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Nuclear energy system's behavior and decision making using machine learning

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ABSTRACT

Early versions of artificial neural networks' ability to learn from data based on multivariable statistics and optimization demanded high computational performance as multiple training iterations are necessary to find an optimal local minimum. The rapid advancements in computational performance, storage capacity, and big data management have allowed machine-learning techniques to improve in the areas of learning speed, non-linear data handling, and complex features identification. Machine-learning techniques have proven successful and been used in the areas of autonomous machines, speech recognition, and natural language processing. Though the application of artificial intelligence in the nuclear engineering domain has been limited, it has accurately predicted desired outcomes in some instances and has proven to be a worthwhile area of research. The objectives of this study are to create neural networks topologies to use Oregon State University's Multi-Application Small Light Water Reactor integrated test facility's data and evaluate its capability of predicting the systems behavior during various core power inputs and a loss of flow accident. This study uses data from multiple sensors, focusing primarily on the reactor pressure vessel and its internal components. As a result, the artificial neural networks are able to predict the behavior of the system with good accuracy in each scenario. Its ability to provide technical data can help decision makers to take actions more rapidly, identify safety issues, or provide an intelligent system with the potential of using pattern recognition for reactor accident identification and classification. Overall, the development and application of neural networks can be promising in the nuclear industry and any product processes that can benefit from utilizing a quick data analysis tool.

1. Introduction

There has been significant scientific interest in understanding and imitating natural and biological process, particularly neural biology. One of the first neural methodologies was first achieved with the creation of the perceptron capable of reproducing some of the Boolean operators (Rosenblatt, 1958). Later in the mid 80's there was a lot of effort to find a powerful synaptic modification rule that will allow an arbitrarily connected neural network to develop an internal structure that is appropriate for a particular task (Rumelhart et al., 1986); in other words, a self-organizing method that can be used in machines to learn a task without being explicitly programmed. The application of neural methods has been found useful in addressing problems that usually require the recognition of complex patterns or complex classification decisions. In the domain of computers science, there has been a rapid improvement of self-organizing methods along with advancements in data storage, parallel computing, and processing speeds, which have made possible for these methods to succeed in the development of new products and technologies. In the engineering domain, particularly in nuclear engineering, the application of machine learning methods, e.g. neural networks, utilizing full-scale facilities or real components data has been rather limited. In early applications researchers have used neural networks to assess the heat rate variation using the thermal performance data from the Tennessee Valley Authority Sequoyah nuclear power plant, where a small artificial neural network was used to determine the variables that affect the heat rate and thermal performance of the plant by looking at the partial derivative of the different input patterns (Zhichao and Uhrig, 1992). Others have developed monitoring systems based on auto-associative neural networks and their application as sensor calibration systems and sensor fault detection systems (Hines et al., 1996) using the High Flux Isotope Reactor operated at Oak Ridge National Laboratory and an

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experimental Breeder Reactor (Upadhyaya and Eryurek, 1992). During the mid-1990s a group of scientists explored the application of neural networks in the area of multiple-failures detection with the objective to develop an operator support system that can support operators during severe accidents in a nuclear power plant, referred as Computerized Accident Management System (Fantoni and Mazzola, 1996). In nuclear operations the inclusion of redundant, independent and diverse systems is necessary to ensure adequate defense-in-depth; however, the increase in systems lead to more complex human–machine interactions. Neural networks have also been trained with data from a simulator, and the results proved to be very satisfactory at modeling multiple sensor failures and component failure identification (Sirola and Talonen, 2012). Other areas outside of nuclear surveillance and diagnostics have also shown interest in the application of neural networks; for instance, in two-phase flow the use of neural methods as a method to predict two-phase mixture density (Lombardi and Mazzola, 1997) or flow regime identification (Tambouratzis and Pàzsit, 2010). More recently, researchers have applied advanced optimization algorithms for the prediction of the behavior of systems components such as a printed circuit heat exchanger (Ridluan et al., 2009; Wijayasekara et al., 2011), power peaking factor estimations (Montes et al., 2009), key safety parameter estimation (Mazrou, 2009) and functional failures of passive systems (Zio et al., 2010). The reduction in computational cost and the availability of data facilitates further the use of such methods where predicting more complex tasks is desired. In this research the application of neural methods using two transient events from a prototypic test facility is presented, where noise and uncertainty are present as an inherently natural phenomenon of a realistic problem.

2. Materials and methods

2.1. Multi-application small light water reactor

The Multi-Application Small Light Water Reactor (MASLWR) is an integral pressurized test facility developed by Idaho National Engineering and Environmental Laboratory, Oregon State University and NEXANT-Bechtel (Reyes et al., 2007), with the conceptual design shown in Fig. 1. The MASLWR module includes a self-contained vessel, steam generator and containment system that rely on natural circulation for its normal operation. The test facility is scaled at 1:3 length scale, 1:254 volume scale and 1:1 time scale, and it is designed for full pressure (11.4 MPa) and full temperature (590 K) prototype operation and is constructed of all stainless steel components (Reyes et al., 2007). The purpose of this facility is to study the behavior of a small light water reactor concept design that uses natural circulation for both steady-state and transient operation. The MASLWR concept was the predecessor to the NuScale small modular reactor design.

The data used in this study has been collected for the International Atomic Energy Agency as an International Collaborative Standard Problem (ICSP). Two different data sets were used to train two different neural networks. The first, ICSP-3, characterize the steady-state (S.S.) natural circulation in the primary side during various core power inputs (Mai and Hu, 2011). The test procedure was to increase the power inputs of the heaters stepwise from 10% to 80% full power in the core by 10% increments and had a total duration of 6348 s (~1.76 h). The second, ICSP-2, characterizes the activation of safety systems of the MASLWR test facility, and the long-term cooling of the facility to determine the progression of a loss-of-feedwater transient (LOFW). For this test, first, the facility was brought to steady state at 75% core power, 8.62 MPa and the main feed water running in the steam generator, then, the main feed water was shut off, the core was set to decay power, and a blow-down procedure was conducted until the High Pressure Containment (HPC) and Reactor Pressure Vessel (RPV) were at equal pressures (Mai and Ascherl, 2011). This transient had a total duration of 16,483 s (~4.58 h).

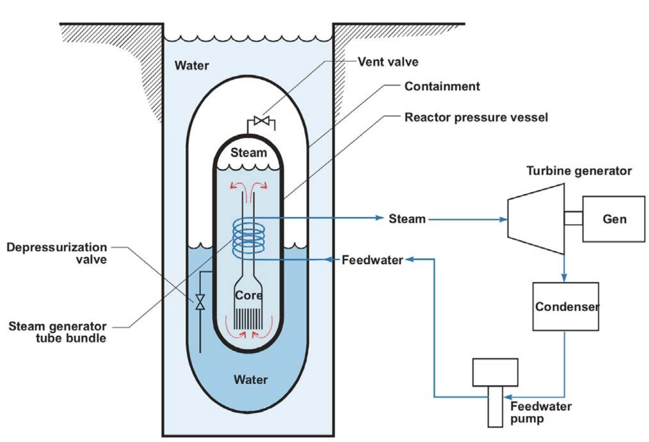

Fig. 1. MASLWR's conceptual design.

2.2. Data

Data recorded from 58 different sensors was used as labeled data for the supervised learning process, with the purpose of capturing the behavior inside of prototype's RPV. Given that the data collected in the test facility inherently contains noise and uncertainty, the use of a neural network along with the backpropagation algorithm is suitable as this algorithm is robust to noise (Mitchel, 1997). However, the main challenge of the application of such method to this particular application is to find the suitable parameters that are to represent the problem, also known as feature selection. The selection of the features has been based on the sensors that are mainly controlled by the test facility's operator. Table 2 and Table 1 show the sensors used as inputs and outputs.

Moreover, given the different scales in the data, the entire set had to be normalized, using Eq. (1), to a [0,1] range to improve learning and avoid the saturation regions of the sigmoid function.

$$X' = (X_{max} - X_{min})\frac{X - X_{min}}{X_{max} - X_{min}} + X_{min} \tag{1}$$

The implementation of other normalizing techniques can also be used as long as it scales within the output range of the selected activation function.

Table 1
MASLWR instrumentation used as output parameters.

Sensor Label	Description
TF-[611-615]	Thermocouples Inside the Outer Coil Pipe of the Steam Generator Inlet
TF-[621-625]	Thermocouples Inside the Middle Coil Pipe of the Steam Generator Inlet
TF-[631-634]	Thermocouples Inside the Inner Coil Pipe of the Steam Generator Inlet
TF-[701-706]	Steam Generator Liquid Temperature
PT-602	Main Steam Pressure
FVM-602-T	Main Steam Temperature
FVM-602-P	Main Steam Pressure
FVM-602-M	Main Steam Pressure Volumetric Flow Rate
TH-[141-146]	Core Heater Rod Temperatures
TF-132	Primary Water Temperature inside Chimney below Steam Generator Coils
DP-101	Pressure Loss in the Core
DP-102	Pressure Loss between Core Tope and Cone
DP-103	Pressure Loss in the Riser cone
DP-104	Pressure Loss in the Chimney
DP-105	Pressure Loss across the Steam Generator
DP-106	Pressure Loss in the annulus below Steam Generator