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Analysis of Tehran Research Reactor Dynamics Behavior in Reactivity Insertion Accidents by Recurrent Neural Network

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Abstract: Reactivity Insertion Accident (RIA) is one of the main factors of the design basis accidents in nuclear reactor design. In this study a neural model of Tehran Research Reactor (TRR) is developed for analysis of RIA. The model has been built using the Multi-Layer Neural Network (MNN) to simulate the TRR Input-Output behavior. The MNN has been trained using the Levenberg-Marquardt learning algorithm. Parameters of the learning process have been optimized, to improve the efficiency and accuracy of the training process. This neural model was trained by standard code results and experimental data of TRR in various transients. The model was used for developing a neural simulator. The resultant simulator is reliable and could be able to accelerate the prediction of the reactor exhibit and it enables to determine the safety margins and criteria in RIA. The results of the simulations are in good agreement with experimental and theoretical outcomes and show that the TRR could maintain in the design basis criteria during RIA.

Key words: Nuclear research reactor, neural network, reactivity induced accidents (RIA), simulator

Introduction

The nuclear reactor simulators are being recognized for the training and safety analysis purposes, in response to the concerns of the TMI and Chernobyl accidents about the human factor. The reactor simulation is generally done by using large Safety Analysis System codes. The SAS codes use a lot of computer central processing time, which makes them incapable of real time prediction of reactor behavior in RIA (Mirza, 1997).

Recently, many attempts have been presented to show the efficiency of the neural network for modeling dynamics of non-linear systems (Parlos *et al*., 1992). The simplicity and the robustness of neural model help in constructing and developing of simulators for several dynamic of linear or even non-linear systems.

The neural simulator which is designed by neural network can substitute the original system. This simulator follows the system response with the minimum error within the constraint of learning rule. This method is a safe and easy way to study the different characteristics and behaviors of the system under study without disturbing the system due to testing procedures. The advantages of using neural simulator for simulating reactor behavior are:

- High-speed calculation of neural simulator with respect to SAS codes.
- No need for precision mathematical and physical calculation.
- Fast prediction of reactor dynamic behavior in accident such as RIA.
- Ability to provide estimation of the system response in the case of missing measurements (Adali, 1997).

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Therefore, neural simulator is ideal for analysis of the evolution of a complicated system in which robust, fault tolerant and real-time mode operation is essential. By using this simulator, we can analyze various scenarios in nuclear reactor operation such as slow and fast reactivity insertion transients and generate training and test data sets, which obviously cannot easily be obtained in a real nuclear reactor.

Materials and Methods

The existing TRR is a 5MW pool-type research reactor with MTR type fuel elements of Low Enriched Uranium (LEU) with 20% enrichment Uranium fuel in the form of U_3O_8_Al. TRR has been active since 1968 and its fuel assembly has been replaced from HEU to LEU in the late 1980s. Detailed explanation of TRR core and its relevant irradiation facilities is described elsewhere (AEOI, 1989). The core is built upon an Aluminum grid plate, on which there are $9\times6 = 54$ holes to accommodate either 18 standard fuel elements with five control fuel elements and other tools such as irradiation boxes. The basic tasks of TRR control system are safe startup, neutron flux controlling and protection TRR against elements malfunctions. For measurement and control of neutron flux, TRR control system is comprised of one Fission Chamber (FC), one Compensated Ionization Chamber (CIC) and two Uncompensated Ionization Chamber (UIC). TRR control system could be able to scram the reactor in tow conditions, first, while neutron flux or reactor power becomes more than legal value (high flux) and second in the case of the neutron flux increasing ratio reaches to more than legal value (short period).

In this study a neural model of a nonlinear, complex dynamic system is designed and developed for simulation of RIA at TRR. This model includes MNN with feedback loop and time delay of input and output. This model was trained by standard code results and experimental data of TRR in various transients. Presented Neural network can predict the system behavior in slow and fast reactivity insertion accidents.

TRR Model Identification

Reactor core dynamic equations are classified as non-linear with variant coefficients, which are function of the core working conditions (power level, coolant and fuel temperatures) (Hamilton and Duderstadt, 1976). Predicting reactor behavior (neutron flux, thermal power), needs solving these equations simultaneously which in turn, requires a large amount of time and memory on digital computers. One way to improve accuracy and speed of the reactor behavior predicting is to use a

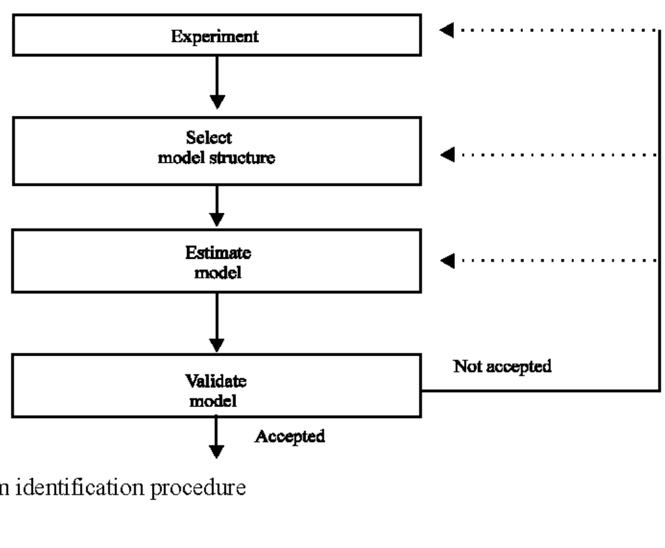

Fig. 1: System identification procedure

neural network. The ability of neural network to approximate large classes of nonlinear functions makes them prime candidates for use in dynamic model for presentation of nonlinear plants. The procedure which must be executed when attempting to identify a dynamical system consists of four basic steps including experiment, model structure selection, model training and model validation (Fig.1).

Experiment

In this step it is possible to use experimental data from various operation regimes as well as deterministic tools. In our case we used practical data, which is collected during reactor operations in normal operation condition. Also we used the PARET code to simulate some important transients, which is needed for our study. The main parameters are power, reactivity, fuel and clad temperatures.

Model Structure Selection

Model structure selection is an important step in the overall identification cycle because it forces some inherent limitations on the accuracy of the identified model and it also dictates the nature of the training algorithm to be used (Parlos *et al*., 1992).

Considering the number of neural topologies and training algorithms available, the choice of an appropriate pair (architecture, learning) depends on the purpose. The critical issues in the choice of the network architecture are the number and type of neurons and the location of the feedback loops.

Generally, the reactor dynamics have been modeled using the point reactor equations with contains thermal and hydrodynamic reactivity feedback consideration. The point reactor assumption is valid for small cores such as TRR. In the point kinetics equations, the time behavior of the reactor power, P and number of precursors, C, is described by the following equations (Hamilton and Duderstadt, 1976):

$$\frac{dP(t)}{dt} = (\frac{\rho(t)-\beta}{\Lambda})P(t) + \sum_{i=1}^{N}\lambda_i C_i(t)$$

$$\frac{dC_i(t)}{dt} = \frac{\beta_i}{\Lambda}P(t) - \lambda_i C_i(t), \qquad i = 1, 2, ..., N$$

In present study, simulation of transients was carried out using a recurrent input-output model of TRR dynamic identification in various operation conditions. This model can be described by the following nonlinear difference equation (Narendra and Parthasarathy, 1990).

$$y\,(k+1) = g\ \{y_p\,(k), ..., y_p\,(k-n+1);\ u\,(k), ..., u\,(k-m+1)\}$$

Where $[u\,(k), y_p(k)]$ represents the input–output pair of the plant at time k and $m \leq n$.

In this model, the output of the plant at time k+1 depends both on its passed n values $y_p(k-I)$ ($I = 0, ..., n-1$) as well as the passed m values of the input $u\,(k-j)$ ($j = 0, ..., m-1$).

Based on the point kinetic model, the dynamic state variables of a nuclear reactor in short-term are reactivity and power. Therefore suggested structure for predicting reactor behavior based on MNN model, should include these state parameters. The proposed model structure for TRR is given in Fig. 2. The inputs are reactivity, power, fuel and clad temperature at time k and it's passed values. The number of time delay of input-output pairs of the simulations determines 4 and 5 respectively. Using the above values of delay time numbers of inputs and outputs, the input layer neurons is 19 and according to Kolmogorove theorem (Kolmogorov, 1957), the number of hidden layer neurons is $2n_{in}+1 = 39$.

The objective of this study is to design a neural simulator for predicting reactor behavior in both normal operation and RIA conditions. To achieve the desired objectives, neural model must be learned reactor dynamics for these conditions. To have this ability, the reactor operation conditions are categorized in three groups and we used three parallel neural models with a similar structure as shown in Fig. 3. In this structure, the first model was used for identification of TRR core dynamics in normal condition, the second model was used for identification of TRR core dynamics during slow reactivity

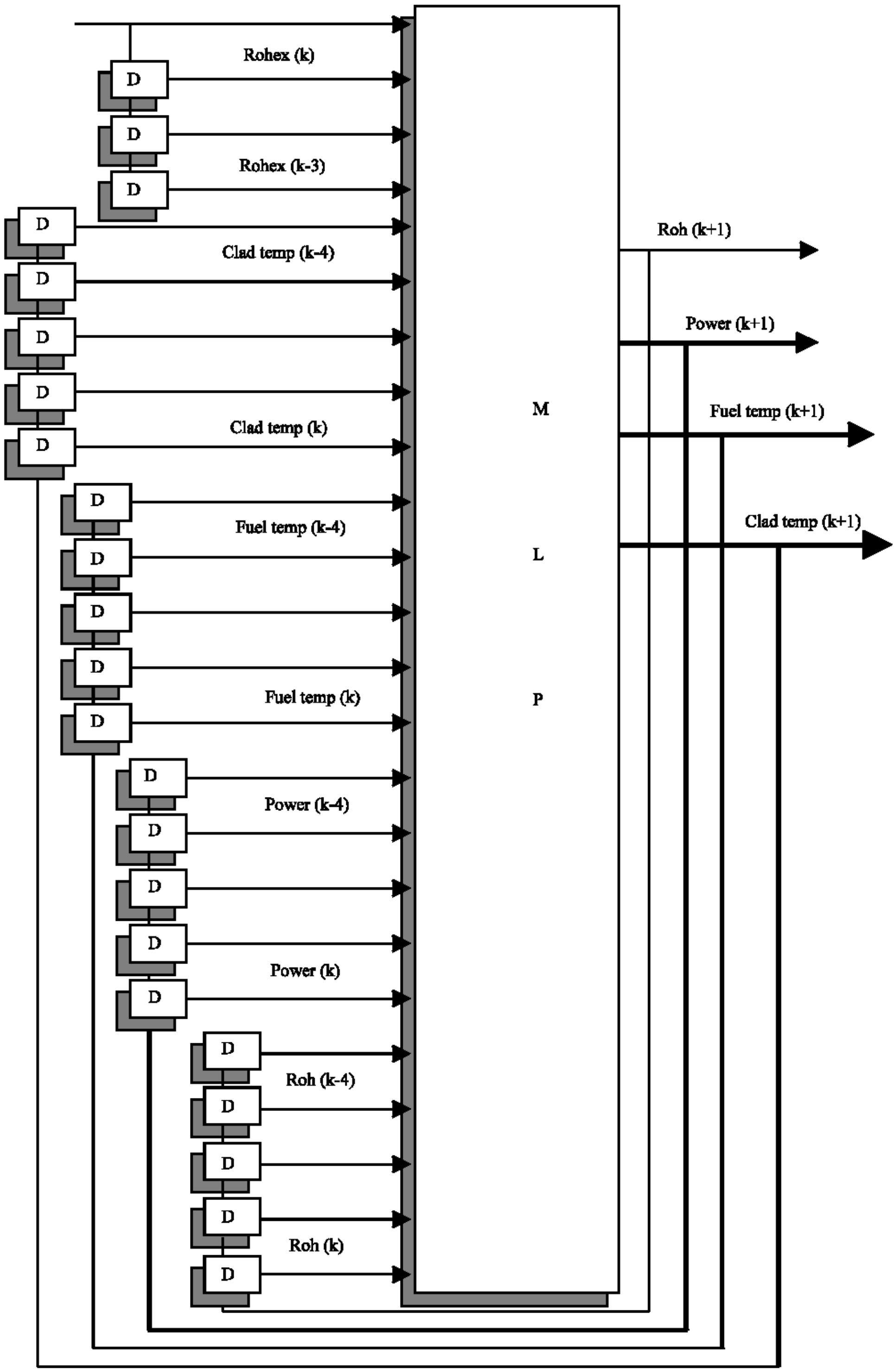

Fig. 2: Neural model structure for TRR model building

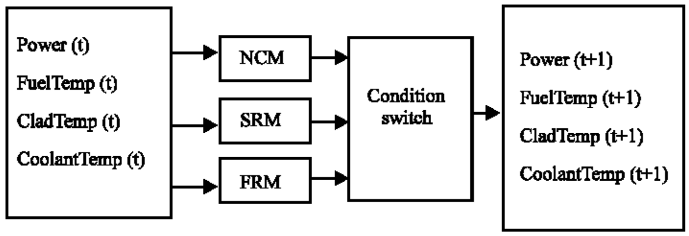

Fig. 3: TRR model block diagram

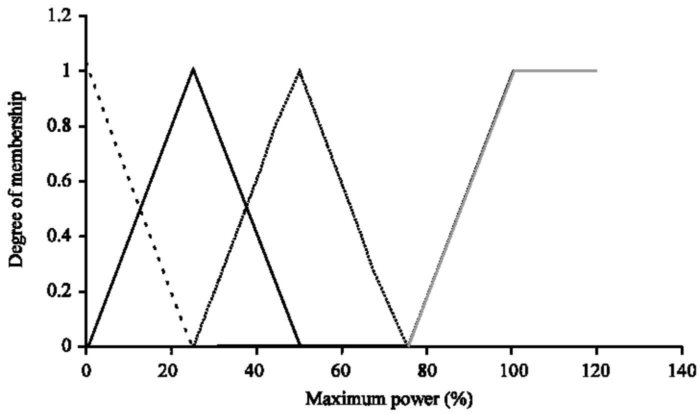

Fig. 4: TSK membership funtion

insertion transients and the third one was used for identification of TRR core dynamics during fast reactivity insertion transients. The range of reactivity insertion rate for these three groups of ANN is as follows:

- Normal operation Condition Model (NCM): 0<Reactivity rate<0.052$/sec
- Slow Reactivity insertion Model (SRM): 0.052$/sec<Reactivity rate<0.09$/sec
- Fast Reactivity insertion Model (FRM): 0.09$/sec<Reactivity rate<1.5$/sec

The proposed model must respond suitably in all operating powers, so a kind of gain-scheduling is necessary. To this end, we will Train several neural models in different powers (namely 1, 25, 50, 75 and 100% of nominal power) and use Takagi-Sugeno-Kang (TSK) fuzzy system for covering the other power values. The rule of this fuzzy system is:

Rule I: if power is P_i Then: out = NN_i (x, Power)
I = 1, 25, 50, 75 and 100

As Fig. 4 shows, TSK membership function have been chosen in such a way that in each working point, the simulator output is a combination of two models output. Using the above model, TRR identification is equivalent to determination of MNN weights.

Model Training

Despite the great potential of neural networks to predict the system behavior, a successful practical application of this model is limited to several drawbacks. One of them is the computational efficiency of the Training stage, which depends on the initial weights and the other is the information content of what is learned, which depends on the data set.

The objective of the training process is to minimize errors and speedup the learning process by adjusting the neural network parameters. This could be done based on a given set of input-output pairs.

Table 1: Values of used parameters in learning data scaling

Fast reactivity insertion	Slow reactivity insertion	Normal condition	Description	Parameter name
30	12	6	Max Power	PRmax (MW)
4.5	2	0.2	Max Reactivity	Rohmax ($)
-10	-10	-0.2	Min Reactivity	Rohmin ($)
400	350	300	Max FuelTemp	FTmax (°C)
300	200	150	Max CladTemp	CTmax (°C)

In fact, the training should ideally occur exclusively parallel to the learning neural networks at a high speed from any initial set of weights. In order to achieve useful neural model for TRR, it is necessary to have efficient online training algorithms.

In this study training data was supplied in three categories including normal, slow and fast reactivity conditions in the base of sampling time interval. According to the relation between sampling time interval and minimum period of system (Ljung, 1987), the sampling time interval was determined for above-mentioned three categories of 1sec, 0.01 and 0.001sec, respectively. Then learning data were scaled between-1 and+1 using five relations as follows:

$$\text{Power} = \frac{\text{Power} - (\text{PR}\max/2)}{(\text{PR}\max/2)}$$

$$\text{Rohex} = (2/(\text{Roh}\max - \text{Roh}\min))*\text{Rohex}$$

$$\text{Roh} = (2/(\text{Roh}\max - \text{Roh}\min))*\text{Roh}$$

$$\text{FuelTemp} = \frac{\text{FuelTemp} - (\text{FT}\max/2)}{(\text{FT}\max/2)}$$

$$\text{CladTemp} = \frac{\text{CladTemp} - (\text{CT}\max/2)}{(\text{CT}\max/2)}$$

Where Power is the reactor thermal power in MW, Rohex is external reactivity in ($), Roh is core reactivity in ($), FuelTemp is fuel temperature in (°C) and CladTemp is clad temperature in (°C). Table 1 gives the values of constant parameters.

For training the TRR model, the output of the plant was used as a feedback into the identification model, which named series-parallel method. Since no feedback loop exists in series-parallel learning method, the static learning algorithm such as Levenberg-Marqudart was used to train the neural model. This algorithm reduces the computational overhead substantially (Narendra and Parthasarathy, 1990). To speed up the network's training process and to improve the precision, the learning process parameters have been optimized.

Model Validation

When a network has been trained, the next step according the procedure is to evaluate it. Neural network models are data driven and therefore resist analytical or theoretical validation. These models are constructed by training using a data set, i.e., the model alters from a random state to a trained state and must be empirically verified. The most common method of validation is to investigate the residuals (predication errors) by cross-validation on a test set. In this work we perform a number of such tests including autocorrelation function of the residuals and cross-correlation function between model input and residuals. For performing these tests, the data is divided into two sets; one set to construct the model (train the neural network) and the other set to validate the model (test the neural network). Autocorrelation function of output error for model validation is an approximation to white noise autocorrelation function (Billings *et al*., 1992).

Three transient (NCM, SRM, FRM) cases were studied. As it is observed from Fig. 5, the autocorrelation function of power prediction error is an approximation to white noise autocorrelation function and the cross-correlation function between reactivity and power prediction error almost stay within their standard deviations.

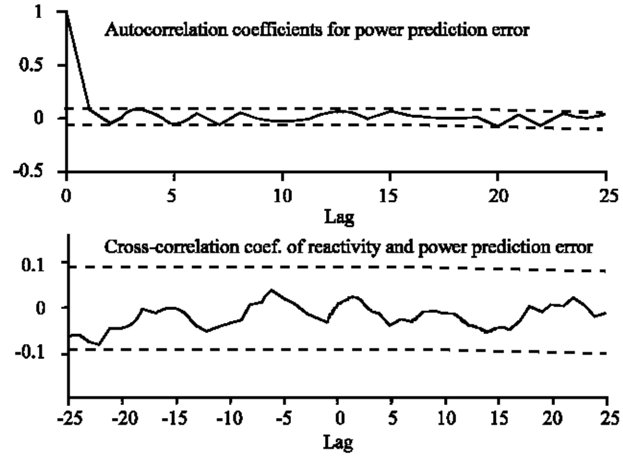

Fig. 5: TRR model validation

Results and Discussion

For normal reactor operating conditions, it is expected that the rate of heat generation in the fuel will be the same as the rate of removal of heat by the coolant. Any imbalance in this state is likely creating a perturbation, which may lead to an accident. Transients induced by reactivity insertions put the reactor in a super critical state; include a sudden power rise to levels beyond the cooling capabilities of the reactor. The transient behavior depends on the design features of the reactor, the rate and magnitude of the reactivity inserted and the operating condition before the initiation of the excursion.

To analyze the results of the designed and developed TRR simulator by neural model various modes of RIA were investigated. The accidents considered are:

- Start-up accident.
- Drop of fuel element accident.
- Beam tube flooding.
- Movement of core towards thermal column.
- Removal of an in-pile experiment.

In this simulation, the protection and safety circuits each one assumed to fail except the overpower trip at 120% nominal power. A delay time of 25 ms has been considered between attainment of trip level and start of shutdown reactivity insertion (-10$/0.5 sec).

Simulated scenarios by neural simulator and PARET code has been discussed in the following. The comparisons between PARET code and neural simulator results (Table 2) are in good agreement. The results of the various transients investigated are plotted in Fig. 6 for peak powers and peak clad temperatures as function of reactivity insertion.

Startup Accident

In this accident, all of the control rods are withdrawn at maximum movement rate due to circuit malfunction during startup of the reactor. The startup transients were initiated by ramp insertions of 0.048$\Delta k/k$/s starting with the reactor critical at an initial power of 1W. The predicted peak power of 6.85MW in 15.8 sec agrees favorably with the PARET code result of 6.42MW (Fig. 6a).

Table 2: Time histories of power level and fuel and clad temperature in various RIA

RIA Accident Parameter	Startup PARET code	Startup Neural simulator	Drop of fuel element PARET code	Drop of fuel element Neural simulator	Beam tube flooding PARET code	Beam tube flooding Neural simulator	Movement towards thermal column PARET code	Movement towards thermal column Neural simulator	Removal of in-pile Experiments PARET code	Removal of in-pile Experiments Neural simulator
Trip Time (ms)	15860	15690	685	676	4310	4280	3285	3310	110	115
Peak Power (MW)	6.42	6.85	21.89	20.53	6.32	6.61	6.45	6.9	16.25	16.9
Max Fuel Temp (°C)	90.8	92.6	103.8	105.3	91.8	93.2	92.8	94.5	96.5	98.5
Max Clad Temp (°C)	88.4	91.15	99.6	102.1	89.5	91.7	90.1	92.4	94.7	96.1

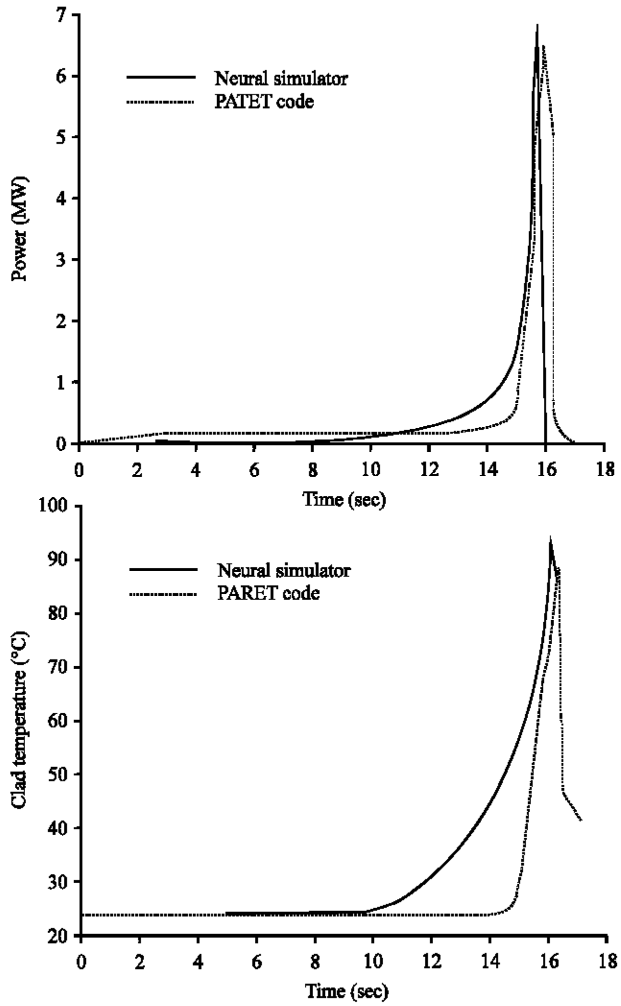

Fig. 6a: Time histories of power and clad temperature in startup accident

Drop of Fuel Element Accident

A fresh fuel element is dropped on the core due to an operator error during fuel loading. This accident has been analyzed for an initial power of 1 W. The results of the study indicated the peak power was 20.53 MW in 676 ms and the corresponding peak clad temperature is about 102.1°C (Fig. 6b). This predicted peak power is also in agreement with the PARET code result of 21.89 MW.

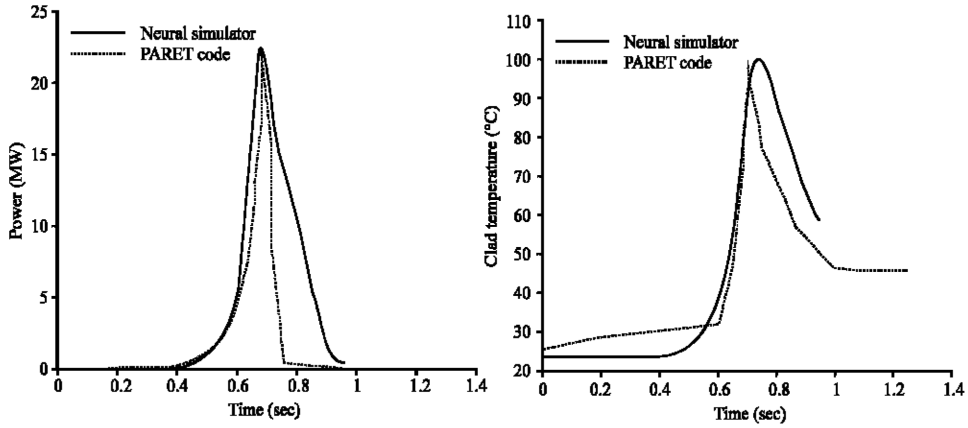

Fig. 6b: Time histories of power and clad temperature in drop of fuel element accident

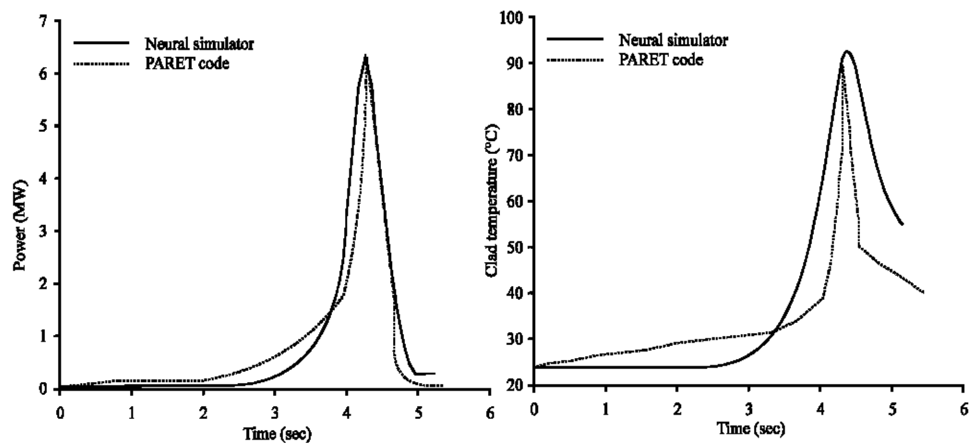

Fig. 6c: Time histories of power and clad temperature in beam tube flooding accident

Beam Tube Flooding

TRR has six radial beam tubes. When not in use, these beam tubes are plugged with shielding blocks and filled with water. When an experiment is to setup, water is drained and plugs are removed. The transition from the air filled to water filled state adds a positive reactivity into the core. This transient has been studied for an initial power of 1 W. The peak power of 6.61 MW is predicted which is almost the same as the PARET code results of 6.32 MW and the corresponding peak clad temperature of 91.7°C (Fig. 6c).

Movement of Towards Thermal Column

When the reactor core is moved from a position in which it is completely surrounded by water into the stall operating position, a portion of its water reflector is replaced by graphite thermal column. This adds a positive reactivity into the core. This transient has been analyzed for an initial power of 1 W. In this case, the peak power is about 6.9 MW and peek clad temperature is about 92.4°C. Fig. 6d illustrates the comparison between the calculations using the PARET code and neural simulator results for this transient.

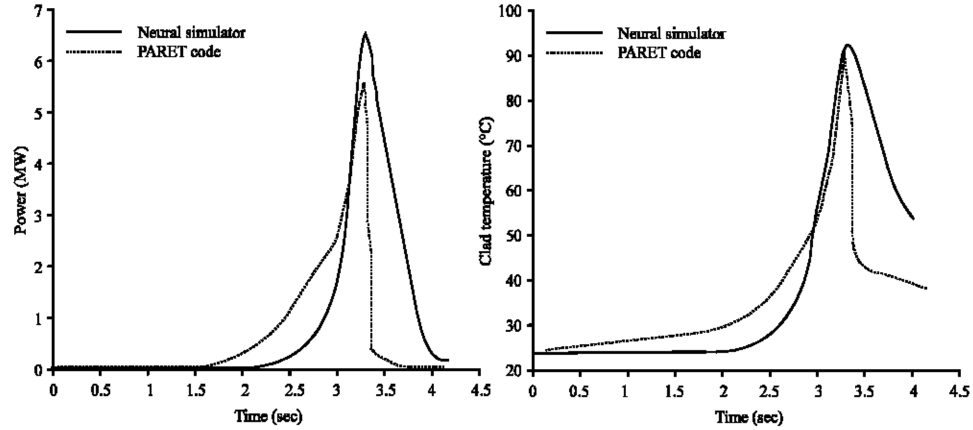

Fig. 6d: Time histories of power and clad temperature in movement of core against thermal column accident

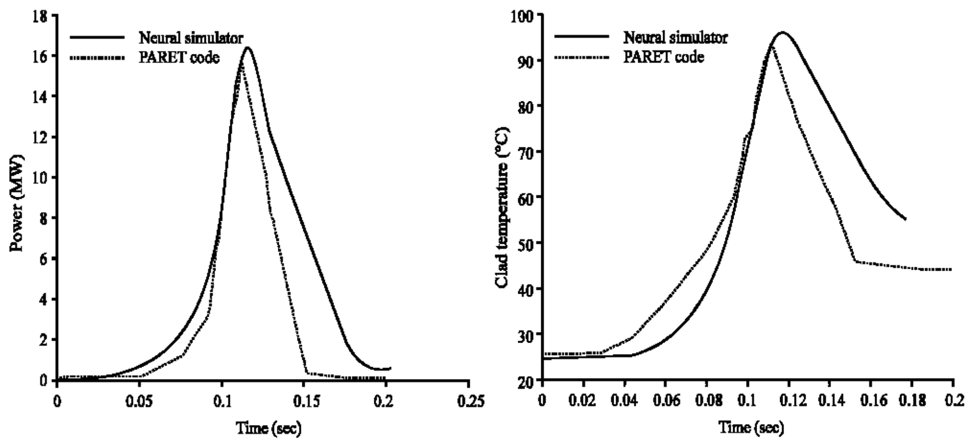

Fig. 6e: Time histories of power and clad temperature in removal of in pile accident

Removal of In-pile Experiment

The experiments which are placed inside the reactor represent a potential means of imparting a sudden increase of the core to this transient shows the peak power predicted about 16.9 MW and peak temperature at fuel centerline and clad surface are 98.5 and 96.1°C, respectively (Fig. 6e).

Conclusions

The developed of neural network model is studied and analysis of the dynamic behavior of TRR in normal operation, slow and fast reactivity insertion accidents is achieved. For this purpose, the TRR simulator has been designed and developed with neural model. The advantages of TRR core modeling by neural network is:

- Providing speed-ups in system prediction by using dedicated hardware, which provides faster than real-time prediction power.
- Ability estimates of the system response in the absence of measurements.

- Ability to start prediction from arbitrary initial condition due to its access to all dynamics state variables at the network input.
- Fast and accurate estimation of core safety margins.

This study shows that by employing the neural model, the severe operational transient in TRR can be predicted in real time. Also, the results of RIA simulation were compared with analytical routine methods such as PARET and are in good agreements. In the worst case, the peak-clad temperature is about 102.1°C in fuel element drop accident, which is far below the clad melting point. It is concluded that TRR can operate at full power without any potential hazard of reactivity-induced accident.

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