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Evolutionary multi-objective fault diagnosis of power transformers

Abdolrahman Peimankar[a], Stephen John Weddell[a], Thahirah Jalal[b], Andrew Craig Lapthorn[a,*]

[a] *Department of Electrical and Computer Engineering, University of Canterbury, Christchurch 8041, New Zealand*
[b] *Unison Networks Limited, Hastings 4156, New Zealand*

A R T I C L E I N F O

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A B S T R A C T

This paper introduces a two step algorithm for fault diagnosis of power transformers (2-ADOPT) using a binary version of the multi-objective particle swarm optimization (MOPSO) algorithm. Feature subset selection and ensemble classifier selection are implemented to improve the diagnosing accuracy for dissolved gas analysis (DGA) of power transformers. First, the proposed method selects the most effective features in a multi objective framework and the optimum number of features, simultaneously, which are used as inputs to train classifiers in the next step. The input features are composed of DGA performed on the oil of power transformers along with the various ratios of these gases. In the second step, the most accurate and diverse classifiers are selected to create a classifier ensemble. Finally, the outputs of selected classifiers are combined using the Dempster-Shafer combination rule in order to determine the actual faults of power transformers. In addition, the obtained results of the proposed method are compared to three other scenarios: 1) multi-objective ensemble classifier selection without any feature selection step which takes all the features to train classifiers and then applies MOPSO algorithm to find the best ensemble of classifiers, 2) a well-known classifier ensemble technique called random forests, and 3) another powerful decision tree ensemble which is called oblique random forests. The comparison results were favourable to the proposed method and showed the high reliability of this method for power transformers fault classification.

1. Introduction

Today power companies can deliver higher quality of services to their clients by performing intelligent asset management activities and reducing operating costs. One of the most critical asset classes to deliver electric power is power and distribution transformers whose risk of failure increases with ageing [1]. A transformer failure usually results in a widespread outage in the network. Replacing a power transformer is expensive. A unit can cost up to 1 million dollars and long lead times are typical [2]. It is therefore imperative for any electricity company to manage such assets effectively. Electricity companies require new approaches, such as intelligent fault diagnosing algorithm, to reduce the operating costs and the failure rate of their assets [3].

Currently, most electricity companies rely on expert individuals to analyse the data gathered from transformers and to make a decision about the status of their transformers using conventional methods. This can be difficult when the experts concerned are unavailable. Besides, conventional methods are sometimes unable to generate comprehensive results. Thus, we are developing an intelligent fault diagnosing system that will help electricity companies manage their transformer fleet intelligently [4].

Dissolve gas analysis (DGA) is one of the most important condition monitoring techniques for power transformers. Several conventional methods are currently used to analyse data obtained from the DGA technique, however these may lead to an incorrect and uncertain assessment [5].

Up to now, most power transformers fault diagnosis and condition assessment models have placed emphasis on single classification algorithms (learning algorithms). Ganyun et al. [6] used a multi-layer support vector machine (SVM) that consists of three SVM classifiers to diagnose faults of transformers using the relative content of the five dissolved gases plus the amount of the most abundant gas as an input feature vector. Fei et al. [7] proposed a Genetic Algorithm (GA)-based SVM to detect faults of power transformers which can tune the parameters of SVM using a genetic algorithm. In [7,8] the possibility of forecasting the ratios of dissolved gases has been studied by applying GA-based SVM and PSO-based SVM, respectively. These two studies can enhance the reliability of transformers by providing useful information about the rate of failures in a short and medium period of time. Illias et al. [9] proposed a successful PSO based artificial neural network algorithm to diagnose faults of transformers based on DGA. In another study, Illias et al. [10] implemented an artificial neural

* Corresponding author.
E-mail address: andrew.lapthorn@canterbury.ac.nz (A.C. Lapthorn).

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network based method for classifying faults of transformers called hybrid modified evolutionary particle swarm optimization-time varying acceleration coefficient-artificial neural network (MEPSO-TVAC-ANN). In this study, they modified particle swarm optimization algorithm to achieve a better searching behavior. Souahlia et al. [11] developed a fault diagnosis algorithm using a multi-layer perceptron artificial neural network. They applied a cross validation [12] technique to determine the parameters of the model using the value of dissolved gases as inputs. In [13] the authors combined a feedforward neural network with an expert system to diagnose the fault of power transformers. They have implemented a two level detecting system in which they first classified normal/abnormal cases and then diagnosed the faults of abnormal transformers. Prior to this, Lin et al. [14] had developed a rule-based expert system using a fuzzy logic. Other research using fuzzy logic technique for fault diagnosis of power transformers is reported in [15] which defines several fuzzy rules corresponding to each fault class. In [16] a neural network was trained using five different set of ratios of DGA as input features. Each network was trained twice with two different number of neurons in the hidden layer. Flores et al. [17] designed an expert system for fault diagnosis of power transformers using type-2 fuzzy logic systems. In this algorithm, besides the value of dissolved gases, the oil chemical characteristics are also considered as inputs to achieve a more comprehensive knowledge about the status of transformers. Ma et al. [18] developed a multi-agent system to monitor and assess the condition of transformers. This study reported that an SVM classifier has a better interpretation accuracy for DGA of power transformers compared to a radial basis function network. Ashkezari et al. [19] investigated the effect of feature selection techniques on improving the classification accuracy of SVM. Two different feature selection techniques, called correlation based and minimum-redundancy-maximum-relevance, have been used to select the most correlated features and assign a health index to each transformer using SVM.

All of the aforementioned works implemented a single objective framework to diagnose faults of power transformers. Although the aforementioned diagnosing algorithms have been well trained, there are still some questions that need to be more investigated such as; 1) how the diagnosing algorithm can be generalized to deal with new dataset to avoid overfitting problem?, and 2) how can we choose the most accurate classification algorithms which result in maximizing the accuracy?. The purpose of this paper is to develop an intelligent multi objective framework using machine learning techniques to design a reliable fault diagnosis system that will overcome inaccuracies and uncertainties that exist in conventional diagnosis methodologies.

In machine learning, feature selection techniques are commonly used for dimensionality reduction and finding the most relevant features in order to enhance classification capability [20]. They have been used in a wide range of real-world applications such as biomedical studies [21], face recognition [22], and medicine [23]. In recent years, evolutionary algorithms (EA) have been of great interest to researchers to be used as a search algorithm in finding the best subset of features in feature selection problems [24]. Traditionally, most of the feature subset selection approaches use a single objective search algorithm [25]. In this paper, feature selection is dealt with a multi-objective optimization problem [26]. There is not a single solution for a multi-objective optimization problem that could optimize all objectives simultaneously. Therefore, in multi-objective optimization problems the strategy is not finding an optimal solution but selecting efficient solutions which are called non-dominated solutions in the objective space. Non-dominant solutions have superior performance in all objectives over all other solutions. A single non-dominated solution can be found in each simulation run of a multi-objective algorithm. Since it is desired to find several non-dominated solutions in each run, population-based EAs is one of the best choices for solving multi-objective optimization problems.

Particle swarm optimization (PSO) is categorised as a population-based metaheruristic algorithm developed by Kennedy and Eberhart [27]. Generally, swarm intelligence predicates agents that are not able to handle a problem individually and try to achieve a unique goal in a swarm. Unlike other evolutionary algorithms, such as the genetic algorithm (GA) [28] and Ant Colony Optimization algorithm (ACO) [29], the mechanism of PSO gives the ability to make a well-balance between local and global optima to achieve an efficient exploration and exploitation in shorter computation time compared to its counterparts. However, one of the drawbacks of PSO is the high sensitivity of this algorithm in terms of parameters which need to be fine tuned. Some research was done to address this problem and suggest a way for a better convergence of PSO algorithm [30–32]. However, the single objective PSO algorithm has been successfully applied in power systems engineering applications [33], fault diagnosis [34], and reliability engineering [35].

A multi-objective version of PSO, named MOPSO, has been applied to multi-objective optimization problems [36]. In a subsequent study, an archive based MOPSO is introduced by Coello et al. [37]. This algorithm is inspired by a traditional PSO algorithm [38] to deal with multi-objective problems. Since then, the literature continues to show MOPSO improvements which handle multi-objective problems [39–45]. The MOPSO algorithm has shown competitive performance in multi-objective optimization problems compared to non-dominated sorting genetic algorithm [46] which is a multi-objective version of GA, multi-objective evolutionary algorithm based on decomposition [47], and strength Pareto evolutionary algorithm [48].

In the first phase of our proposed method (2-ADOPT), multi-objective PSO selects the best subset of features corresponding to each fault class of power transformers. Then, in the second stage, we take advantage of ensemble learning systems to classify actual faults of transformers. Using ensemble learning increases the chance of selecting more accurate classifiers by avoiding selection of a single weak classifier [49]. Ensemble learning systems are frequently used for decision making in various applications, such as financial [50], biomedical [51], and power engineering [52–54]. Generally, all ensemble learning systems consist of three main steps [49]:

1. Sampling from a dataset to make a training set,
2. training a group of classifiers,
3. combining the output of classifiers.

There are five major techniques for classifier selection which are Classifier Fusion, Static Classifier Selection [55], Static Ensemble Selection [56], Dynamic Classifier Ensemble [57], and Dynamic Ensemble Selection [58]. In this paper a Static Ensemble Selection approach using the MOPSO algorithm is applied to diagnose faults of power transformers. To classify faults of transformers, we consider two criteria to design a diverse classifiers to classify faults of transformers. First, three types of neural networks (NN) as unstable classifiers, which can define different decision boundaries by selecting different parameters, are used in the ensemble [59]. Second, different classifiers are used as base learners. These are Support Vector Machine (SVM) [60], Fuzzy K-Nearest Neighbour (FKNN) [61], Naive Bayes (NB) [62], Kernel Ridge Regression Classifier (KRIDGE) [63], Random Vector Functional Link (RVFL) [64–66], Cascade-forward Neural Network (CFNN) and Feed-forward Neural Network (FFNN) [67]. Each of these unique classifiers is trained with different parameter settings and training functions. So, the ensemble is composed of thirty classifiers. A list of classifiers used in this paper are given in Section 3.2. In addition, Dempster-Shafer theory is used as a combination rule for combining the outputs of the classifiers.

The remainder of this paper consists of 9 sections. In Section 2 fault diagnosis using DGA is briefly described. In Section 3, feature subset selection and ensemble classifier selection using MOPSO are explained. Pareto optimality in multi-objective optimization and MOPSO algorithm are explained in Sections 4 and 5, respectively. Section 6 gives a brief