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A fuzzy Petri net based approach for fault diagnosis in power systems considering temporal constraints

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ABSTRACT

The fuzzy Petri net is a promising and efficient approach that can tackle the complexities of power system fault diagnosis. In this work, the temporal constraint between event occurrences in power systems is investigated. Then, it is introduced to a fuzzy Petri net (FPN) for fault diagnosis. The temporal attributes are assigned to the propositions in the Petri net, so that temporal information can be taken into account, which makes the true hypothesis distinguishable from the false ones. The modified matrix execution algorithm can enhance computational efficiency, with a "weighted average" operation included to improve the fault-tolerance. The developed model possesses a modular structure, which is easy to adapt to topology changes, and to accommodate modern protection schemes. A preliminary evaluation of the operating performance of protective devices is also carried out after fault section identification. The testing results on the IEEE 14-bus power system and Zhejiang provincial power system in China demonstrate that the developed model is correct and efficient. Compared with three existing fault diagnosis methods, the proposed one has stronger fault-tolerance with lower computational cost, and is suitable for on-line fault diagnosis in large-scale power systems.

Introduction

A fault that occurs on a section in power systems can trigger protective devices to operate, and raise corresponding alarm messages consequently. The fault diagnosis problem is to identify the fault section and to interpret the received alarms by providing summarized and synthesized information instead of raw alarm data. Then, based on the diagnosis result, the network could be restored rapidly. Such a task becomes more stressful, time-consuming, and less accurate when multiple faults, malfunctions of protective devices, and/or false or missing alarms are involved. The operator might be overwhelmed by the large amount of alarm messages and cannot be able to react quickly. Therefore, it would be a significant improvement to develop an online fault diagnosis module, to assist the operator in the decision-making of maintaining a secure and reliable operation of the power system. Various kinds of methods have been proposed for power system fault diagnosis, such as expert system (ES), artificial neural networks (ANNs), analytic models, Petri nets (PNs), fuzzy sets, and rough sets.

The ES-based fault diagnosis method can accommodate the operating logics of protective relays (PRs) and circuit breakers (CBs), as well as the diagnosis experience of operators, and has been used in several practical power systems [1–4]. For instance, a logic-based ES, employing the technique developed in [2], is integrated into the energy-management system (EMS) environment at the control center in Italy. The method proposed in [4] uses the General Diagnostic Engine to automatically analyze the received alarms and assess the operating performance of protective devices. However, ES-based techniques have some common drawbacks, such as the cumbersome procedure of knowledge acquisition and maintenance, and slow inference mechanism.

The advantage of the ANN-based methods is that no explicit rules are required to precisely define the power system configuration and PR schemes [5–9]. However, this kind of methods suffers the "curse of dimensionality" problem with numerous training

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samples in large-scale power systems [5,6]. It also encounters difficulties in tackling topology changes [7], and excessive training burden [8]. To avoid above problems, the ANN based method presented in [9] utilizes an alarm preprocessing module to transform the alarm states into common inputs of percentage values.

In the analytic model based methods [10–14], the fault diagnosis problem is formulated as an optimization problem. Optimization algorithms, such as the genetic algorithm (GA) [10] and Tabu search (TS) [11,12], are employed to solve the optimization model, so as to find the most plausible fault hypothesis or hypotheses to explain the alarm messages. Before the diagnosis procedure is initiated, the outage area must be identified. Therefore, the loss of a boundary CB alarm may lead to the failure of such method.

The main features of the Petri net-based methods include parallel information processing and strong inclusiveness. Enhanced with the well-established fuzzy logic, the fuzzy Petri nets (FPNs) [15–20], superior to the traditional Petri nets [21,22], are capable of modeling inexactness and uncertainties. Graphical FPN models are built in [16] for fault section identification, but the model structure is not optimized and the matrix execution algorithm is not addressed. Based on [16], a FPN is further presented in [17] with aforementioned problems solved to some extent. The method in [19] introduces the "adaptive" concept into FPN, so as to employ advantages of both FPN and ANN.

Despite best efforts, the aforementioned methods still suffer from one or more of the following problems: (1) temporal information, as an important characteristic of alarm messages, is not well utilized; (2) the existing models cannot accommodate new protection schemes or adapt to topological changes due to not being well structured; (3) the evaluation of operating performance of protective devices is not investigated.

In recent years, the timestamp accuracy of alarm messages has been significantly improved with the wide deployment of global positioning system (GPS) clocks in substations. Given this background, a temporal reasoning fuzzy Petri net (TRFPN) model is presented in this paper and applied to fault diagnosis in power systems. The following three aspects are the major features of this work.

(1) Capable of handling temporal constraints and fuzzy information, the presented fault diagnosis model can deal with malfunctions of protective devices and distortions of alarm message. The introduction of temporal constraints can distinguish the true hypothesis/hypotheses from the false ones, making the diagnosis result more reliable.
(2) The modular structure is convenient to accommodate various protection configurations, and adapt to topology changes. The modified matrix algorithm features high computational efficiency. And the rule-based evaluation module could provide the operator preliminary but valuable information about the malfunctioned protection devices.
(3) A framework is established for online fault diagnosis application. Based on the developed fault diagnosis model, a software package is designed and implemented to meet the actual requirement.

This paper is structured as follows. Temporal elements in power systems are defined, and temporal constraints as well as temporal reasoning explained in Section 'Temporal constraints and temporal reasoning'. Next, the mathematical description of TRFPN and the modified matrix execution algorithm are given in Section 'FPN enhanced with temporal constraints'. The fault diagnosis model based on TRFPN is presented in Section 'Fault diagnosis model based on TRFPN'. Issues are addressed regarding how to structure the model, impose the temporal constraints on the propositions, determinate the candidate hypothesis set, and evaluate the operating performances of protective devices. Then, a framework for online applications of the TRFPN-based fault diagnosis model is presented in Section 'The Framework of TRFPN based online fault diagnosis'. Finally, case studies on the IEEE 14-bus power system and Zhejiang provincial power system in China are served for demonstrating the feasibility and efficiency of the developed approach in Section 'Case studies'. Concluding remarks are given in Section 'Conclusions'.

Temporal constraints and temporal reasoning

Overview of temporal elements in power systems

Temporal constraints and temporal reasoning are defined in [14], and are modified here to fit the proposed method. For the convenience of presentation, several objects are defined as follows.

(1) E, E_C, and E_A are the event set, cause set, and alarm set, respectively, where $E = E_C \cup E_A$;
(2) e_i, c_i, and a_i are the ith element in E, E_C, and E_A, respectively;
(3) $N(E)$ is a function that gives the dimension of set E, and is applicable to other sets;
(4) t_{ei} is a time point of occurrence of e_i;
(5) $T(t_{ei}) = [t_{ei}^-, t_{ei}^+]$ is a time interval defined as the time-point constraint of t_{ei}, where t_{ei}^- and t_{ei}^+ are the lower and upper bounds, respectively. It becomes t_{ei} if $t_{ei}^- = t_{ei}^+$;
(6) $d(t_{ei}, t_{ej}) = t_{ej} - t_{ei}$ is defined as a time-distance, referring to the time difference between two time points;
(7) $D(t_{ei}, t_{ej}) = [\Delta t_{ij}^-, \Delta t_{ij}^+]$ is a time interval defined as the time-distance constraint of $d(t_{ei}, t_{ej})$, where Δt_{ij}^- and Δt_{ij}^+ are lower and upper bounds, respectively;
(8) (e_i, t_{ei}) is an event-time pair, meaning that "the event e_i happened at t_{ei}";
(9) $(e_i, T(t_{ei}))$ is an event-interval pair, meaning that "the event e_i happened during the time interval $T(t_{ei})$";

If the occurrence of e_i can trigger e_j to take place, they are cause-effect related, denoted as $\langle e_i, e_j \rangle$. The time-distance constraint is denoted as $D(t_{ei}, t_{ej})$. The cause-effect relationship is extendable. As shown in Fig. 1, a link of e_i to e_j represented by $L = \{\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_{N(L)}\}$, satisfies: (a) $N(L) \geqslant 2$; (b) $\varepsilon_1 = e_i$ and $\varepsilon_{N(L)} = e_j$; (c) $\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_{N(L)} \in E$; (d) for $k \in \{1, \ldots, N(L) - 1\}$, $\langle e_k, e_{k+1} \rangle$. Then, e_i and e_j are cause-effect related along L, denoted as $\langle e_i, e_j \rangle_L$. The time-distance constraint between t_{ei} and t_{ej} could be determined as

$$D_L(t_{ei}, t_{ej}) = \sum_{k=1}^{N(L)-1} D(t_{\varepsilon k}, t_{\varepsilon k+1}) = \left[\sum_{k=1}^{N(L)-1} \Delta t_{k,k+1}^-, \sum_{k=1}^{N(L)-1} \Delta t_{k,k+1}^+ \right] \quad (1)$$

In power systems, alarms refer to the received messages about operation or warning information of equipment from substations, such as SOE. For example, "MP4335 in the Jianshan substation operated at 08:21:04 70 ms". Causes refer to the faults which can trigger the reported alarms. For instance, the cause "a grounding fault occurred on the transmission line L4335 at 08:21:04 50 ms" could trigger the aforementioned alarm. Protective devices are coordinated to achieve selectivity and reliability. Thus, the same cause could also trigger the alarm "LBP4335 in the Jianshan substation operated at at 08:21:04 30 ms 550 ms" only if the fault is not cleared in the first place. Here, MP and LBP stands for main protection and local backup protection, respectively. The time-distance constraint $D(t_{ei}, t_{ej})$ is determined by the intentional time delay of PRs, or the breaking delay of CBs, with random error taken into account.