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The Application of Artificial Intelligence to Nuclear Power Plant Safety

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Abstract. Through application of artificial intelligence (AI), the burden of analytical computational load for analysis of any given problem where countless variables have to be taken into account, is virtually eliminated. Since for engagements in real life operations and instantaneous actions are of paramount importance and vital, AI can be a strong alternative to overcome the complex problem solving in short time frames. As such, in this study a brief review of AI basics is given and literature for AI applications in nuclear field such as defect detection in nuclear fuel assembly, dose prediction in nuclear emergencies, fuel and component failure detection, core monitoring for reactor transients, core fuel optimization models, gamma spectroscopy analysis and specifically nuclear reactor safety in operation are assessed. Afterwards, an AI model for analyzing transients in VVER type nuclear power plants that is being built in Turkey is proposed. This model must keep up with instantaneous data flow and giving actionable feedback to the operator both for the cause and the solution. A semi-autonomous AI control system that help the operator decision making is a significant contributor to the safety of a reactor.

Keywords: Artificial Intelligence, Artificial Neural Networks, Nuclear Reactor Safety, Nuclear Reactor Operation, VVER 1200, Transient Analysis

1 Artificial Intelligence

Artificial Intelligence (AI), the art of making a computer learn like a human, is a strong alternative for addressing and analyzing complex real world problems. While Rule Based-Expert Systems are valid approaches, they do not perform well in terms of encompassing the volatile and co-dependent parameters of the physical problems. Machine Learning (ML) is a sub-branch of AI which allows code to learn through assessing data and predicting or forecasting from accumulated experience of the set. Although there are many classifications, ML has three main classes.

1.1 Supervised Learning

Supervised learning works with a labelled data set, a set of observations associated with their respective outcomes [1]. Deriving a function from training data set, model

predicts an outcome which is classified as regression or predict a label/category which is classified as classification.

1.2 Unsupervised Learning

Unsupervised learning uses a set of algorithms to infer a conclusion from data sets without an outcome. Cluster analysis is the most common unsupervised learning method, which analyzes pattern and groupings in the data set [2].

1.3 Reinforced Learning

Reinforcement learning assigns a goal in a complex environment where model employs trial and error. For every result it gets a reward or a penalty, thus reaching a robust model. Designer sets the policy for reward-penalty but does not guide the model towards a specific model [2]

1.4 Artificial Neural Network

The Artificial Neural Network (ANN) is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain as seen in Figure 1 [3]. Each connection, like synapses in a biological brain, can transmit a signal to other neurons. An artificial neuron receives a signal then processes it and can signal neurons connected to it. The "signal" at a connection is a real number, and the output of each neuron is computed by some non-linear function of the sum of its inputs. Neurons and edges typically have a weight that is adjusted as learning proceeds. The weight increases or decreases the strength of the signal at a connection [4]. Neurons may have a threshold such that a signal is sent only if the aggregate signal crosses that threshold. The adjective "deep" in deep learning refers to the use of multiple layers in the network [5].

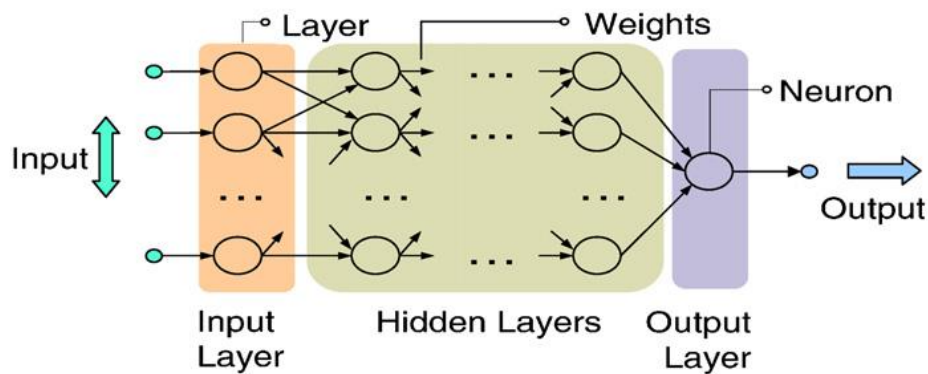


Fig. 1. Exemplary Artificial Neural Network Structure [3]

2 Applications in Nuclear Field

2.1 Defect Detection in Nuclear Fuel Assembly

Fuel assembly is made out of fuel rods where fission reaction occurs. The clad of fuel rods carries high thermal and mechanical requirements and standards, since its integrity is directly correlated with nuclear power plant (NPP) safety. There is a regular inspection program for inspection of fuel assemblies to maintain safety standards. These in service inspections are executed manually and visually (camera assisted). Since this is a time consuming and subjective procedure, it is prone to errors. An alternative is the sipping test that determines whether the fuel assembly contains a defect by checking the amount of Kr-85 radioisotope contained in the fluid sample. But the sipping test cannot be executed for in operation assemblies.

To optimize and deliver accurate results, deep convolutional neural network was proposed to detect the scratches on nuclear fuel assembly. The proposed framework achieves 0.98 TPR (True Positive Rate) against 0.1 FPR (False Positive Rate) that is significantly higher than most of current detection method. A test case for trained R-CNN in Figure 2, demonstrates the model's accuracy, not only by distinguishing between real defects thus resulting in a high TPR, but also between water stains and other false positives thus resulting in a low FPR. [6]



Fig. 2. The detected image of testing data [6]

2.2 Dose Prediction in Nuclear Emergencies

NPP accidents can result in release of radioactive materials to the atmosphere. To predict the atmospheric dispersion and equivalent doses with respect to distance from accident site is vital since evacuation of population and assessment of the environmental impact are key parameters [7]. Deriving this result analytically can be done with great computational cost.

In order to predict spatial effective doses for a wide range of atmospheric conditions, the Deep Rectifier Neural Network (DRNN) was evaluated considering two realistic accident scenarios simulated with the atmospheric dispersion system used in a Brazilian NPP. In the more simplified scenario, the best DRNN achieved an error 25% lower than the 5-MLP with a training 155 times faster. In the more complex scenario, the best DRNN achieved an average error of 0.0213 with a training time of 30 min, demonstrating that DRNNs can improve ANN-based dose prediction in realistic situations [8].

2.3 Fuel and Component Failure Detection

In NPP, fuel cladding is what keeps the radioactive materials in a closed cascade. In case of failure of this component, the release of radioactive materials to primary circuit is inevitable. The common method for failure detection is isotopic ratios method where the ratio of released isotopes to the coolant is checked for and if it is above a threshold, the detection of the failure takes place.

Four-layer ANN, which consists of an input layer, two hidden layers, and an output layer was proposed for fuel failure detection as seen in Figure 3. The neurons receive total values from the preceding layer and transmit to the next layer by the activation function. The inputs of the ANN are normalized specific activities of 23 typical fission products, include Br-83, Kr-85, Kr-85 m, Kr-87, Kr-88, Sr-90, Te-131, Te-131 m, I-129, I-131, I-134, I-135, Xe-133, Xe-133 m, Xe-135, Xe-135 m, Xe-138, Cs-134, Cs-134 m, Cs-137, Cs-139, Pr-143. [9]

Comparing to the isotopic ratios method, the ANN proves to be more responsive when the fuel cladding is defective.

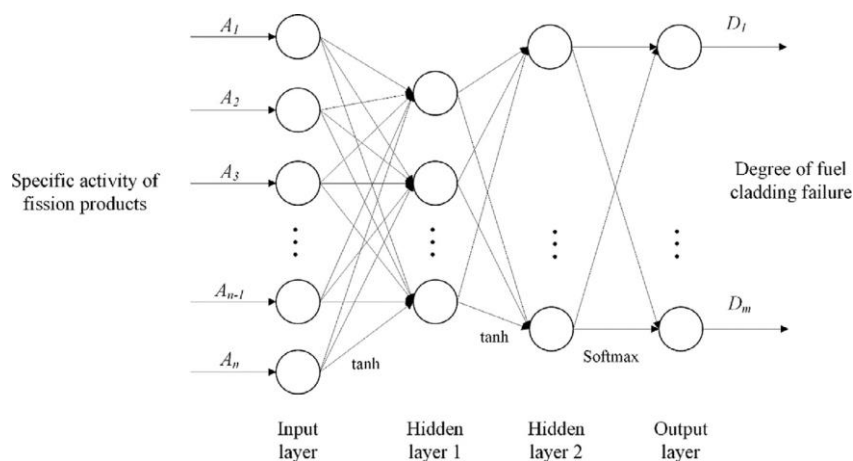


Fig. 3. The architecture of the ANN for fuel failure detection [9]

2.4 Core Monitoring for Reactor and Transients

A real-time monitor for 3D reactor power distribution is critical for nuclear safety and high efficiency of NPP's operation as well as for optimizing the control system, especially when the nuclear power plant (NPP) works at a certain power level or it works in load following operation [10]. Also NPP experiences transients which may occur be due to equipment failure or malfunctioning of process systems. The operator has to carry out diagnostic and corrective actions with respect to determined transient. ANN performs diagnosis fast and within acceptable error margin. This presents the opportunity of reduction in human evaluation error and fast response to the scenario at hand. A benchmark for identification performance of the transients together with initiating events is listed in Table 1. With these error rates, after decreasing it to an acceptable level, a decision support system becomes feasible and executable [11].

Table 1. IEs and their average identification errors [11]

Initiating Event	Average identification error (%)
Steam generator tube rupture	
SG1TR (Steam Generator)	4.5
SG2TR (Steam Generator)	5.2
SG3TR (Steam Generator)	4.9
SG4TR (Steam Generator)	4.6
Moderator heat exchanger tube failure	
MODHX1TR (Moderator heat exchanger)	5.3
MODHX2TR (Moderator heat exchanger)	5.5
Bleed cooler tube rupture	7.4
Shut down cooling heat exchanger tube fail	8.2

2.5 Core Fuel Optimization Models

In any NPP, the optimization of nuclear fuel configuration in the core is one of key performance activities [12] and an accurate prediction on the neutronic parameters of a nuclear reactor core is a major design concept for both economic and safety reasons [13]. Due to burn-up limitations, fuel loading and shuffling generally take place annually. During refueling, the highly burned fuel assemblies are discharged from the core, the rest is shuffled and fresh fuel assemblies are placed in the core. The purpose of the refueling is to maximize the effective multiplication factor k_{eff} while keeping power peaking factor P_r below acceptable limit [14].

When Particle Swarm Optimization is utilized to derive a model, it optimized P_r and k_{eff} with the achieved pattern. As a result, an increased k_{eff} by 8.79% and a reduction in P_r by 0.047% compared to classic reference loading pattern was achieved [15].

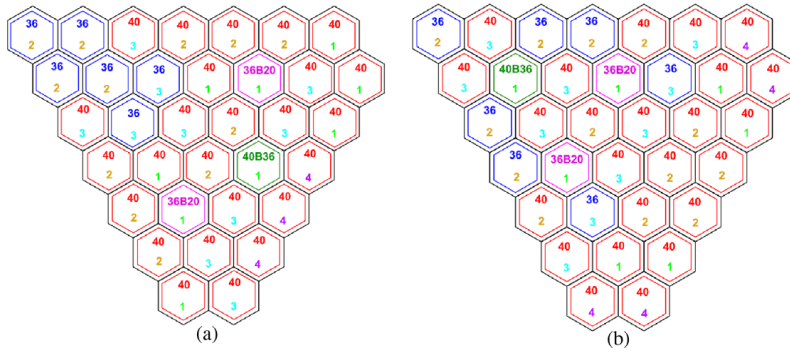


Fig. 4. Comparison of the one-sixth core loading pattern of the reference cycle, with the optimized one: (a) proposed core loading pattern, (b) reference core loading pattern [15]

2.6 Gamma Spectroscopy Analysis

Neutron activation analysis (NAA) is a method for the qualitative and quantitative determination of elements in samples based on the measurement of characteristic radiation from radionuclides formed by irradiating materials with neutrons. ANN algorithm can be usefully applied to the analysis of gamma-ray spectra by recognizing the combined pattern of emitted gamma-ray energies. In the rare situation where there is only a single gamma-ray from a radioisotope and its energy overlaps with other gamma-rays, it becomes difficult for the ANN to identify the exact radioisotope [16].

3 Artificial Intelligence Based Semi-Autonomous Control System to Assist Decision Making of Reactor Operators for VVER 1200

3.1 Transients

Transient is a change in the reactor coolant system temperature, pressure, or both, attributed to a change in the reactor's power output [17]. Transients can be caused by

1. Adding or Removing Neutron Poisons
2. Change in Electrical Load on Generator
3. Accidents

An AI based control system to diagnose reactor transients and present actions to operator with respect to transient that is determined is of high value to Nuclear Reactor Safety [18]. Some transients for nuclear power plants are given below.

- **Startup and Shutdown**

In any Startup or Shutdown operation, Reactor Power, Temperature and Pressure changes.

- **Trips and Controls**

The automatic or manual shutdown of the plant is referred to as a "trip" or "Scram".

- **Starting/tripping Pump**

Pump will trip when motor is overloaded due to running of pump in runout condition. Pump may also trip due to cavitation or mechanical seal damage.

- **Loss of Coolant Accidents (LOCA)**

LOCA describes an event in which the coolant is lost from the core due to rupture of a pipe. The most dramatic scenario is known as a large-break LOCA (LBLOCA) in which a double-ended failure (often referred to as a guillotine rupture) of one of the main primary circuit coolant pipes [19].

- **Loss of Flow Accident (LOFA)**

LOFA occurs when pumping power is lost and the coolant becomes stagnant [20].

- **Loss of Offsite Power (LOOP)**

The loss of offsite power (LOOP) initiating event occurs when all electrical power to the plant from offsite power line is lost. The NPP offsite power system is the transmission power system where NPP is connected.

3.2 VVER 1200

The VVER reactor itself was developed by ROSATOM subsidiary OKB Gidropress, while the nuclear power plants employing the VVER have been developed by the power plant design organizations within ROSATOM: Moscow Atomenergoproekt. The VVER is a pressurized water reactor (PWR), the most common type of nuclear

reactor worldwide employing light water as coolant and moderator. However, there are some significant differences between the VVER and other PWR types, both in terms of design and materials used. Distinguishing features of the VVER include the following:

- Use of horizontal steam generators;
- Use of hexagonal fuel assemblies;
- Avoidance of bottom penetrations in the VVER vessel;
- Use of high-capacity pressurizers. [21]

Table 2. VVER 1200 Parameters [21]

VVER-1200 Parameters	Values
Reactor nominal thermal power, MW	3200
Availability factor	0,9
Coolant pressure at the reactor outlet, MPa	16,2
Coolant temperature at the reactor inlet, °C	298,6
Coolant temperature at the reactor outlet, °C	329,7
Maximum linear heat rate, W/cm	420
Steam pressure at the outlet of SG steam header (abs), MPa	7,0
Primary design pressure, MPa	17,64
Secondary design pressure, MPa	8,1
Max fuel burnup fraction over FAs unloaded, MWD/kgU	70
Refueling period, month	12/(18-24)
Time of fuel residence in the core, year	4-5

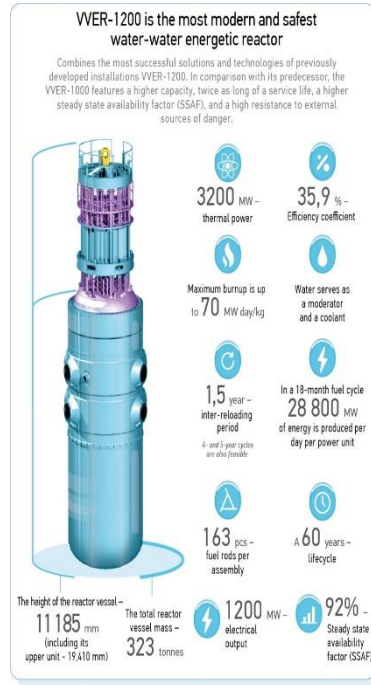


Fig. 5. VVER1200 [21]

3.3 Training Data Acquisition

Production of training data is one of the main challenges for any AI system, more so for a NPP. To overcome the burden, the reactor systems will be nodalized with RELAP5 which is used to simulate the dynamics of a NPP in accidental scenarios and to generate transient datasets of reactors for training neural networks to detect severe accidents [22]. Steady state operation at full power will be simulated first to determine temperature, pressure and void fraction values of the system at critical points. Transients will then be introduced via RELAP5/MOD3 and the associated data will be stored as training data.

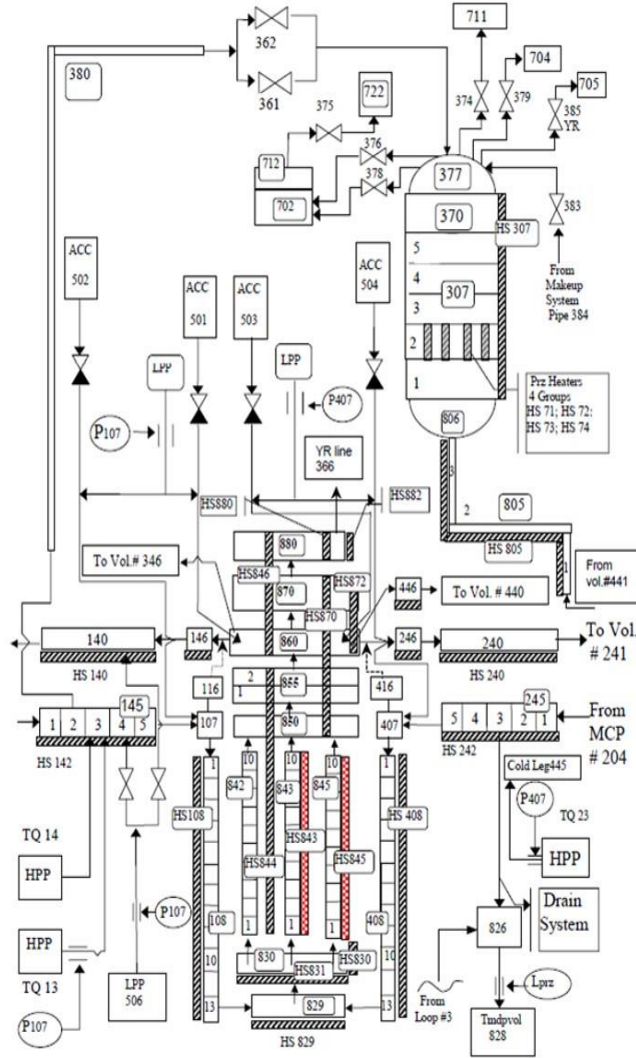


Fig. 6. Sample Nodalization of VVER 1200 [23]

4 Conclusion

Artificial Intelligence (AI) is a dependable and coherent alternative to assist operation of nuclear power plants to detect transients and determine the right course of action. An AI based control system for VVER 1200 reactor would be a useful to the Turkish nuclear industry as a preliminary product since four units of VVER 1200 is being currently built in Akkuyu Site in Turkey. In addition, the Nuclear Regulatory Authority in Turkey can use this system to perform safety analysis of the reactors to control the safety analysis report calculations provided by the licensee. The system developed during this study can also be used to train future operators, free of the cost and risk associated with a real power reactor operation.

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