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A flexible algorithm for fault diagnosis in a centrifugal pump with corrupted data and noise based on ANN and support vector machine with hyper-parameters optimization

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ABSTRACT

Fault detection and diagnosis have an effective role for the safe operation and long life of systems. Condition monitoring is an appropriate way of the maintenance technique that is applicable in the fault diagnosis of rotating machinery faults. A unique flexible algorithm is proposed for classifying the condition of centrifugal pump based on support vector machine hyper-parameters optimization and artificial neural networks (ANNs) which are composed of eight distinct steps. Artificial neural networks (ANNs), support vector classification with genetic algorithm (SVC-GA) and support vector classification with particle swarm optimization (SVC-PSO) algorithm have been considered in a flexible algorithm to perform accurate classification in the manufacturing area. SVC-GA, SVC-PSO and ANN have been used together due to their importance and capabilities in classifying domain. Also, the superiority of the proposed hybrid algorithm (SVC with GA and PSO) is shown by comparing its results with SVC performance. Two types of faults through six features, flow, temperature, suction pressure, discharge pressure, velocity, and vibration, have been classified with proposed integrated algorithm. To test the robustness of the efficiency results of the proposed method, the ability of proposed flexible algorithm in dealing with noisy and corrupted data is analyzed.

1. Introduction

Centrifugal pumps are one of the most important elements in almost all industries and continuous condition monitoring of these crucial parts is essential for preventing early failure, production line break down, improving plant safety, efficiency and reliability. Moreover, the major equipment failures in plants such as oil and gas plants are related to pumps, compressors and piping. Centrifugal pumps are sensitive to: (1) variations in liquid condition (i.e., viscosity, specific gravity, and temperature); (2) suction variations, such as pressure and availability of a continuous volume of fluid; and (3) variations in demand. Several reasons cause mechanical failures; some are induced by cavitations, hydraulic instability, or other system-related problems. Others are the direct result of improper maintenance, maintenance-related problems, improper lubrication, misalignment, unbalance, seal leakage, and a variety of others in which machine reliability is periodically affected by them.

The task of condition monitoring and fault diagnosis of rotating machinery faults is both significant and important but often the failure diagnosis process by human operators is time consuming and human error may lead to a faulty diagnosis.

Hence, in recent years classifiers based on artificial intelligence and learning machines are increasingly being employed to develop diagnostic schemes for centrifugal pumps fault diagnosis. A wide variety of artificial intelligence-based methods are available in literature. Artificial neural networks (ANNs) are the most popular tools used by researchers. Some promising recent studies on the application of ANNs in centrifugal pumps fault diagnosis are presented in Refs. [2–4].

However, ANN, which uses empirical risk minimization (ERM) principle, suffers from local minimum traps and the difficulty of determining the hidden layer size and learning rate [5,6]. Despite the above-mentioned problems, ANN is still considered as one of the precise methods for classifying problems when the practitioners have enough knowledge and experience. Due to their interpretability and transparency, fuzzy rule-base systems (FRBSs) are recommended by some fault diagnosis studies [1,7,8]. However, it should be taken into consideration that FRBSs are not always accurate [9].

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There are also some studies in which neuro-fuzzy method is used [10–14]. The main drawback of fuzzy neural network is poor capability of creating its own structure [9].

Unlike ANN, support vector machine, proposed by Vapnik [5], has a global optimum and exhibits better prediction accuracy due to its implementation of the structural risk minimization (SRM) principle which considers both the training error and the capacity of the classifier model. Some previous studies on SVM-based diagnostic systems in industries are presented in Refs. [15–31].

The main problem with SVM is that one has to set in advance its hyperparameters properly. Unsuitably chosen kernel functions or hyperparameters settings may lead to significantly poor performance [32–34].

In this study, a flexible algorithm based on SVM, genetic algorithm (GA) and particle swarm optimization (PSO) is proposed for centrifugal pumps fault diagnosis. To show the robustness of the proposed algorithm in noisy environments, it is also applied to noisy data.

The rest of the paper is organized as follows: in Sections 2 and 3, a brief introduction to support vector machine hyper-parameters optimization and ANN is presented. In Section 4, a flexible algorithm is presented. Section 5 is computational results in which the proposed algorithm is applied to the real case study and, in the last section, the conclusion is discussed.

2. Support vector machine with hyper-parameters optimization

In this study, we mainly focus on the application of support vector machine in classification tasks which is called support vector classification (SVC). Suppose a set of training data $D=\{(x_1, y_1), \ldots, (x_i, y_i)\}$, where $x \in R^d$ is the training input, $y \in \{-1, 1\}$ is class label and $i=1, \ldots, l$. In SVC an optimum separating hyperplane that maximizes the margins (the distance between the hyperplane and the nearest data point of each class) is constructed by minimizing the following objective function:

$$\begin{aligned} &\text{Min} && \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{1}\xi_i \\ &\text{Subjected to} && y_i[w^T \cdot \phi(x)_i + b] \ge 1 - \xi_i \\ &&& \xi_i \ge 0, \quad i = 1, \ldots, l \end{aligned} \tag{1}$$

where ξ_i are slack variables to handle misclassifications, w is a weight vector, b is scalar called bias and c is the cost parameter denoting the trade-off between the model complexity and the training error. In Eq. (1), $\phi(x)_i$ is a nonlinear function to map the input data to a high dimensional feature space in which the data can be separated linearly. To solve Eq. (1), one can take the Lagrangian, consider the necessary conditions for optimality and finally turn the minimization problem to the following dual form:

$$\begin{aligned} &\text{Max} && \sum_{i=1}^{1}\alpha_i - \frac{1}{2}\sum_{i=1}^{1}\sum_{j=1}^{1}\alpha_i\alpha_j y_i y_j K(x_i, x_j) \\ &\text{Subjected to} && \sum_{i=1}^{1}\alpha_i y_i = 0 \\ &&& 0 \le \alpha_i \le C, \quad i = 1, \ldots, l \end{aligned} \tag{2}$$

where $K(x_i, x_j)$ is a kernel function representing inner product $\langle\phi(x_i), \phi(x_j)\rangle$ and α_i are Lagrangian multipliers. By solving Eq. (2), the optimal separating hyperplane is obtained as following:

$$\sum_{SV}\alpha_i y_i K(x_i, x_j) + b = 0 \tag{3}$$

And the optimal classifying rule is:

$$f = \operatorname{sgn}\left(b + \sum_{SV}[(\alpha_i y_i)K(x_i, x_j)]\right)$$

where SV denotes the support vectors for which the corresponding Lagrangian multipliers are positive.

In this study, the following common kernel functions are employed to construct the best SVC-based model for centrifugal pumps fault diagnosis:

$$\text{Polynomial}: \quad K(x_i, x_j) = (\gamma \cdot \langle x_i, x_j\rangle + s)^d \tag{4}$$

$$\text{Gaussian radial basis function}: \quad K(x_i, x_j) = -\gamma \cdot \left\|x_i - x_j\right\|^2 \tag{5}$$

$$\text{Linear}: \quad K(x_i, x_j) = \langle x_i, x_j\rangle \tag{6}$$

$$\text{Quadratic}: \quad K(x_i, x_j) = (\langle x_i, x_j\rangle + 1)^2 \tag{7}$$

Detailed explanation about the basic concepts of SVM theory can be found in Ref. [5]. To construct an accurate fault diagnostic system based on SVC, optimization methods are needed to tune SVC hyperparameters such as cost (C), γ and s. Among myriad available optimization algorithms, in this study, genetic algorithm (GA) and particle swarm optimization are used due to their versatility and robustness in solving optimization problems. In the following section, the integration of these two algorithms with support vector classification is explained.

2.1. Support vector classification with genetic algorithm (SVC-GA)

Genetic algorithms (GAs) are heuristic search techniques based on evolutionary principles. They repeatedly incorporate genetic operations including selection, crossover and mutation to modify a population of artificial strings of chromosomes and finding the best possible solution which optimizes a specified fitness (objective) function. In this study, GA is used to minimize the following fitness function:

$$\begin{aligned} \text{Fitness function} &= 1-\text{percentage of correct predicted classes} \\ &= 1 - \frac{N_c}{N_T} \end{aligned} \tag{8}$$

where N_c is the number of correct predicted fault classes by SVC and N_T is the total number of predicted fault classes. In the following, the SVC-GA procedure implemented in this study is presented.

First, the initial values of SVC hyper parameters including cost (C) and kernel function hyper parameters are generated randomly. In this procedure, for each kernel function type, the appropriate kernel parameters are considered. Then, the generated parameters are encoded into a binary format and are represented by a chromosome composed of genes of binary numbers. In this study 40 bits are assigned to each gene.

Second, SVC is trained based on each chromosome in the population and the trained model is applied to the data. Third, the best chromosomes are selected by roulette wheel principle and genetic operations, including crossover and mutation, are implemented to the selected chromosomes. A detailed explanation of crossover and mutation operations can be found in Ref. [35].

If the number of iterations reaches to a given scale, the above procedure stops and the best chromosome is considered as the best solution to Eq. (8). Fig. 1 shows the procedure of SVC-GA.

2.2. Support vector classification with particle swarm optimization (SVC-PSO) algorithm

Particle swarm optimization (PSO) algorithm is a metaheuristic optimization technique inspired by the behavior of animal swarms