Progress in Nuclear Energy 92 (2016) 22–28

Contents lists available at ScienceDirect

Progress in Nuclear Energy

journal homepage: www.elsevier.com/locate/pnucene

A dynamic ordered concept lattice based algorithm for early diagnosis of NPP faults

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ARTICLE INFO

Article history:
Received 10 November 2015
Received in revised form
31 May 2016
Accepted 3 June 2016

Keywords:
Dynamic ordered concept lattice based method
Early diagnosis
Nuclear power plant (NPP) faults

ABSTRACT

In this paper, a dynamic ordered concept lattice-based algorithm is developed by building up an ordered concept lattice using the theory of concept lattice, and proposed for early diagnosis of NPP faults. The effectiveness of the proposed algorithm in identifying NPP faults is verified through simulation tests. Test results indicate that, compared with other methods such as BP neural network, the proposed algorithm can be used to achieve early diagnosis of NPP faults within shorter time.

1. Introduction

The numbers of failures and disruptions are now increasing with the complexity of equipment installed in the industrial field causing immediate shut-down of a machine, and/or undermining proper functioning of an entire production system (Karabadji et al., 2014). In general, 99 accidents were reported at NPP from 1952 to 2009; including: most and recent serious NPP accidents of the Fukushima Daiichi nuclear disaster (2011), Chernobyl disaster (1986), Three Mile Island accident (1979), and the SL-1 accident (1961) (Sovacool, 2008, 2010; Friedman, 2011; Inoue et al., 2012; Cilliers, 2013; chwartz, 2004; Lv et al., 2013). All the above mentioned accidents resulted in dramatic casualty tolls including massive deaths and/or injuries, significant environmental damages, and tremendous financial losses (Park and Jung, 2015). It is, therefore, crucial to find ways and means ensuring e safe operation of a complex social-technical system, such as NPP, an off-shore industry, or a marine transportation system. Much work has been done on this particular aspect in recent years to ensure safe and stable operations at NPPs (Li and Upadhyaya, 2011; Li et al., 2012). Artificial neural network (ANN) (Ayaz, 2008), fuzzy logic (FL), data fusion (Ma et al., 2011), and hybrid intelligence approach (Arroyo-Figueroaa et al., 2000; Ntalampiras et al., 2015) have all been used to alleviate the consequences of accidents (Liu et al., 2014; Nawel et al., 2015; Jharko, 2015; Xin et al., 2013). For example, Baraldi et al. (2015) proposed a feature extraction procedure to evaluate the functional similarity among different operational or faulty transients. Ma and Jiang (2015) developed a fault diagnosis scheme based on semi-supervised classification (SSC). Liu et al. (2014) proposed a hybrid intelligence approach for the fault diagnosis at NPP. Kamal et al. (2011) presented a fault recognition and classification method based Artificial Neural Network (ANN). Cesare Alippi et al. (2013) introduced a fault diagnosis system (FDS) in the distributed sensor networks considering the advantage of spatial and temporal relationships to distinguish changes in the environment and false positives induced by model bias in the hidden Markov models.

Wille proposed, in 1982, the theory of concept lattice, followed by further enhancement by Carpineto and Romano (2004), Ganter et al. (2005), and Wei et al. (2008) Jonas Poelmans et al. reviewed 1072 papers on the subject of formal Concept Analysis (FCA) published between 2003 and 2011, and found FCA had been widely used for logical, relational, temporal and triadic concept analyses (Jonas Poelmans et al., 2013). As an efficient tool of data analysis and knowledge processing (Mao, 2014), the theory of concept lattice has now been applied to such fields as knowledge engineering,

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http://dx.doi.org/10.1016/j.pnucene.2016.06.001
0149-1970/

data mining, information searches and software engineering (Li et al., 2014; Le et al., 2013; Shao et al., 2015).

Therefore, in this research, a dynamic ordered concept lattice-based algorithm is developed by building up an ordered dynamic concept lattice with the time sequence of faults using the theory of concept lattice.

2. Principle

2.1. Dynamic ordered concept lattice

The dynamic ordered concept lattice, with the time sequence of faults, can be expressed by a dynamic subsequence searching and matching process as shown below.

$$I \lessdot U \otimes A \tag{1}$$

where $U = \{x_1,x_2,\ldots,x_n\}$ are the objects, $A = \{a_1,a_2,\ldots,a_m\}$ are the attributes and U is a set of objects $x_i(i \le n)$ is an object. A is a set of attribute, $a_j(j \le m)$ is a property. $(x,a)\in I$ means x with attribute a. $(x,a)\notin I$, means x without attribute a."1", expresses $(x,a)\in$I, and "0" expresses$(x,a)\notin$I, and so, the background can be formed as a list of "0" and "1" only.

U is a set of different types of faults and A is a set of different symptoms of faults in fault diagnosis field. $(x,a)\in I$ expresses symptom a will appear when fault x occurs. (x,a)$\notin$I, expresses symptom a will not appear when fault x occurs. For example, when U-tube break and main feed-water pipe rupture are diagnosed, these two faults are the elements of set U, and the symptoms of faults are the elements of set A.

Ordinal sequence $\{s_1,s_2,\ldots,s_l\}(1 \le l \le m)$ can be expressed as $\{a_1,a_2,\ldots,a_m\}$ and another ordinal sequence can be expressed as $\{b_1,b_2,\ldots,b_m\}$. If a serial of integer$i_1,i_2,\ldots,i_n$, satisfies $i_1 \le i_2 \le \ldots \le i_n$, and $a_1 \subseteq b_{i1},a_2 \subseteq b_{i2}, \ldots ,a_n\subseteq b_{in}$(Zhang and Qiu, 2005). Ordinal sequence {{a}, {b}} and ordinal sequence {{b, c}} are the subsequences of ordinal sequence {{a}, {d}, {b, c}}.

A typical dynamic ordered concept lattice model is shown in Fig. 1, t_i is the stamp of time in seconds when abnormal parameters appear. a_j and a_s are the different abnormal parameters, which means when the faults have occurred in t_i seconds, $a_j \ldots a_s$ will become abnormally.

2.2. Structure of dynamic ordered concept lattice

As shown in Fig. 2, the dynamic ordered concept lattice is dynamically built for the whole development process of faults with symptoms emerging step by step, and it describes not only the deviation of parameters, but also the symptoms in the chronological order.

As shown in Fig. 2, the symptoms are continuously monitored to realise if any abnormal sign goes back to normal in the fault lattice at the last moment. If any symptom data becomes abnormal while its sign is not at the fault concept lattice at the last moment, the sign will then be stored in the fault concept lattices at this time. If the abnormal sign goes back to normal at the last moment, the sign will then be removed from fault concept lattice.

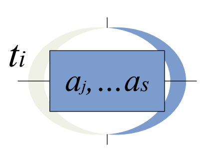

Fig. 1. Model of dynamic ordered concept lattice.

As shown in Fig. 3, a fault dynamic ordered concept lattice is built up for a main feed-water pipe rupture without automatic shutdown procedure as reported by Alexandre and Sylviane (2005). It can be seen from Fig. 3 that core coolant flux a_8 becomes abnormal in 60 s from the insert of fault, and all the other parameters become abnormal in 105 s from the occurrence of the fault.

2.3. Building Hasse diagram

One of the most important steps in the algorithm is to build standard faults dynamic ordered concept lattice. Building Hasse diagrams (HD) helps forming the standard faults concept lattice. HD can be achieved by defining an order between different alternatives on the basis of their criteria values for partial order ranking. (Francesca et al., 2015). Table 1 can be tabulated to provide background composition of faults and their symptoms for the detailed analysis of faults as reported by Alexandre and Sylviane (2005). It can be observed from Table 1 that the loss of coolant in primary loop x_1 is related to symptoms $(a_{10},a_{12},a_{15},a_{16})$, which means parameters $a_{10},a_{12},a_{15},a_{16}$ will be abnormal when fault x_1 occurs.

Theorem1 (Ganter and Wille, 1999) Let (U,A,I) be a context. Then$(\mathscr{L}(U,A,I),\le)$ is a complete lattice in which suprema and infima are given by

$$\bigwedge_{t\in T}(x_t,a_t) = \left(\bigcap_{t\in T} x_t, \left(\bigcup_{t\in T} a_t\right)\right)$$

$$\bigwedge_{t\in T}(x_t,a_t) = \left(\left(\bigcup_{t\in T} x_t\right), \bigcap_{t\in T} a_t\right)$$

In the built concept lattice, a concept is meet irreducible if it cannot be written as meet ($\wedge$) of other concepts. A concept is join irreducible if it cannot be written as join ($\vee$) of other concepts.(Wang and Liu, 2008).

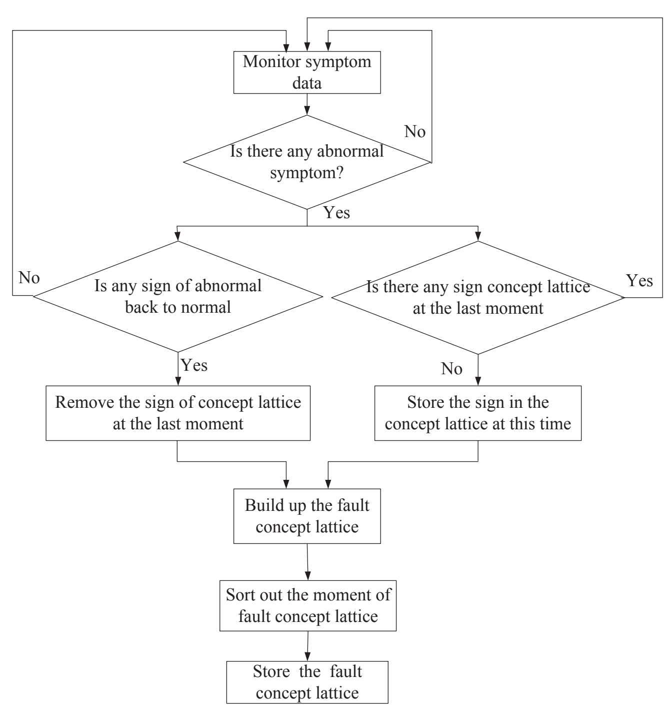

Fig. 2. Flow chart of dynamic fault lattice based algorithm.