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An identification and grouping approach to analyze the output of a dynamic safety assessment

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Abstract

Dynamic Probabilistic Safety Assessment embeds models of the system process (typically thermo-hydraulic models) and of human operator dynamics within stochastic simulation engines. These engines generate sequences of component and operator action events, representing success, failures and other sources of variability. A challenge is to retrieve and organize the scenarios hidden in the large amount of information produced. The present paper discusses an approach for identifying and grouping the produced scenarios, based on possibilistic clustering classification; the aim is to single out the principal patterns of system evolution with respect not only to the final system states but also to the time of events and to the process evolution.

Keywords: Dynamic Probabilistic Safety Assessment; Human Reliability Analysis; possibilistic clustering classification;

1. Main Text

In the Probabilistic Safety Assessment (PSA) of Nuclear Power Plants (NPPs), accident scenarios, which are dynamic in nature, are analyzed with event trees and fault trees. This framework has proven useful for identifying plant weaknesses and led to modifications of the plant, its operating procedures and personnel training. Yet, the current PSA framework has some limitations in handling the timing of automatic and personnel actions, whose variability may influence the successive evolution of the scenarios, and in modeling the interactions between the physical evolution of the process variables (temperatures, pressures, mass flows, etc …) and the behavior of the hardware components and the operating crew (Siu, 1994; Labeau et al., 2000; Chang and Mosleh 2006).

In particular, this paper focuses on Dynamic Event Trees (DETs). The most evident difference between DETs and the event trees (ETs) typically used in industrial PSAs is as follows. ETs are constructed by an analyst who sets success / failure criteria for the events to define their branches. These criteria are based on simulations of the plant dynamics. In contrast, DETs are produced by a software that embeds the models that simulates the plant dynamics into stochastic models of components failure / success and of the crew response (Siu, 1994).

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A challenge arising from the dynamic approach to PSA is the large number of scenarios to be analyzed, so that the a posteriori information retrieval can become quite burdensome and difficult (Labeau et al., 2000). In a first attempt to overcome this difficulty, the authors of the present paper have proposed an approach to identifying and grouping the produced scenarios, with the aim of finding the principal patterns of system evolutions towards failure (Mercurio et al., 2009; Podofillini et al., 2010).

The scenarios are grouped combining information from the end state, the occurrence and sequencing of events and the evolutions of process variables. A first step is the a priori identification of the anticipated scenario classes for the system under analysis and of the relevant classification features. The scenarios will eventually be classified as belonging to a particular class based on the affinity of their features to those characteristic of the class. The successive steps of the procedure are typical of a supervised classification scheme: training of the classifier on patterns of assigned classes and test of the classifier on new patterns. As for the classification technique, a possibilistic Fuzzy C Means (FCM) classifier is used in this work. An important advantage of this technique is its ability to identify unanticipated scenarios, i.e. patterns of evolution that were not foreseen in the a priori analysis and thus do not fall in any scenario class. The possibilistic module filters them out, revealing new dynamic failure patterns that were not identified in the a priori analysis. The clustering algorithm was introduced by some of the authors for the classification of nuclear plants transients, in an effort to aid the plant operators in diagnosing the causes of the transients (Zio and Baraldi, 2005).

In the present paper, the approach is applied on the DET scenarios of a small Loss of Coolant Accident event in a NPP. The DET are generated by the Accident Dynamic Simulator (ADS) software (Chang and Mosleh, 1999). The physical plant model and the operating crew model of the system of interest are linked to the ADS. The crew response is treated by the IDAC model, a crew model including cognitive, emotional, and physical activities during accident scenarios within a procedure-guided response framework (Chang and Mosleh, 1999; Mercurio et al. 2009); the simulation of the plant process is performed by a RELAP thermal-hydraulic transient model.

The presented approach represents a first step of an effort towards the identification of the prime implicants of dynamic systems, which can be thought of as analogues to the cut-sets when dynamic safety techniques are used. The notion of prime implicants accommodates for the combination of the information on the status of the physical parameters with the status of the systems' components that lead to the system failure.

2. References

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