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Power system fault diagnosis based on history driven differential evolution and stochastic time domain simulation ☆

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A B S T R A C T

Fault diagnosis is an important task in power system analysis. In this paper, a hybrid method is proposed to perform online fault diagnosis of transmission lines. Stochastic time domain simulation (STDS) is firstly introduced to generate simulated fault and system data so as to improve the computational speed of fault diagnosis and handle the possible malfunction of protective relays and circuit breakers. The fault diagnosis problem is then formulated as an optimization problem, which can take into account the possible malfunction of protection devices and post-fault system trajectories. We propose a novel optimization algorithm, namely history driven differential evolution (HDDE) to solve the formulated optimization problem. The proposed methodology is finally tested using comprehensive case studies to demonstrate its effectiveness.

1. Introduction

Power systems rely on high voltage transmission lines to transmit electricity over long distance. The faults of transmission lines, if not appropriately handled, will threaten power system security and can potentially trigger large-scale blackouts. Therefore, fault diagnosis of transmission lines plays an important role in power system operation. Generally speaking, transmission line fault diagnosis has two main objectives, the fault location and fault occurring time estimation. Accurate estimation of the fault location is vital for repairing and restoring the faulted transmission line in a timely manner; while fault time estimation is helpful for setting appropriate values of protective relays (PRs).

Fault diagnosis is an active research area which has received significant attention [2,3,10,14,15,17,20,29,31]. There are also a large number of literatures studying fault diagnosis problems in power systems [1,4,5,7,9,11–13,17,22,23,25–28,32]. In general, the existing approaches to power system fault diagnosis can be classified into three main categories, which are respectively artificial intelligence based and optimization based methods. Since in the process of fault diagnosis, complicated logic based reasoning is needed to model the behaviours of the protection system, the expert system (ES) is a natural choice in the fault diagnosis problem [4,11–13]. Till now, some ES based fault diagnosis systems have been integrated with the energy management system (EMS) or supervisory control and data acquisition system (SCADA) to protect real-world power grids [12,13]. However, the ES based method usually relies on the assumption that all protective relays

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(PRs) and circuit breakers (CBs) in the system will work properly. Unfortunately this assumption is not necessarily true in practice. If there are any incorrect or missing alarms due to the malfunction of PRs or CBs, false diagnosis results may be produced.

Neural networks (NN) and other machine learning methods have also been extensively used in fault diagnosis problems [1,5,17]. In [5], the feed-forward neural network and multilayer perception (MLP) network are employed to model the complicated relationship between the protection system and the alarms generated. In [17], the radial basis function (RBF) network is applied to diagnose the fault type and fault location. In [26], the neural network is combined with the support vector machine (SVM) to estimate the fault location based on the information of PRs and CBs. In [1], a parameter selection algorithm with self adaptive growing neural networks is proposed for automatic fault detection and diagnosis in industrial applications. Fuzzy logic is used in [7] for fault classification. Generally, NN based methods have two main advantages: (1) they do not need to model the complex internal logic of the protection system; and (2) to some extent, they can take into account the possible malfunction of PRs and CBs. However, they also suffer from two major difficulties, which prevent them from practical applications. First, the accuracy of NN based methods heavily relies on the quality of training data; however, it is difficult to obtain comprehensive historical data due to the small probability of occurrence of power system faults. Moreover, the structure and the protection system of the power grid are constantly changing; therefore, even sufficient historical data have been collected, they may essentially be sampled from different underlying distributions and thus are unreliable. Besides NN and SVM, the applications of other artificial intelligence methods, such as Petri net [25] and Bayesian networks [32], have also been reported.

The optimization based method is another widely used method for solving fault diagnosis problems [3,5,9,11,18,23,25–28]. The key idea of optimization based methods is to search a fault hypothesis, which can best match the observed states of PRs and CBs. This hypothesis is then output as the diagnosis result. The key advantage of the optimization based method is that it can make decisions given a number of uncertain factors, such as the possible malfunction of PRs and CBs, the uncertain fault time and fault impedance. When using optimization based methods, the fault diagnosis problem is usually formulated as a 0–1 integer or mixed integer optimization problem. A number of optimization algorithms, such as genetic algorithm (GA) [23,28], harmony search algorithm [27], Tabu search (TS) [9], and evolutionary algorithm (EA) [25] have been applied to search the optimal fault hypothesis.

The potential malfunction of PRs and CBs is a major challenge to existing fault diagnosis methods. In practice, a protective relay may incorrectly trip the associated circuit breaker and send alarm signals to the control centre when no fault actually occurs. On the other hand, PRs and CBs may also fail to operate when a fault does happen; the control centre will not receive any alarming signals in this case. The fault diagnosis system may be misled by incorrect or missing alarms and produce false results. In theory, neural networks based methods can take into account the malfunction of PRs and CBs by including the states of PRs and CBs in the training data; however, this is impractical since it is difficult to know whether a PR or CB has worked properly when a fault occurs in practice. Optimization based methods handle this problem by considering the working state of a PR or CB (normal or malfunctioning) as a decision variable in the optimization model. They can then determine whether a PR or CB is malfunctioning by searching the optimal fault hypothesis which can exactly match the received alarm signals. However, this approach also has a theoretical defect: there is no guarantee that the formulated optimal fault hypothesis problem has a unique solution. Due to the possible existence of multiple solutions, the optimal fault hypothesis found may not reflect the true state of the system.

In this paper, a hybrid method is proposed for power system fault diagnosis. The method is called 'hybrid' because unlike existing methods which only rely on alarm signals received by the control centre to do fault diagnosis, the proposed method performs the diagnosis based on both of the alarm signals and real time system trajectories. The main contributions of this paper include:

(1) We take into account the possible malfunction of PRs and CBs by considering their working states as decision variables in an optimization model. To handle the problem of non-unique solutions, our method will produce diagnosis result based on not only the alarm signals received by the control centre, but also the real-time system information (e.g. rotor angles of generators and voltages at substations).
(2) To utilize the real-time system information in the fault diagnosis process, the time domain simulation (TDS) should be performed to obtain the expected trajectories of rotor angles and voltages, which are then compared with the observed system trajectories. Since time domain simulation is computationally intensive, we introduce the stochastic time domain simulation (STDS) to generate a large number of simulated system trajectories off-line. STDS is based on the theory of stochastic calculus, thus can take into account a variety of uncertainties (e.g. load level, fault location, fault time, and protection actions). The system trajectories generated by STDS will then be used in online fault diagnosis to improve computational efficiency.
(3) A novel optimization algorithm namely history driven differential evolution (HDDE) is proposed to solve the formulated optimal fault hypothesis problem. The proposed HDDE algorithm uses the binary partitioning (BP) tree to memorize all the solutions that it has visited before, and utilize the memorized solutions to guide the search process. By employing the BP tree, the HDDE algorithm can effectively avoid local optima and achieve a faster convergence speed.

The rest of this paper is organized as follows. Section 2 introduces the basic idea of the proposed method. In Section 3, the stochastic time domain simulation is discussed in details. In Section 4, the history driven differential evolution algorithm is