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A Regional Sensitivity Analysis-based Expert System for safety margins control

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ABSTRACT

Thermal-Hydraulic (TH) codes are used to simulate the response of nuclear safety systems under transient and accident conditions. The outcomes of the simulations are used to verify the safety margins required for safe operation and make decisions on how to maintain them.

In this work, a novel Expert System (ES) based on Regional Sensitivity Analysis (RSA) is developed to guide a system undergoing an accident scenario towards the safest conditions in the optimal number of operation. The ES proceeds by firstly identifying the (uncertain) system controllable variables (i.e., control rods position, feedwater flow rate, void fraction inside the steam generator, etc.) that most affect the system response by RSA; then, the limit-state function is calibrated on a dataset of outcomes of TH code runs and the system failure boundary (i.e., the limit surface) is defined on the set of (uncertain) TH input variables.

Application of the ES is firstly shown with respect to an analytical case study that artificially simulates the response of a NPP to an accident scenario and, then, to a practical case study concerning the response of the pressurizer of a Pressurized Water Reactor (PWR).

1. Introduction

Safety remains a priority for Nuclear Power Plants (NPPs) design and operation, as the release of radioactive material can result in catastrophic consequences in terms of casualties, environmental pollution and financial losses (Hsieh et al., 2012). For the safety of NPPs, accident-preventive design and operation, and effective consequence mitigation plans are developed (Ma and Jiang, 2011). In practice, Emergency Operating Procedures (EOPs) are defined to provide the technical basis for suitable operator response to Design Basis Accidents (DBAs) and, nowadays also, Beyond Design Basis Accidents (BDBAs) (IAEA, 2006).

Fault Detection and Diagnosis (FDD) methods have been developed for detecting different types of faults and supervising the plant behavior for accident prevention (Ma and Jiang, 2011; Park et al., 2015; IAEA, 2000; IAEA, 2004; IAEA, 2005). Upon localization and isolation, under certain abnormal conditions, manual actions are conducted by the plant operators for restoring normal operating conditions (Hsieh et al., 2012; Park et al., 2015). For this, Abnormal Operating Procedures (AOPs) are provided, where the sequence of actions to undertake are given for different Initiating Events (IEs).

Two practical issues are:

i. it is difficult to ensure sufficient coverage of all possible IEs through AOPs, as they are developed based on historical data and there may exist significant IEs that have not yet been experienced (Park et al., 2015);
ii. human errors may occur during abnormal situations and incorrect AOPs may, then, be followed (Hsieh et al., 2012).

In abnormal situations, time is critical, and the amount of information and data to be examined is large. Decision Support Systems (DSSs) can aid the operators and reduce the possibility of errors (Ma and Jiang, 2011; Hsieh et al., 2012; Park et al., 2015). Examples of DSSs are: the Alarm and Diagnosis-Integrated Operator Support (ADIOS) system that attempts to avoid that too many alarms influence the operators judgement in a wrong way (Kim et al., 2001); the Hidden Markov Model (HMM) for recognizing accidents in NPPs, proposed in (Kwon et al., 1999); the Fault Diagnosis Advisory System (FDAS), based on dynamic neural networks (Lee et al., 2007); the Dynamic System Doctor (DSD), a system-independent interactive software for on-line state/parameter estimation in dynamic system (Aldemir et al., 2001); the Analysis of Dynamic Accident Progression Trees (ADAPT)

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methodology (Hakobyan et al., 2008); the unsupervised clustering technique for NPP components fault diagnosis, based on Haar Wavelet Transform (HWT) and Fuzzy C-Means (FCM) algorithm, in (Baraldi et al., 2013); the hybrid approach for balancing false and missed alarms, based on Correlation Analysis (CA), Genetic Algorithms (GAs) and Sequential Probability Ratio Tests (SPRTs) in (Di Maio et al., 2013); the non-parametric decision strategy in (Al-Dahidi et al., 2014) to detect whether NPP components are in abnormal conditions, using Prediction Intervals (PIs) and Auto-Associative Kernel Regression (AAKR) (Hines and Uhrig, 1998). However, there is no guarantee of improvement in the operators' performance and sometimes the result could be the increase of operator workload, with negative implications on performance (Yoshikawa, 2005; Kim et al., 2007; Hsieh et al., 2012).In this paper, we propose an Expert System (ES) (McBride and O'Leary, 1993; Ikram et al., 2015) for operator aid, based on the system response outcomes obtained from a Thermal-Hydraulic (TH) code and Regional Sensitivity Analysis (Wei et al., 2014). The TH code reproduces the system physical behavior according to a mathematical model m that receives an input vector $\bar{x} \in \Re^n$ (comprised of n input variables) and generates the system response vector $\bar{y} = m(\bar{x})$, containing (at least) one safety parameter y. The input variables set $\Re^n$ can be partitioned into two subsets: one with *controllable* variables ($\Re^q$), i.e. the levers under control of the plant operator, which can be manipulated to increase plant safety (e.g., reactor control rods position, rate of feed-water flow through the plant primary loops, accumulator water temperature and pressure, repair times, etc.), and the other one with *non-controllable* variables ($\Re^{n-q}$) (Di Maio et al., 2016). In practice, the inputs $\bar{x}$ are uncertain (Apostolakis, 1990; Helton et al., 1996; Oberkampf et al., 2004).

With reference to scenario E_F, for which the response of interest Y must be lower than a threshold γ_y (imposed by regulation), the limit-state function G is defined as (Bourinet et al., 2011):

$$G(\overline{X}) = Y(\overline{X}) - \gamma_y \tag{1}$$

The input space can be split into a failure domain $F = \{\overline{X}: G(\overline{X}) > 0\}$ and a safe domain $S = \{\overline{X}: G(\overline{X}) < 0\}$. The system failure boundary (limit surface) $\partial F = \{\overline{X}: G(\overline{X}) = 0\}$, which separates S from F, can be projected onto an input *controllable* subset ($\Re^q$) (Di Maio et al., 2016), which contains the *controllable* variables $X_1, X_2, \ldots, X_q$ that can be varied to increase the system safety margin $\gamma_y - Y(\overline{X})$ (Zio et al., 2010).

While the system is operating in its nominal state $\bar{x}_e$ (usually assumed equal to the expected values $E[\overline{X}]$ of the input variables $\overline{X}$), the safety parameter $\bar{y}_e = m(\bar{x}_e)$ falls well below the safety threshold γ_y, providing a margin of safety with respect to uncertainties in the model (Zio and Di Maio, 2008). In abnormal conditions, the safety margin may decrease and this needs to be kept under control in order to avoid diverging to catastrophic accidents.

An additional difficulty in the problem is due to the fact that any generic *controllable* input variable X_j, $j = 1,2,\ldots,q$, can be affected by epistemic and/or aleatory uncertainty. In this paper, this uncertainty is modeled by considering that when X_j is set equal to $\hat{x}_j$, the input variable actually ranges between $\hat{x}_j - \Delta x_j$ and $\hat{x}_j + \Delta x_j$ according to the modified Probability Density Function (PDF):

$$f^*_{X_j}(x_j) = \frac{t_{X_j}(x_j)}{F_{X_j}(\hat{x}_j + \Delta x_j) - F_{X_j}(\hat{x}_j - \Delta x_j)}, x_j \in [\hat{x}_j - \Delta x_j, \hat{x}_j + \Delta x_j] \tag{2}$$

where $t_{X_j}(x_j)$ is the truncated PDF of X_j over range $[\hat{x}_j - \Delta x_j, \hat{x}_j + \Delta x_j]$:

$$t_{X_j}(x_j) = \begin{cases} 0, x_j \in (-\infty, \hat{x}_j - \Delta x_j) \\ f_{X_j}(x_j), x_j \in [\hat{x}_j - \Delta x_j, \hat{x}_j + \Delta x_j] \\ 0, x_j \in (\hat{x}_j + \Delta x_j, +\infty) \end{cases} \tag{3}$$

Coherently, the system (uncertain) initial state is:

$$\overline{X}_0 = [x_{1,0} - \Delta x_1, x_{1,0} + \Delta x_1] \times [x_{2,0} - \Delta x_2, x_{2,0} + \Delta x_2] \times \ldots \times [x_{q,0} - \Delta x_q, x_{q,0} + \Delta x_q] \tag{4}$$

In this paper, we present the development of an Expert System (ES) for maximizing the safety margin by exploiting the results of a Regional Sensitivity Analysis (RSA) to guide the search for the range (or state of the system $\overline{X}$) closest to $\overline{X}_0$, where $\mathrm{E}[G(\overline{X})]$ is the smallest.

In detail, the ES proposed in this paper is based on the Revised Ratio Functions (RRFs) (Wei et al., 2014)) that measure the impact on the mean (Revised Mean Ratio Function, HM) and variance (Revised Variance Ratio Function, HV) of the model output distribution due to the reduction in the range of variability of an individual input. For our purposes, the effect on the variance is of particular interest and it is here exploited to find which input controllable variable allows obtaining the largest decrease in G (i.e., the largest increase in the expected safety margin) when the system is in its current abnormal state $\overline{X}$.Assuming that the system is operating at $\overline{X}$ and that range $[\hat{x}_j - \Delta x_j, \hat{x}_j + \Delta x_j]$, $j = 1,2,\ldots,q$, is reduced to $\hat{x}_j$, the expected value (E) and variance (Var) of G are, respectively:

$$\mathrm{E}[G|\hat{x}_j] = \int_{x_1-\Delta x_1}^{x_1+\Delta x_1} \ldots \int_{x_\varphi-\Delta x_\varphi}^{x_\varphi+\Delta x_\varphi} \ldots \int_{x_q-\Delta x_q}^{x_q+\Delta x_q} g(x_1,\ldots,x_q|\hat{x}_j) \prod_{\varphi=1,\varphi\neq j}^{n} (f^*_{X_\varphi}(x_\varphi)dx_\varphi) \tag{5}$$

$$Var[G|\hat{x}_j] = \int_{x_1-\Delta x_1}^{x_1+\Delta x_1} \ldots \int_{x_\varphi-\Delta x_\varphi}^{x_\varphi+\Delta x_\varphi} \ldots \int_{x_q-\Delta x_q}^{x_q+\Delta x_q} (g(x_1,\ldots,x_q|\hat{x}_j) - \mathrm{E}[G|\hat{x}_j])^2 \prod_{\varphi=1,\varphi\neq j}^{n} (f^*_{X_\varphi}(x_\varphi)dx_\varphi) \tag{6}$$

The original RSA technique defines HV_j of input X_j, $j = 1,2,\ldots,q$, as the ratio between the residual variance $Var[G|\hat{x}_j]$ with respect to the residual mean $\mathrm{E}[G|\hat{x}_j]$, and the full variance $Var[G]$ (Wei et al., 2014):

$$HV_j = \frac{Var[G|\hat{x}_j]}{Var[G]} \tag{7}$$

where:

$$Var[G] = \int_{x_1-\Delta x_1}^{x_1+\Delta x_1} \ldots \int_{x_\varphi-\Delta x_\varphi}^{x_\varphi+\Delta x_\varphi} \ldots \int_{x_q-\Delta x_q}^{x_q+\Delta x_q} (g(x_1,\ldots,x_q) - \mathrm{E}[G])^2 \prod_{\varphi=1}^{n} (f^*_{X_\varphi}(x_\varphi)dx_\varphi) \tag{8}$$

$$\mathrm{E}[G] = \int_{x_1-\Delta x_1}^{x_1+\Delta x_1} \ldots \int_{x_\varphi-\Delta x_\varphi}^{x_\varphi+\Delta x_\varphi} \ldots \int_{x_q-\Delta x_q}^{x_q+\Delta x_q} g(x_1,\ldots,x_q) \prod_{\varphi=1}^{n} (f^*_{X_\varphi}(x_\varphi)dx_\varphi) \tag{9}$$

As Eq. (7) shows, HV_j indicates the actual reduction of the model output variance due to the restriction of the range of X_j. The larger HV_j is, the more function G varies (i.e., decreases or increases) for a perturbation of the other inputs X_φ ($\varphi \neq j$). Therefore, we define the revised HV_j^* as the ratio between the variance of G, computed over the range $[\hat{x}_j - \Delta x_j, \hat{x}_j + \Delta x_j]$, $j = 1,2,\ldots,q$, and the reduced range ($\hat{x}_\varphi$) of each of the other inputs X_φ, $\varphi = 1,2,\ldots,q, \varphi \neq j$, and the full variance $Var[G]$. It is clear that the larger HV_j^* is, the more function G varies and, thus, a larger increase in the system safety margins can be achieved through a perturbation of the j-th input.

Through the approach described, we aim at providing the plant operator with an effective and unequivocal AOP to keep the safety margins and avoid system failure, giving clear indications of which *controllable* variables to modify and by how much, when an IE has occurred.

The rest of the paper is organized as follows. Section 2 illustrates the proposed approach. Section 3 shows an application of the approach to an analytical case study that artificially simulates the response of a NPP to an accident scenario. Section 4 contains the application of the approach to the pressurizer of a Pressurized Water Reactor (PWR). Conclusions are given in Section 5.