Systems with Applications*, 2009, 36(3): 6244–6255.
51. J M Li, Y G Zhang, P Xie. A new adaptive cascaded stochastic resonance method for impact features extraction in gear fault diagnosis. *Measurement*, 2016, 91: 499–508.
52. N Lu, Z H Xiao, O P Malik. Feature extraction using adaptive multiwavelets and synthetic detection index for rotor fault diagnosis of rotating machinery. *Mechanical Systems and Signal Processing*, 2015, 52–53: 393–415.
53. W S Su, F T Wang, H Zhu, et al. Rolling element bearing faults diagnosis based on optimal Morlet wavelet filter and autocorrelation enhancement. *Mechanical Systems and Signal Processing*, 2010, 24(5): 1458–1472.
54. X A Yan, M P Jia. Parameter optimized combination morphological filter-hat transform and its application in fault diagnosis of wind turbine. *Joural of Mechanical Engineering*, 2016, 52(13): 103–110.(in Chinese)
55. W Zhang, M P Jia, L Zhu. An adaptive Morlet wavelet filter method and its application in detecting early fault feature of ball bearings. *Joural of southeast university (Natural Science Edition)*, 2016, 46(3): 457–463.(in Chinese)
56. X A Yan, M P Jia, L Xiang. Compound fault diagnosis of rotating machinery based on OVMD and a 1.5-dimension envelope spectrum. *Measurement Science and Technology*, 2016, 27: 75002.
57. C Ciancio, G Ambrogio, F Gagliardi, et al. Heuristic techniques to optimize neural network architecture in manufacturing applications. *Neural Computing and Applications*, 2016, 27(7): 2001–2015.
58. M Unal, M Onat, M Demetgul, et al. Fault diagnosis of rolling bearings using a genetic algorithm optimized neural network. *Measurement*, 2014, 58: 187–196.
59. H Shao, H Jiang, X Zhang, et al. Rolling bearing fault diagnosis using an optimization deep belief network. *Measurement Science and Technology*, 2015, 26: 115002.
60. M Demetgul, M Unal, I N Tansel, et al. Fault diagnosis on bottle filling plant using genetic-based neural network. *Advances in Engineering Software*, 2011, 42(12): 1051–1058.
61. F Leung, H Lam, S Ling, et al. Tuning of the structure and parameters of a neural network using an improved genetic algorithm. *IEEE Transactions on Neural Networks*, 2003, 14(1): 79–88.
62. F Chen, B Tang, T Song, et al. Multi-fault diagnosis study on roller bearing based on multi-kernel support vector machine with chaotic particle swarm optimization. *Measurement*, 2014, 47: 576–590.
63. M Unal, M Onat, M Demetgul, et al. Fault diagnosis of rolling bearings using a genetic algorithm optimized neural network. *Measurement*, 2014, 58: 187–196.
64. F Chen, B Tang, R Chen. A novel fault diagnosis model for gearbox based on wavelet support vector machine with immune genetic algorithm. *Measurement*, 2013, 46(1): 220–232.
65. H Sadegh, A N Mehdi, A Mehdi. Classification of acoustic emission signals generated from journal bearing at different lubrication conditions based on wavelet analysis in combination with artificial neural network and genetic algorithm. *Tribology International*, 2016, 95: 426–434.
66. A Saxena, A Saad. Evolving an artificial neural network classifier for condition monitoring of rotating mechanical systems. *Applied Soft Computing*, 2007, 7(1): 441–454.
67. M Ahmed, F Gu, A Ball. Feature Selection and Fault Classification of Reciprocating Compressors using a Genetic Algorithm and a Probabilistic Neural Network// *2011 9th International Conference on Damage Assessment of Structures (DAMAS)*, London, United Kingdom, July 11–13, 2011: 12112.
68. M Cerrada, R Sánchez, D Cabrera, et al. Multi-Stage Feature Selection by Using Genetic Algorithms for Fault Diagnosis in Gearboxes Based on Vibration Signal. *Sensors*, 2015, 15(9): 23903–23926.
69. M Cerrada, G Zurita, D Cabrera, et al. Fault diagnosis in spur gears based on genetic algorithm and random forest. *Mechanical Systems and Signal Processing*, 2016, 70–71: 87–103.
70. C Rajeswari, B Sathiyabhama, S Devendiran, et al. A Gear Fault Identification using Wavelet Transform, Rough set Based GA, ANN and C4.5 Algorithm. *Procedia Engineering*, 2014, 97: 1831–1841.
71. L B Jack, A K Nandi. Support vector machines for detection and characterization of rolling element bearing faults. *Proceedings of the Institution of Mechanical Engineers Part C-Journal of Mechanical Engineering Science*, 2001, 215(9): 1065–1071.
72. P Konar, P Chattopadhyay. Bearing fault detection of induction motor using wavelet and Support Vector Machines (SVMs). *Applied Soft Computing*, 2011, 11(6): 4203–4211.
73. N Li, R Zhou, Q Hu, et al. Mechanical fault diagnosis based on redundant second generation wavelet packet transform, neighborhood rough set and support vector machine. *Mechanical Systems and Signal Processing*, 2012, 28: 608–621.
74. J Cheng, D Yu, J Tang. Application of SVM and SVD technique based on EMD to the fault diagnosis of the rotating machinery. *Shock and Vibration*, 2009, 16(1): 89–98.
75. X Zhang, Y Liang, J Zhou, et al. A novel bearing fault diagnosis model integrated permutation entropy, ensemble empirical mode decomposition and optimized SVM. *Measurement*, 2015, 69: 164–179.
76. S Wang, A Mathew, Y Chen, et al. Empirical analysis of support vector machine ensemble classifiers. *Expert Systems with Applications*, 2009, 36(3): 6466–6476.
77. J Tian, H Gu, W Liu. Imbalanced classification using support vector machine ensemble. *Neural Computing and Applications*, 2011, 20(2): 203–209.
78. J Zheng, H Pan, J Cheng. Rolling bearing fault detection and diagnosis based on composite multiscale fuzzy entropy and ensemble support vector machines. *Mechanical Systems and Signal Processing*, 2017, 85: 746–759.
79. S Abe. Fuzzy support vector machines for multilabel classification. *Pattern Recognition*, 2015, 48(6): 2110–2117.
80. J Hang, J Zhang, M Cheng. Application of multi-class fuzzy support vector machine classifier for fault diagnosis of wind turbine. *Fuzzy Sets and Systems*, 2016, 297: 128–140.

81. Z Yin, J Hou. Recent advances on SVM based fault diagnosis and process monitoring in complicated industrial processes. *Neurocomputing*, 2016, 174: 643–650.
82. X Zhang, W Chen, B Wang, et al. Intelligent fault diagnosis of rotating machinery using support vector machine with ant colony algorithm for synchronous feature selection and parameter optimization. *Neurocomputing*, 2015, 167: 260–279.
83. X Zhang, B Wang, X Chen. Intelligent fault diagnosis of roller bearings with multivariable ensemble-based incremental support vector machine. *Knowledge-Based Systems*, 2015, 89: 56–85.
84. Y Li, M Xu, Y Wei, et al. A new rolling bearing fault diagnosis method based on multiscale permutation entropy and improved support vector machine based binary tree. *Measurement*, 2016, 77: 80–94.
85. Z Shen, X Chen, X Zhang, et al. A novel intelligent gear fault diagnosis model based on EMD and multi-class TSVM. *Measurement*, 2012, 45(1): 30–40.
86. R Liu, B Yang, X Zhang, et al. Time-frequency atoms-driven support vector machine method for bearings incipient fault diagnosis. *Mechanical Systems and Signal Processing*, 2016, 75: 345–370.
87. C Vong, P Wong, L Tam, et al. Ignition Pattern Analysis for Automotive Engine Trouble Diagnosis using Wavelet Packet Transform and Support Vector Machines. *Chinese Journal of Mechanical Engineering*, 2011, 24(5): 870–878.
88. M J Zhang, J Tang, X M Zhang, et al. Intelligent diagnosis of short hydraulic signal based on improved EEMD and SVM with few low-dimensional training samples. *Chinese Journal of Mechanical Engineering*, 2016, 29(2): 396–405.
89. C Hu, B D Youn, P F Wang, et al. Ensemble of data-driven prognostic algorithms for robust prediction of remaining useful life. *Reliability Engineering & System Safety*, 2012, 103: 120–135.
90. J Lee, F J Wu, W Y Zhao, et al. Prognostics and health management design for rotary machinery systems—Reviews, methodology and applications. *Mechanical Systems and Signal Processing*, 2014, 42(1-2): 314–334.
91. A M Riad, H K Elminir, H M Elattar. Evaluation of Neural Networks in the Subject of Prognostics As Compared To Linear Regression Model. *International Journal of Engineering & Technology*, 2010, 10(6): 52–58.
92. Z Y Zhang, Y Wang, K S Wang. Fault diagnosis and prognosis using wavelet packet decomposition, Fourier transform and artificial neural network. *Journal of Intelligent Manufacturing*, 2013, 24(6): 1213–1227.
93. Z G Tian, L Wong, N Safaei. A neural network approach for remaining useful life prediction utilizing both failure and suspension histories. *Mechanical Systems and Signal Processing*, 2010, 24(5): 1542–1555.
94. F Ahmadzadeh, J Lundberg. Remaining useful life prediction of grinding mill liners using an artificial neural network. *Minerals Engineering*, 2013, 53: 1–8.
95. J A Rodríguez, Y E Hamzaoui, J A Hernández, et al. The use of artificial neural network (ANN) for modeling the useful life of the failure assessment in blades of steam turbines. *Engineering Failure Analysis*, 2013, 35: 562–575.
96. A Malhi, R Q Yan, R X Gao. Prognosis of Defect Propagation Based on Recurrent Neural Networks. *IEEE Transactions on Instrumentation and Measurement*, 2011, 60(3): 703–711.
97. A K Mahamad, S Saon, T Hiyama. Predicting remaining useful life of rotating machinery based artificial neural network. *Computers & Mathematics with Applications*, 2010, 60(4): 1078–1087.
98. B Chen, P C Matthews, P J Tavner. Wind turbine pitch faults prognosis using a-priori knowledge-based ANFIS. *Expert Systems with Applications*, 2013, 40(17): 6863–6876.
99. S Hong, Z Zhou, E Zio, et al. Condition assessment for the performance degradation of bearing based on a combinatorial feature extraction method. *Digital Signal Processing*, 2014, 27: 159–166.
100. K Javed, R Gouriveau, N Zerhouni. A New Multivariate Approach for Prognostics Based on Extreme Learning Machine and Fuzzy Clustering. *IEEE Transactions on Cybernetics*, 2015, 45(12): 2626–2639.
101. C Zhang, P Lim, A K Qin, et al. Multiobjective Deep Belief Networks Ensemble for Remaining Useful Life Estimation in Prognostics. *IEEE Transactions on Neural Networks and Learning Systems*, 2016: 1–13.
102. C F Baban, M Baban, M D Suteu. Using a fuzzy logic approach for the predictive maintenance of textile machines. *Journal of Intelligent & Fuzzy Systems*, 2016, 30(2): 999–1006.
103. R Stetter, M Witczak. Degradation Modelling for Health Monitoring Systems. *Journal of Physics: Conference Series*, 2014, 570(6): 62002.
104. R Ishibashi, C L N Júnior. GFRBS-PHM: A Genetic Fuzzy Rule-Based System for PHM with Improved Interpretability// *Proceedings of the IEEE Conference on Prognostics and Health Management (PHM)*, Milan, Italy, September 8–11, 2013: 1–7.
105. X M Tian, Y P Cao, S Chen. Process fault prognosis using a fuzzy-adaptive unscented Kalman predictor. *International Journal of Adaptive Control and Signal Processing*, 2011, 25(9): 813–830.
106. E Zio, F Di Maio. A data-driven fuzzy approach for predicting the remaining useful life in dynamic failure scenarios of a nuclear system. *Reliability Engineering & System Safety*, 2010, 95(1): 49–57.
107. C J Zhang, X F Yao, J M Zhang, et al. Tool Condition Monitoring and Remaining Useful Life Prognostic Based on a Wireless Sensor in Dry Milling Operations. *Sensors*, 2016, 16(6): 795.
108. J Gokulachandran, K Mohandas. Comparative study of two soft computing techniques for the prediction of remaining useful life of cutting tools. *Journal of Intelligent Manufacturing*, 2015, 26(2): 255–268.
109. J B Ali, B Chebel-Morello, L Saidi, et al. Accurate bearing remaining useful life prediction based on Weibull distribution and artificial neural network. *Mechanical Systems and Signal Processing*, 2015, 56–57: 150–172.
110. B D Chen, P C Matthews, P J Tavner. Wind turbine pitch faults prognosis using a-priori knowledge-based ANFIS. *Expert Systems with Applications*, 2013, 40(17): 6863–6876.
111. F G ZHAO, J CHEN, L GUO, et al. Neuro-fuzzy Based Condition Prediction of Bearing Health. *Journal of Vibration and Control*, 2009, 15(7): 1079–1091.
112. C C Chen, B Zhang, G Vachtsevanos. Prediction of Machine Health Condition Using Neuro-Fuzzy and Bayesian Algorithms. *IEEE Transactions on Instrumentation and Measurement*, 2012, 61(2): 297–306.
113. E Ramasso, R Gouriveau. Remaining Useful Life Estimation by Classification of Predictions Based on a Neuro-Fuzzy System and Theory of Belief Functions. *IEEE Transactions on Reliability*, 2014, 63(2): 555–566.
114. W Wang, D Z Li, J Vrbanek. An evolving neuro-fuzzy technique for system state forecasting. *Neurocomputing*, 2012, 87: 111–119.
115. T Boukra. Identifying New Prognostic Features for Remaining Useful Life Prediction Using Particle Filtering and Neuro-Fuzzy System Predictor// *Proceedings of the IEEE 2015 15th International Conference on Environment and Electrical Engineering*, Rome, Italy, June 10–13, 2015: 1533–1538.
116. Z L Du, X M Li, Q Mao. A new online hybrid learning algorithm of adaptive neural fuzzy inference system for fault

prediction. *International Journal of Modeling Identification and Control*, 2015, 23(1): 68–76.

117. C C Chen, B Zhang, G Vachtsevanos, et al. Machine Condition Prediction Based on Adaptive Neuro – Fuzzy and High-Order Particle Filtering. *IEEE Transactions on Industrial Electronics*, 2011, 58(9): 4353–4364.
118. C C Chen, G Vachtsevanos, M E Orchard. Machine remaining useful life prediction: An integrated adaptive neuro-fuzzy and high-order particle filtering approach. *Mechanical Systems and Signal Processing*, 2012, 28: 597–607.
119. C C Chen, G Vachtsevanos. Bearing condition prediction considering uncertainty: An interval type-2 fuzzy neural network approach. *Robotics and Computer-Integrated Manufacturing*, 2012, 28(4): 509–516.
120. G Bosque, I Del Campo, J Echanobe. Fuzzy systems, neural networks and neuro-fuzzy systems: A vision on their hardware implementation and platforms over two decades. *Engineering Applications of Artificial Intelligence*, 2014, 32: 283–331.
121. Y Pan, M J Er, X Li, et al. Machine health condition prediction via online dynamic fuzzy neural networks. *Engineering Applications of Artificial Intelligence*, 2014, 35: 105–113.
122. L Zhang, G L Xiong, L P Liu, et al. Gearbox health condition identification by neuro-fuzzy ensemble. *Journal of Mechanical Science and Technology*, 2013, 27(3): 603–608.
123. V Vapnik. *The nature of statistical learning theory*. New York: Springer, 1995.
124. C Lu, J Chen, R J Hong, et al. Degradation trend estimation of slewing bearing based on LSSVM model. *Mechanical Systems and Signal Processing*, 2016, 76–77: 353–366.
125. S J Dong, T H Luo. Bearing degradation process prediction based on the PCA and optimized LS-SVM model. *Measurement*, 2013, 46(9): 3143–3152.
126. X F Chen, Z J Shen, Z J He, et al. Remaining life prognostics of rolling bearing based on relative features and multivariable support vector machine. *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, 2013, 227(12): 2849–2860.
127. W Caesarendra, A Widodo, B Yang. Combination of probability approach and support vector machine towards machine health prognostics. *Probabilistic Engineering Mechanics*, 2011, 26(2): 165–173.
128. A Widodo, B Yang. Machine health prognostics using survival probability and support vector machine. *Expert Systems with Applications*, 2011, 38(7): 8430–8437.
129. V T Tran, H Thom Pham, B Yang, et al. Machine performance degradation assessment and remaining useful life prediction using proportional hazard model and support vector machine. *Mechanical Systems and Signal Processing*, 2012, 32: 320–330.
130. T H Loutas, D Roulias, G Georgoulas. Remaining Useful Life Estimation in Rolling Bearings Utilizing Data-Driven Probabilistic E-Support Vectors Regression. *IEEE Transactions on Reliability*, 2013, 62(4): 821–832.
131. K He, Q S Xu, M P Jia. Modeling and Predicting Surface Roughness in Hard Turning Using a Bayesian Inference-Based HMM-SVM Model. *IEEE Transactions on Automation Science and Engineering*, 2015, 12(3): 1092–1103.
132. H Z Huang, H K Wang, Y F Li, et al. Support vector machine based estimation of remaining useful life: current research status and future trends. *Journal of Mechanical Science and Technology*, 2015, 29(1): 151–163.
133. Z L Liu, M J Zuo, Y Qin. Remaining useful life prediction of rolling element bearings based on health state assessment. *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, 2016, 230(2): 314–330.
134. Q Zhang, F Liu, X Wan, et al. An Adaptive Support Vector Regression Machine for the State Prognosis of Mechanical Systems. *Shock and Vibration*, 2015, 2015: 1–8.
135. Y N Pan, J Chen, L Guo. Robust bearing performance degradation assessment method based on improved wavelet packet–support vector data description. *Mechanical Systems and Signal Processing*, 2009, 23(3): 669–681.
136. T Benkedjouh, K Medjaher, N Zerhouni, et al. Remaining useful life estimation based on nonlinear feature reduction and support vector regression. *Engineering Applications of Artificial Intelligence*, 2013, 26(7): 1751–1760.
137. H Kim, A C C Tan, J Mathew, et al. Bearing fault prognosis based on health state probability estimation. *Expert Systems with Applications*, 2012, 39(5): 5200–5213.
138. T H Yi, H N Li. Methodology Developments in Sensor Placement for Health Monitoring of Civil Infrastructures. *International Journal of Distributed Sensor Networks*, 2012, 2012: 1–11.
139. A R M Rao, G Anandakumar. Optimal placement of sensors for structural system identification and health monitoring using a hybrid swarm intelligence technique. *Smart Materials and Structures*, 2007, 16: 2658–2672.
140. D S Li, H N Li, C Fritzen. Load dependent sensor placement method: Theory and experimental validation. *Mechanical Systems and Signal Processing*, 2012, 31: 217–227.
141. H Y Guo, L Zhang, L L Zhang, et al. Optimal placement of sensor for structural health monitoring using improved genetic algorithms. *Smart Materials and Structures*, 2004, 13: 528–534.
142. S H Mahdavi, H A Razak. Optimal sensor placement for time-domain identification using a wavelet-based genetic algorithm. *Smart Materials and Structures*, 2016, 25: 65006.
143. R Dutta, R Ganguli, V Mani. Swarm intelligence algorithms for integrated optimization of piezoelectric actuator and sensor placement and feedback gains. *Smart Materials and Structures*, 2011, 20: 105018.
144. K Worden, A P Burrows. Optimal sensor placement for fault detection. *Engineering Structures*, 2001(23): 885–901.
145. H Pan, X Wei. Optimal Placement of Sensor in Gearbox Fault Diagnosis Based on VPSO// *Proceedings of the IEEE 2010 6th International Conference on Natural Computation*, Yantai, China, August 10–12, 2010: 3383–3387.
146. Y Ren, Y Ding. Optimal sensor distribution in multi-station assembly processes for maximal variance detection capability. *IIE Transactions*, 2009, 41: 804–818.
147. N Shukla, D Ceglarek, M K Tiwari. Key characteristics-based sensor distribution in multi-station assembly processes. *Journal of Intelligent Manufacturing*, 2015, 26(1): 43–58.
148. M M Abdullah, A Richardson, J Hanif. Placement of sensors/actuators on civil structures using genetic algorithms. *Earthquake Engineering & Structural Dynamics*, 2001, 30(8): 1167–1184.
149. P Tongpadungrod, T D L Rhys, P N Brett. An approach to optimise the critical sensor locations in one-dimensional novel distributive tactile surface to maximise performance. *Sensors and Actuators A: Physical*, 2003, 105(1): 47–54.
150. J J Lian, L J He, B Ma, et al. Optimal sensor placement for large structures using the nearest neighbour index and a hybrid swarm intelligence algorithm. *Smart Materials and Structures*, 2013, 22: 95015.
151. H M Chow, H F Lam, T Yin, et al. Optimal sensor configuration of a typical transmission tower for the purpose of structural model updating. *Structural Control and Health Monitoring*, 2011, 18(3): 305–320.
152. Z Zhao, Q S Xu, M P Jia. Sensor network optimization of gearbox based on dependence matrix and improved discrete

shuffled frog leaping algorithm. *Natural Computing*, 2015: 1–12.
153. K He, M P Jia, Z Z Zhao. Sensor Optimization for Cutting Status Monitoring in Single Manufacturing Unit. *Advanced Materials Research*, 2012, 569: 636–639.
154. K He, M P Jia, Q S Xu. Optimal Sensor Deployment for Manufacturing Process Monitoring Based on Quantitative Cause-Effect Graph. *IEEE Transactions on Automation Science and Engineering*, 2016, 13(2): 963–975.

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