Annals of Nuclear Energy 87 (2016) 217–227

Contents lists available at ScienceDirect

Annals of Nuclear Energy

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

Transient identification by clustering based on Integrated Deterministic and Probabilistic Safety Analysis outcomes

Francesco Di Maio [a,*], Matteo Vagnoli [a], Enrico Zio [a,b]

[a] Energy Department, Politecnico di Milano, Via Ponzio 34/3, 20133 Milano, Italy
[b] Chair on System Science and Energetic Challenge, Foundation EDF – Electricite de France, Ecole Centrale, Paris, and Supelec, Paris, France

ARTICLE INFO

Article history:
Received 16 February 2015
Received in revised form 2 September 2015
Accepted 13 September 2015

Keywords:
Integrated Deterministic and Probabilistic Safety Analysis (IDPSA)
Prime Implicants
Near Misses
On-line clustering
Steam Generator

ABSTRACT

In this work, we present a transient identification approach that utilizes clustering for retrieving scenarios information from an Integrated Deterministic and Probabilistic Safety Analysis (IDPSA). The approach requires: (i) creation of a database of scenarios by IDPSA; (ii) scenario post-processing for clustering Prime Implicants (PIs), i.e., minimum combinations of failure events that are capable of leading the system into a fault state, and Near Misses, i.e., combinations of failure events that lead the system to a quasi-fault state; (iii) on-line cluster assignment of an unknown developing scenario. In the step (ii), we adopt a visual interactive method and risk-based clustering to identify PIs and Near Misses, respectively; in the on-line step (iii), to assign a scenario to a cluster we consider the sequence of events in the scenario and evaluate the Hamming similarity to the sequences of the previously clustered scenarios. The feasibility of the analysis is shown with respect to the accidental scenarios of a dynamic Steam Generator (SG) of a NPP.

1. Introduction

The safe operation of hazardous installations, such as Nuclear Power Plants (NPPs), depends on the capability of timely detecting possible accidental transients and promptly taking adequate actions to avoid catastrophic failures (Carlos Canedo Medeiros and Schirru, 2008). Upon occurrence of an initiating failure event, it is important to predict whether the scenario that follows would lead to safe conditions or become an accidental scenario. In practice, this is done relying on the awareness of skilled operators who monitor and analyze recorded operational data of process variables, for early detection and diagnosis and, then, based on their own expert judgment follow the Emergency Operating Procedures (EOPs) and, if necessary, the Severe Accident Management Guidelines (SAMGs) to mitigate the scenario consequences. However, even for less dangerous accidental scenarios that do not lead to core damage but only to unplanned outage of production, it is sometimes difficult, if not impossible, for operators to promptly and accurately assess the plant and distinguish the occurring accidental scenario status simply by observing the large volume of operational data (Alaei et al., 2013). For this reason, the decision process by the emergency management staff must be supported.

For such support, it is possible to devise automatic pattern recognition methods to predict the future evolution of a scenario initiated by a failure event. With this aim, we propose a novel method that combines post-processing of the outcomes of an Integrated Deterministic and Probabilistic Safety Analysis (IDPSA) and on-line clustering of data from the developing scenario.

We use Multiple-Valued Logic (MVL) theory for modeling the behavior of the system, accounting for the timing and order of occurrence of component failure events (Di Maio et al., 2015a).

Post-processing of the IDPSA results is performed for the: (i) identification of the Prime Implicants (PI), i.e., those minimal sequences of failure events that are capable of leading the system into a fault state and cannot be covered by more general implicants (Quine, 1952), (ii) identification of the Near Misses, i.e., those safe sequences of events that reach values of the safety parameters close to, but not exceeding, the corresponding acceptable thresholds (Zio et al., 2009).

In this work, we use a visual interactive method and a risk-based clustering method that have been shown effective for PI and Near Misses identification, respectively (Di Maio, 2014b; Di Maio et al., 2015).

For on-line identification of accidental transients, several methods have been presented in literature. Some of these are based on statistical techniques (Di Maio et al., 2013; Fink et al., 2015), which may have limitations with regards to the choice of parameters and difficulty in coping with noise in data (Markou et al., 2003); others,

* Corresponding author.
E-mail address: francesco.dimaio@polimi.it (F. Di Maio).

http://dx.doi.org/10.1016/j.anucene.2015.09.007
0306-4549/

like neural networks and support vector machines (Basu et al., 1994; Palade et al., 2002; Widodo et al., 2007), require prior knowledge of the fault data set (Alaei et al., 2013); and others are based on clustering by means of Euclidean metrics for measuring the similarity between transients (Schirru et al., 1999; Beringer et al., 2006; Collaghan et al., 2002) and fuzzy means (Zio et al., 2012; Baraldi et al., 2013).

In this paper, we develop an on-line clustering algorithm based on the Hamming distance (Hamming, 1950) to measure the similarity between developing transients and those obtained by IDPSA. At any instant of time, we compute the Hamming distance between the vector containing the event data of the developing accidental sequence with the vectors of the IDPSA post-processing scenarios, and identify the characteristics of the developing scenario as soon as any change in the trend of a process variable is detected. Finally, the developing transient is assigned to a cluster of safe scenarios, PIs, or, Near Misses, depending on its characteristics. In this way, we overcome the limitations of the methods already proposed in literature because (i) the MVL approximation can be easily accommodated within a Hamming-based similarity definition (rather than using an Euclidean metric), (ii) there is no need of additional efforts in tuning any parameter of the algorithm (as for the statistical techniques).

A case study is considered, regarding dynamic accidental scenarios occurring in the Steam Generator (SG) of a NPP (Aubry et al., 2012). The paper is organized as follows. In Section 2, the SG model used to generate the scenarios for the dynamic reliability analysis is presented. In Section 3, a visual interactive method (Di Maio et al., 2015b) is applied for PIs identification, and, a risk-based Near Misses identification is performed. In Section 4, the on-line clustering method is introduced with reference to the case study considered. In Section 5, conclusions and remarks are given.

2. Case study

2.1. The U-Tube Steam Generator (UTSG) model

We consider a U-Tube Steam Generator (UTSG) (Fig. 1), part of the secondary circuit of a 900 MW Pressurized Water Reactor (PWR) (Aubry et al., 2012). The improper control of the water level can be a major cause of this NPP unavailability (Kothare et al., 2000; Habibiyan et al., 2004). The difficulties arises from non-minimum phase plant characteristics, i.e., plant strong inverse response behavior, particularly at low operating power, due to the so-called "swell and shrink" effects (Kothare et al., 2000).

The model and the parameters used serve the scope of mimicking the actual data of the real UTSG (Aubry et al., 2012). A detailed model is, indeed, necessary for IDPSA because real data, necessary incomplete, would only partially cover the whole set of possible sequences of failure events and, therefore, endanger the identification of the set of PIs and Near Misses. Once the capability of the online identification clustering hereafter proposed is shown to be reliable with respect to the whole (simulated) set of accidental scenarios, we can be confident that its performance can be guaranteed on real (sparse) accidental scenarios, that, incidentally have already been classified by resorting to simulated scenarios.

The reactor coolant enters the UTSG at the bottom, moves upward and then downward in the inverted U-tubes, transferring heat to the secondary fluid before exiting at the bottom. The secondary fluid, the feedwater (Q_e), enters the UTSG at the top of the downcomer, through the space between the tube bundle wrapper and the SG shell. The value of Q_e is regulated by a system of valves: a low flow rate valve, used when the operating power (P_o) is smaller than 15% of nominal power (P_n), and a high flow rate valve when $P_o > 0.15\ P_n$ (Aubry et al., 2012). In the secondary side

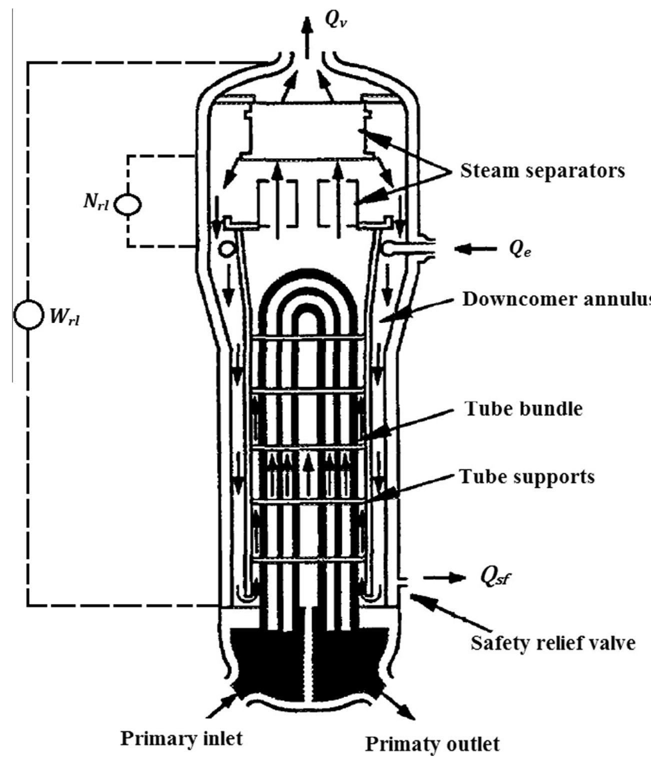

Fig. 1. Schematic of the UTSG (IAEA-TECDOC-981, 1997).

of the tube bundle, water heats up, reaches saturation, starts boiling and turns into a two-phase mixture. The two-phase fluid moves up through the separator/riser section, where steam is separated from liquid water, and through the dryers, which ensure that the exiting steam (Q_v) is essentially dry. The separated water is recirculated back to the downcomer. The balance between the exiting Q_v and the incoming Q_e governs the change in the water level in the SG. Because of the two-phase nature, two types of water level measurements are considered, as shown in Fig. 1, each reflecting a different level concept: the Narrow Range Level (N_{rl}) is calculated by pressure difference between two points close to the water level and indicates the mixture level, whereas, the Wide Range Level (W_{rl}) is calculated by pressure difference between the two extremities of the SG (steam dome and bottom of the downcomer) and indicates the collapsed liquid level that is related with the mass of water in the SG.

"Swell and shrink" phenomena are also modeled to reproduce the dynamic behavior of the SG: when Q_v increases, the steam pressure in the steam dome decreases and the two-phase fluid in the tube bundle expands causing N_{rl} to initially swell (i.e., rise), instead of decreasing as would have been expected by the mass balance; contrarily, if Q_v decreases or Q_e increases, a shrink effect occurs. A similar model has been presented in (Aubry et al., 2012).

The N_{rl} is governed by Q_e and Q_v across the tube bundle region of the SG as shown by the following transfer function:

$$N_{rl}(s) = \frac{1}{T_n s}\left(Q_{ef}(s) - Q_{GV}(s)\right) \tag{1}$$

where Q_{ef} is the flow-rate of the incoming water in the tube bundle, (Eq. (2)), Q_{GV} is the equivalent steam-water mixture flow-rate exiting the tube bundle region, (Eq. (3)), T_n is a time constant that accounts for the N_{rl} dynamics.

The incoming water flow-rate Q_{ef} is proportional to Q_e:

$$Q_{ef}(s) = \frac{1}{(1+T_h s)(1+\tau s)} Q_e(s) \tag{2}$$