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Identification of Design Basis Accidents of a PWR Nuclear Power Plant Using LSTM Autoencoders

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1. Introduction

Nuclear power plants (NPPs) are highly complex systems, designed and operated based on strictly defined standards and guidelines. The safety analysis of NPPs aims to ensure that the probability of a radiological accident to be as low as it is reasonably possible, despite the great risk posed by the radioactivity inventory in the reactor core. In this context, the NPPs are constantly monitored and controlled by a team of highly trained operators, so that in the case of an abnormal event, such as transients and accidents, the operators must quickly and correctly identify the occurring event, in order to initiate appropriate corrective actions, ensuring the integrity and safety of the NPP. However, in such cases, due to the amount of information, provided in real-time by multiple variables, which must be quickly analysed, the performance of the operators can be impaired, with the possibility of failures in the diagnosis. Therefore, considering, that a misidentification could generate grave consequences for the NPP, one of the main challenges of the Human Factors Engineering field is the development of systems capable of being able to solve the nuclear accident identification problem (NAIP).

Considering that, during an abnormal event, it is possible to observe the evolution in time of the output signal generated by the several NPP monitoring instruments, each one of these instruments represents a state variable in the NAIP and the evolution in time provided by each of these variables are represented by specific curves (patterns), that are unique with respect to the accident type, which makes them useful to identify the accident. Therefore, many statistical and artificial intelligence approaches have been applied to the NAIP in order to solve it. Through the years, many statistical and artificial intelligence techniques have been applied to the NAC in order to solve it (Pinheiro and Schirru, 2019; Nicolau and Schirru, 2017; Mol et al., 2003; Kwon and Kim, 1999). However, only in the recent year, with the advent of modern architectures of Artificial Neural Networks (ANNs), nowadays also called deep learning models or Deep Neural Networks (DNNs), complex scenarios of NAC task, with several similar accidents, have been started to be solved (Peng et al., 2018; Saeed et al., 2020; Santos et al., 2021; Santos et al., 2019a; Santos et al., 2019b; Yang et al., 2020).

Therefore, due to the recent success of different DNN architectures, this paper continues the study presented by Santos et al., 2019b of the use Deep Autoencoder (DAE) Neural Networks in the context of NAIP, however in this present study is proposed the use of Long Short Term Autoencoder (LSTM-AE) architectures, to solve the NAIP. In order to investigate the performance of the LSTM-AEs approach, a case considering 16 simulated operational scenarios (15 postulated accidents + normal operation), for a PWR-type NPP was used in the experiments.

2. Methodology

The Autoencoder (AE) (Kramer, 1992) is a specific type of ANN, which is not exactly an architecture in itself, but rather, a way of designing and training an ANN model so that the model learns to reproduce the input data as the output data. Therefore, a LSTM Autoencoder (Sutskever et al, 2014) is an autoencoder with LSTM (Hochreiter and Schmidhuber, 1997) architecture, which is able to model and learn to reproduce sequential input data, such as time series. Given the ability of AEs to learn to reconstruct the original trained data with a minimum reconstruction error, when an AE model, after training, is faced with an input that deviates in some way from the data used during training, a high reconstruction error will be generated by the model. Thus, the LSTM-AE model can also be used to identify if an input time series pattern belongs to a certain class.

In this context, in this approach, 16 LSTM-AE were developed, each of them was trained with data of one of the 16 operational scenarios (16 postulated accidents + normal operation), simulated by Alvarenga (1997) and listed in Table 1, for a Brazilian PWR-type NPP. The data that represents the operational scenarios is formed by 61 seconds-long-time signatures of 16 state variables (that is, the time evolution of the variables, forming a pattern specific for each event).

Moreover, in order to supply a proper amount of training examples to the LSTM-AEs to improve their performance, the original dataset was augmented simulating instrumentation oscillations to the original data by means of overlapping, to each variable, white noise with normal distribution and 1% standard deviation. Also, the data was modeled using the sliding window technique (SWT) which is a method that facilitates the modeling and analysis of a time series. The SWT consists of using a fixed-size temporal window to divide a time series into multiple subsequences that have the same size as the window. In this sense, in the presented method, a temporal window of size 25 was applied to the augmented dataset.

Table I. Operational Scenarios

ID	Scenario	Description
1	BLACKOUT	Loss of electrical power
2	BLACKSEM	Loss of electrical power without reactor shutdown
3	LOCA	Loss of coolant of the primary system
4	MEFWISEM	Main and auxiliary feed water isolation without shutdown of the reactor
5	MEFWISO	Main and auxiliary feed water isolation
6	MFWBR	Main feed water break
7	MFWBRSEM	Main feed water break without reactor shutdown
8	MFWISEM	Main feed water isolation without reactor shutdown
9	MFWISO	Main feed water isolation
10	MSTMISEM	Main steam line isolation without reactor shutdown
11	MSTMISO	Main steam line isolation
12	NORMAL	Normal operation at 100% power level
13	SGTR	Steam generator tube rupture
14	STMLIBR	Steam line break
15	TRIPREA	Shutdown of the turbine without reactor shutdown
16	TRIP	Shutdown of the reactor and turbine

After completion of the training and testing of all 16 LSTM-AEs, a method of identifying accidents using the LSTM-AEs was developed. The basis of this approach is that a LSTM-AE generates a low reconstruction error for inputs sufficient similar to the patterns used for its training, whereas for sufficiently different inputs the reconstruction error is high. In this way, it is possible to identify to which operating scenario an input belongs through the LSTM-AE which presented the lower reconstruction error.

3. Results and Discussion

In order to assess the performance of the LSTM-AE accident identification method, a test set containing 3500 samples for each operational scenario, in total 56000 samples, was utilized. Figure 1 shows that the proposed method was able to achieve 100% of accuracy in the classification of the operational scenarios.

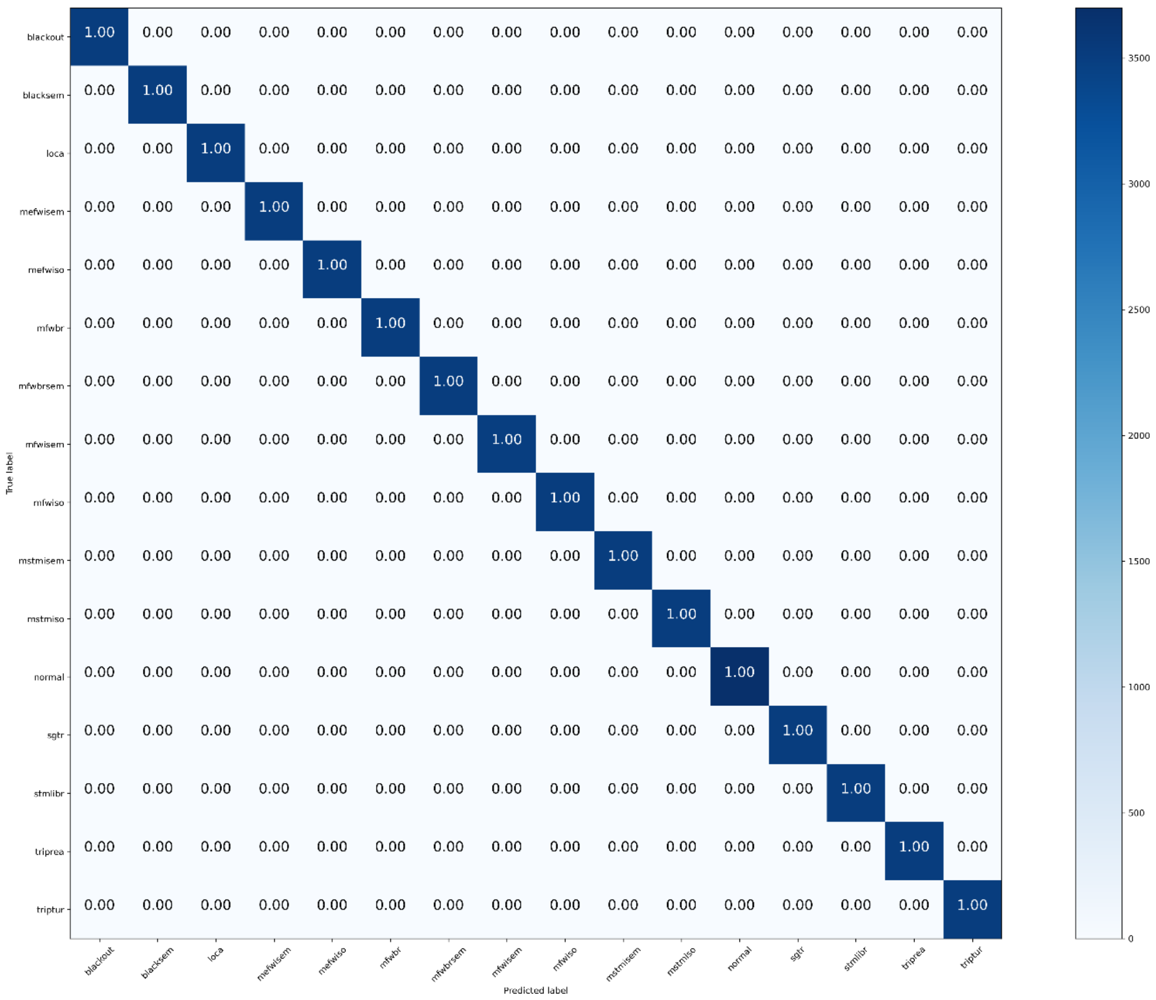

Figure 1: Nuclear accident identification method based on LSTM- AE normalized confusion matrix

4. Conclusions

The work presented in this paper improved the nuclear accident identification method based on Deep Autoencoders (DAEs), proposed by Santos et al., 2019b, substituting the DAEs by LSTM-AEs, which via the LSTM aspect of the architecture gives these ANN models a far better capacity to deal with time-series patterns, while maintaining, via the AE aspect of the model, the capacity to learn to how to reconstruct its input data as its output data. In this context, in order to evaluate this approach, a scenario composed of a simulated dataset of 16 operational scenarios of a Brazilian PWR-type NPP was utilized. Based on this, 16 LSTM-AE models were developed, where each of them was trained with data of one of the 16 operational scenarios, and to supply a proper amount of training examples, the data was augmented using white noise with normal distribution and 1% standard deviation. Besides that, the data was also modeled using the sliding window technique, with a temporal window of size 25 being applied to the augmented dataset.

After completion of the training, a nuclear accident identification method based on the LSTM-AEs trained models was used based on the premise that for inputs sufficient similar to the patterns used for its training, the LSTM-AE shows a low reconstruction error, while for sufficiently different inputs the reconstruction error will be high. Making it possible to identify to which operating scenario an input belongs according to LSTM-AE which demonstrated the lower reconstruction error for this input. In a test containing 3500 samples for each operational scenario, in total 56000 samples, the proposed method was able to achieve a performance of 100% accuracy in the classification of the 16 operational scenarios.

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