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Available recovery time prediction in case of an accident scenario for NPP component

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ABSTRACT

In nuclear power plant operations, there is a possibility that a stimulating event can initiate undesired accident. Therefore, prediction of the available recovery time (the time within which restorative measures can be taken without compromising the threshold safety limits) is a serious challenge to avoid any accident scenario. Recent advances in sensor technology has made it possible to continuously monitor the plant component parameters. Fuzzy logic based artificial intelligence data-driven systems compare real time operational parameters with the pre-stored reference failure database to provide an effective estimate of the recovery time available. This paper demonstrates the prediction of available recovery time in case of an accident scenario in U-tubes of Nuclear Power Plant (NPP) heat exchanger. When a failure scenario evolves, its evolution pattern is compared with the reference failure database using fuzzy similarity analysis. A reference failure database consisting of actual accidental history is not feasible. In this research, an effort has been made to generate reference failure database employing Computational Fluid Dynamics (CFD) tool of commercial code ANSYS 16.2. Reference failure database consists of data collected from multiple U-tube temperature based failure scenarios. The validity of this procedure is checked by estimating recovery times for several test patterns. Moreover, the actual and predicted recovery times have been compared for the test patterns. A framework has been presented, in which temperature threshold is detected and a comparison is made between the evolving patterns and the reference database. This study gives a roadmap for the implementation of fuzzy logic prediction to enhance the safety of Nuclear Power Plant (NPP) components.

1. Introduction

In a Nuclear Power Plant (NPP), the reliability of all components need to be ensured, in order to maintain the safety standards of the plant. Therefore, it is essential to continuously monitor all the components for providing advanced warnings for managing the accidents (IAEA, 2003), so that restorative measures can be taken to mitigate the effects of any stimulating event. In light of the recent advances in sensor technology (Azirah et al., 2013), it has been made possible to continuously monitor both input and output parameters of the components through data collection. Such data, acquired by sensors, is useful for the identification of potential failure events.

The collected data can be used to perform various prognostic tasks which, are important in reliability and safety (Chiang et al., 2001) analyses of the system or that of the component of concern. Such approaches are classified into model-based and data-driven categories. Model-based approach requires the physical model of the system for RT prediction, as in most of the cases, the cost/benefit ratio (Zio and Di Maio, 2010) of using the physical model of the system is not favorable. Therefore, such a method is not suitable for this application. On contrary, data driven method employs online-monitored data related to system or component of concern, making it well suited for online estimation of RT. The method has the ability to transform high dimensional noisy data into lower dimensional information (Elena Dragomir et al., 2007), being all-the-more useful for decision-making.

Data-driven methods can be classified into two classes; the statistical method and the artificial intelligence techniques. The most common statistical method is fitting a curve to the available data by using regression models. These methods may result in large errors due to their inability to deal with uncertainties and non-

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Nomenclature

t	Time(s)
μ	Membership value
D	Database matrix
d	Distance score
n	Number of time steps
N	Number of failure patterns
T	Temperature (K)
t	Time(s)
w	Weight
W	Normalized weight
α	Membership function constant
β	Membership function constant
δ	Point-wise difference

Superscript

*	Normalized value

Subscripts

i	Row index
j	Column index
s	Sum of weights

Abbreviation

ANSYS	Analysis of Systems
ASME	American Society of Mechanical Engineers
CFD	Computational fluid dynamics
CFX	Computational Fluid Xerography
DAQ	Data acquisition
FT	Failure time
ICEM	Integrated Computer Engineering and Manufacturing
MATLAB	Matrix Laboratory
MF	Membership function
NPP	Nuclear power plant
RT	Recovery time
PWR	Pressurized water reactor

linearities. On contrary artificial intelligence tools employ neural networks for prediction. For prognosticating purposes, the most reliable techniques are recurrent neural networks and neuro fuzzy logic methods (Zio et al., 2010). Due to the lack of systematic approach of the earlier method, limitations exist for their application in critical systems. On contrary neuro-fuzzy logic technique has acquired considerable importance due its ability to deal with uncertainties and non-linearities in real life problems.

The concept of fuzzy logic relies on the idea of relatively-graded membership function, which is inspired by the human sense of perception and cognitive ability. Ground work in the fuzzy logic sets was laid out by (ZADEH, 1965). It is an extremely powerful tool of prediction, which has been used for diversified real-life applications ranging from facial pattern recognition to the prediction of stock market.

The principal purpose of purposing neuro-fuzzy logic based online condition monitoring system is to predict whether a component can perform its intended functions (Tyan et al., 1995) during its lifespan. If not, it is inevitable to predict the time to failure by recognizing the failure mode. This failure time is identified as recovery time (RT) for that particular component.

The goal of this study is to develop a road map for an on-line monitoring tool that can be embedded in the operator support system, which could identify any stimulating accident scenario and help the operator in decision making process. The idea has been conceived from the effective use of fuzzy logic prediction which maps the current stimulus of an initiating event in a system with its past projections and reflects a prediction for future.

U-tubes are critical components of PWR Nuclear Power Plants. These tubes carry highly pressurized and radioactive primary water coolant which is used to heat the secondary-side fluid. Beside performing its main functions, heat exchanger tubes must provide a reliable pressure boundary (Obrutsky et al., 2009) between primary and secondary fluid because any leakage could result in radioactivity release to the secondary fluid. Therefore, this procedure is applied on U-tube for estimating its RT.

The complete computational framework has been presented, which shows the implementation of neuro-fuzzy logic based data-driven monitoring system. As its application, this artificial intelligence tool requires some past historical failure database of the concerned component for failure prediction. The past projections of dynamic failure scenarios of U-tube heat exchanger are obtained through multiple transient analyses using Computational Fluid Dynamics (CFD) tool of the commercial code ANSYS 16.2. These failures scenarios are developed by introducing severe conditions at the U-tube inlet and the average wall temperature of the fluid domain is monitored after each timestep. The time, when a failure scenario strikes the threshold value of temperature, is identified as recovery time (RT).

The article is arranged as follows: section 2 presents the CFD transient analysis of U-tube to create failure pattern database. An algorithm for neuro-fuzzy based similarity analysis has been presented in section 3. In section 4, this algorithm was implemented on a reference database collected through CFD transient analysis of U-tube. In section 4, results have been presented, showing the implementation of this approach on a U-tube heat exchanger. Finally, a conclusion is drawn in section 4, based on the results.

2. Database generation

Equipment historical failure database can be generated by using CFD tools. Since the heat exchanger consists of hundreds of tubes (in which the coolant distributes itself equally), only a single tube is analyzed instead of the whole heat exchanger, for obtaining the past failure patterns.

In this study, the database is generated by modelling a fluid domain using ICEM. The wall material is considered to be Inconel 600 (a typical U-tube material in heat exchangers). According to ASME Code Section II-part D (ASME, 2004), the design temperature for Inconel 600 with alloy designation N06022 should be 616 K. Thereby, the average temperature at the wall of the fluid domain should not exceed this threshold value.

Average temperature at the wall of U-tube can be obtained through CFD transient analysis of the U-shaped fluid domain. To obtain temperature based failure patterns of U-tube, severe conditions are introduced at the inlet of U-tube and average wall temperature is plotted with respect to time. Both fluid domain and temperature distribution are shown for the U-tube (Fig. 1 & Fig. 2) for an accident case.

The time when an average wall temperature strikes the threshold value (616 K) is identified as failure time. This is shown in Fig. 3.

For the sake of simplicity, some assumptions have been proposed in this study (Pu et al., 2015):