Prediction of LOCA Break Size and Position Based on Deep Rectifier Neural Networks

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This report presents an approach for identification of break locations and sizes of loss of coolant accidents (LOCA) in nuclear power plant (NPP). Under LOCA condition, it is quite important a quick identification the location and the size of the rupture. However, it is very difficult to carry out this identification only by observing the time trend of the information shown by sensors and panels in the control room. The identification of the rupture location is modeled as classification problem, in which a discrete set of possible locations is considered. The size of rupture is a regression problem.

Artificial neural networks (ANN) are mathematical models originally inspired in human brain, with the ability to learn by examples and model their relationships. One of the main aspects of ANNs is the use of non-linear activation function utilized to activate the neurons of the hidden layers. For a long time, the sigmoid functions (as the logistic sigmoid) were the most used activation functions option, including for ANNs architectures However, the gradient vanishing problem, pointed by Glorot and Bengio [1], is accentuated in ANNs with high number of layers (deep neural nets), in which performance is significantly affected. Then, a novel ANN architecture was proposed by Glorot et al., (in 2011) [2], substituting the sigmoid functions for rectifier linear functions, thus receiving the name of Deep Rectifier Neural Network (DRNN).

This work uses a DRNN architecture (Figure 1) that is capable of dealing, simultaneously, with two aspects of a LOCA: i) equivalent size and ii) the location of ruptures. The DRRN is trained with data collected at Human System Interface Laboratory (LABIHS) from simulations of LOCAs carried out at 5 locations of the nuclear plant.

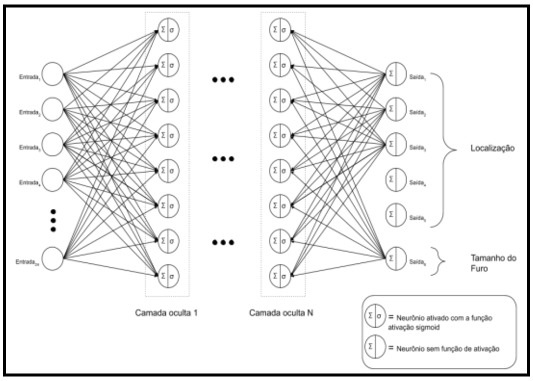

Figure 1. DRRN model.

Preliminary tests have been showing good results, presented in Table 1. The results presented in column labeled “Test” are related to data not used by the model during its training phase.

Table 1. Results of DRRN models.

	Train	Test	Validation
Location accuracy (%)	96.299	75.145	95.953
Rupture area (MAE)	0.023	0.207	0.085
Error < 10% (size of rupture)	99.125	74.587	92.868

This work is in its very beginning and makes part of a D.Sc. thesis in collaboration with COPPE/UFRJ. It is supposed to be applied to improve decision support systems in NPP operations rooms and simulators. More detailed results can be seen in [3].

References

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