NUCLEAR REACTOR CORE PRESSURE LOSS ADJUSTMENT WITH NEURAL APPROACH

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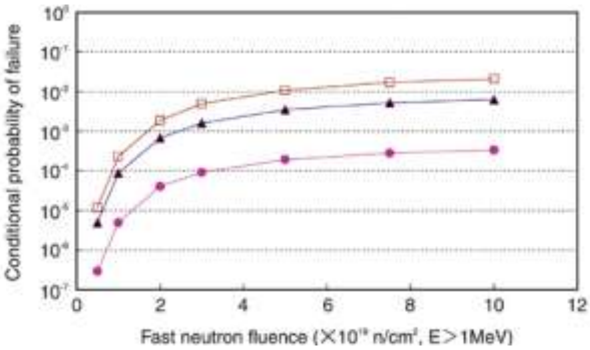
ABSTRACT

To investigate loss of pressure control on nuclear reactor design models artificial neural networks supports plant operators by training with process parameter database pertaining to accident conditions. The pressure-loss adjusting member can suppress problems due to a flow of a primary coolant, while easily distributing the flow rate of the primary coolant to fuel assemblies. Accordingly, the flow rate of light water flowing toward the fuel assembly can be reduced by arranging the pressure-loss adjusting member between a lower nozzle of a fuel assembly having a small pressure-loss and the lower core support plate, and rattling or the like of the pressure-loss adjusting member can be suppressed by engaging the core support plate engaging unit with the lower core support plate. The pressure distribution and flow patterns in a unit cell, corresponding to ¼ of fuel assembly, of the top fuel region are obtained with Computational Fluid Dynamics (CFD) model. ANN provides a better diagnostic and prognostic system essential for the identification of pressure loss scenarios in reactor core.

Keywords: Artificial neural network, CFD Models, Pressure loss adjusting member, Simulation.

I. INTRODUCTION

Most commercial reactors use pressure vessel to prevent to prevent boiling in the core which would lead to nuclear meltdown [1].Thermal stratification, rupture of the pressurizer, spray nozzle failure, mechanically clogged piping may lead to loss of pressure control which have been the reports on Analysis of Severe Accidents in Pressurized Heavy Water Reactors [2]. During an inspection on March 2002 Davis-Besse Nuclear Power Station identified a football-sized cavity in the units' reactor vessel head. The cavity was next to a leaking nozzle with a through-wall crack and was in an area of the vessel head that had been covered with boric acid deposits for several years [3]. When a loss-of-coolant accident occurs in a reactor, the emergency core cooling system injects water in the Reactor Pressure Vessel (RPV), resulting in cooling of the inside of the vessel with high pressure maintained. This induces a high tensile stress at the inner surface of the RPV, so called Pressurized Thermal Shock (PTS). The structural integrity of the RPV during PTS should be evaluated assuming the existence of a flaw at the inner surface [4].



An important aspect of nuclear reactor core analysis involves the determination of the optimal coolant flow distribution and pressure drop across the core. On the one hand, higher coolant flow rates will lead to better heat transfer coefficients. On the other hand, higher flow rates will also result in larger pressure drops across the core, hence larger required pumping powers and larger dynamic loads on the core components. Thus, the role of the hydrodynamic and thermal-hydraulic core analysis is to find proper working conditions that assure both safe and economical operation of the nuclear power plant. Artificial Neural Network attempt to simulate, within specialized hardware or sophisticated software, with multiple layers of neurons. A general characteristic of a neural network is the ability that quickly recognizes the various conditions or states of a complex system once it has been suitably trained. Transient data was generated and first order resilient back propagation with batch mode training was used. Training of ANN was carried out on a typical Pentium IV processor with 1.5GHz and 512MB of RAM [5].In this paper the Resilient Back propagation algorithm is used as a local adaptive learning scheme. The motivation behind this algorithm is to eliminate the influence of the magnitude of the partial derivative. Only the sign of the derivative can determine the direction of the weight update. The size of the weight changes is determined by a separate update value. In the training phase, the P prototypes of the learning dataset are presented to the network in sequential and iterative manner. Regressors are used to describe the nonlinear and linear functions. MATLAB has a number of verification techniques available to validate the model structures that are identified. Validation is required to verify that the model structure replicates the behavior of the identified system within acceptable levels.

II. PRESSURE LOSS ADJUSTING CHAMBER

In the pressurized water reactor, fuel assemblies are mounted on a lower core support plate provided in a lower part of a reactor vessel. Light water circulating in the reactor internal flows upward from below the core support plate, passes through the holes in the lower core support plate and then the holes in the lower nozzle, and flows toward the fuel assembly on the lower nozzle. Accordingly, the light water circulates in the primary cooling system, while being exposed to the heat at the time of a. fuel reaction. At the time of circulation of light water, light water passes through the holes in the lower core support plate and in the lower nozzle and flows to the circumference of the fuel assembly. However, a flow rate of light water flowing to the circumference of the fuel assembly may be different according to an arrangement position of the fuel assembly. Further, when the performance of the reactor at the time of operation is considered, it may be desired to adjust the flow rate thereof to the fuel assembly. Therefore, the conventional reactor may have a structure for adjusting the flow rate of light water flowing to the fuel assemblies.

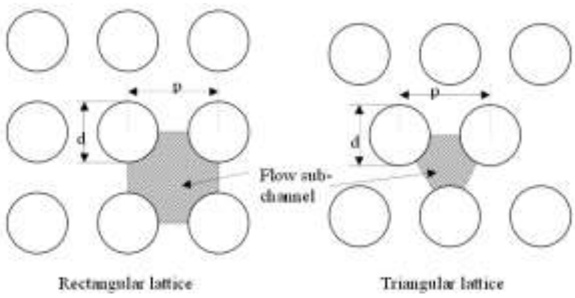


Fig 1 Fuel Assembly

One can identify several mechanisms that will cause pressure drop along the fuel assembly:

1. Friction losses from the fuel rod bundle

2. Local loses from the spacer grids

3. Local loses at the core inlet and exit (contraction and expansion)

4. Elevation pressure drop (Fig 1)

The total pressure drop can be calculated from the following equation:

$$\Delta p_{tot} = -\Delta p_{fric} - \Delta p_{loc} - \Delta p_{elev} = \frac{4Cf\ L}{Dh}\left(+ \sum_i \xi i \quad \frac{G2}{2\rho} \right) + L\rho g \sin\varphi \qquad (1)$$

Here C_f is the Fanning friction coefficient, L is the length of the channel, G is the mass flux, D_h is the channel hydraulic diameter and ρ is the coolant density.

2.1 Primary and Secondary Cooling system

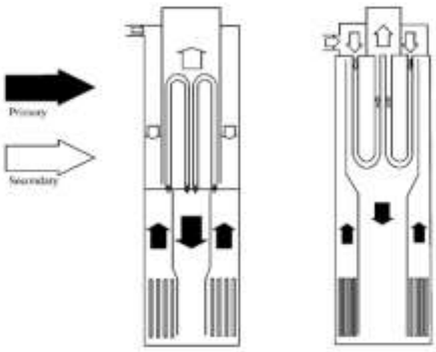


Fig 2 Cooling System

The time of extracting energy is separated into a primary cooling system and a secondary cooling system in PWR. In the primary cooling system, light water exposed to heat at the time of a fuel reaction is made high-temperature and high-pressure water[11].Pressurizing light water circulating in the reactor does not allow light water does not boil. In the secondary cooling system, light water circulating in the secondary cooling system is exposed to heat of the high-temperature and high-pressure water in the primary cooling system so that light water is brought to a boil, and energy is extracted as high-temperature and high-pressure steam. The pressure drop inside the tubes is so high, that natural convection at full power in the primary side is not established for reasonable module heights. Since the module must be extracted from the top, after removing the fuel element from the bottom, the total length should not exceed 12 m. When the water of the secondary system flows inside the tubes, the pressure drop is higher, because of the two-phase flow (Fig 2). But in the secondary system pumps establish the flow. The decay heat can still be removed by natural circulation in secondary circuit at low flow. Steam drums are used to collect and separate the vapor. In order to fulfill the natural convection requirement at decay heat, the position of the steam drum must be determined to provide the buoyancy force necessary to balance the pressure drop.

As the fluid travels up the length of the fuel assembly, there is pressure losses associated with frictional, gravity, form, and acceleration factors. The largest factor is the frictional pressure drop. This consists of a relation of a frictional factor, geometry, and velocity of the fluid. For turbulent flow, the frictional term can be solved for using the McAdams relation for smooth pipes of f = 0.184*Re-0.2. It is important to remember to use a hydraulic diameter and area associated with fuel rods. For example, for a square array, the area equals the pitch squared minus the cross sectional area of the rod and the hydraulic diameter is four times the area divided by the perimeter of a rod. When grid spacers are introduced, the pressure loss is greatly increased [12] Grid spacers are used for support of the fuel rods from vibration but also external loads of the coolant. Another advantage of spacers is that they increase the heat transfer coefficient by creating additional mixing and direction of the coolant. Modern day spacers provide proper mixing to allow for a swirling affect along the length of a section of the rod. As the mixing increases, the pressure loss increases.

2.2 CFD Model

Pressure distribution and flow fields in reactor core have significant impacts on fuel performance as well as the integrity of reactor vessel internals. Steeper pressure drops are observed at locations where the flow area is reduced at the entrances to the top grid, top nozzle, hold down device, and upper core plate hole. Moderate effects on the pressure decrease and recovery are obtained by refining the meshes in the fluid region adjacent to hold-down device and region in front of the upper core plate hole.

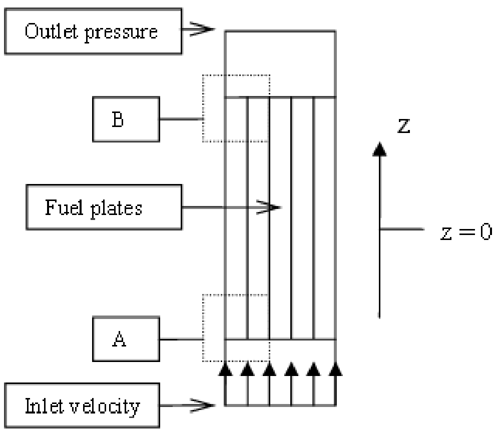


Fig 3 Boundary conditions on Fuel Assembly

Under normal operating conditions, the core is cooled with forced circulation. The average velocity in coolant channels is 8.2 m/s which corresponds to 5.08 m/s of inlet velocity at the inlet of the “lower plenum” (Fig 3). The pressure drop under normal operating condition is reported to be 240 kPa . Corresponding CFD simulations show a pressure drop of only 180 kPa. Errors can be further reduced using neural network. The pressure drop is calculated by, Loss Coefficient = $\frac{\Delta P}{(\frac{1}{2})\rho V2}$ where the P is the difference of the area-averaged total pressures at the entrance of the top grid and at the outlet of the upper core plate hole, ρ is the density, and V is the inlet velocity.

TABLE 1 CFD Model

Inlet velocity (m/s)	Pressure Drop of Assembly CFD with Structure Details (Pa)
0.01	131.7
0.025	349.1
0.05	773.3
0.1	1650.3
0.5	6188.5
1.0	14819
2.0	45279

III. ARTIFICIAL NEURAL NETWORK

A neural network model of the thermodynamics of a power plant can be used to determine the influence of changes in different variable upon the heat rate through the use of sensitivity coefficients, where the signs indicate the directions of change in the variable that will improve heat rate, and the magnitude indicates the relative importance of the different variables. This information can be used to provide guidance to the plant operators and engineers as to where they should expand their efforts to improve the heat rate. ANN based modeling for pressure drop coefficient for cyclone separators is done by [11].

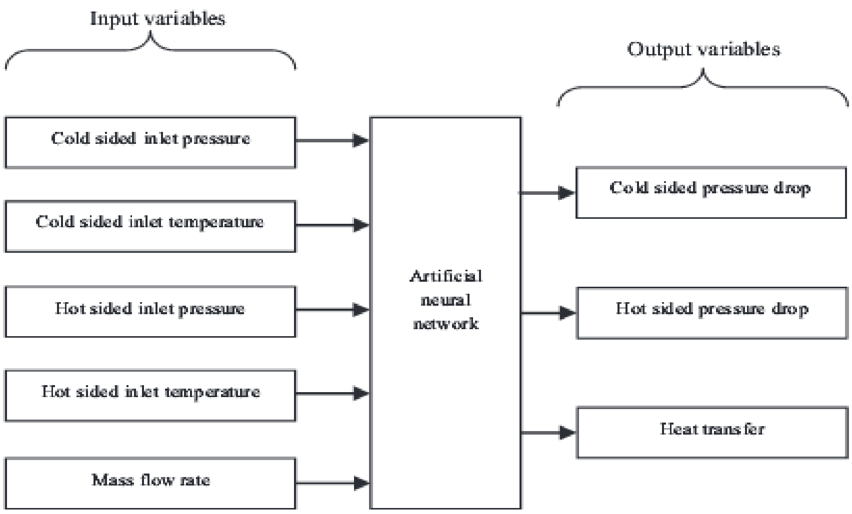


Fig 4 ANN Modeling of Reactor Core Pressure Drop

Resilient back Propagation algorithm is a local adaptive learning scheme performing supervised batch learning in feed forward neural networks. The basic principle of this algorithm is to eliminate the harmful influence of the size of the partial derivative on the weight step. RPROP modifies the size of the weight step taken adaptively, and the mechanism for adaptation in RPROP does not take into account the magnitude of the gradient as seen by a particular weight, but only the sign of the gradient (positive or negative). This allows the step size to be adapted without having the size of the gradient interfere with the adaptation process [13].

Resilient Back propagation Algorithm is generally much faster than the standard steepest descent algorithm. It also has a very good feature that it requires only a modest increase in memory requirements. It is a systematic method to train the neural network. The purpose of it is to eliminate the harmful effects of the magnitudes of the partial derivatives. Only the sign of the derivative is used to determine the direction of the weight update and the magnitude of the derivative has no effect on the weight update. Different trials have been carried out in the training phase to get the optimal values for different number of hidden nodes and learning rates for back propagation algorithm. Fig 5 shows mean square error parameter with respect to the number of iterations for various learning rates and number of hidden nodes. At first the value of learning rate was varied keeping number of hidden nodes constant. Then the number of hidden nodes was varied keeping learning rate constant.

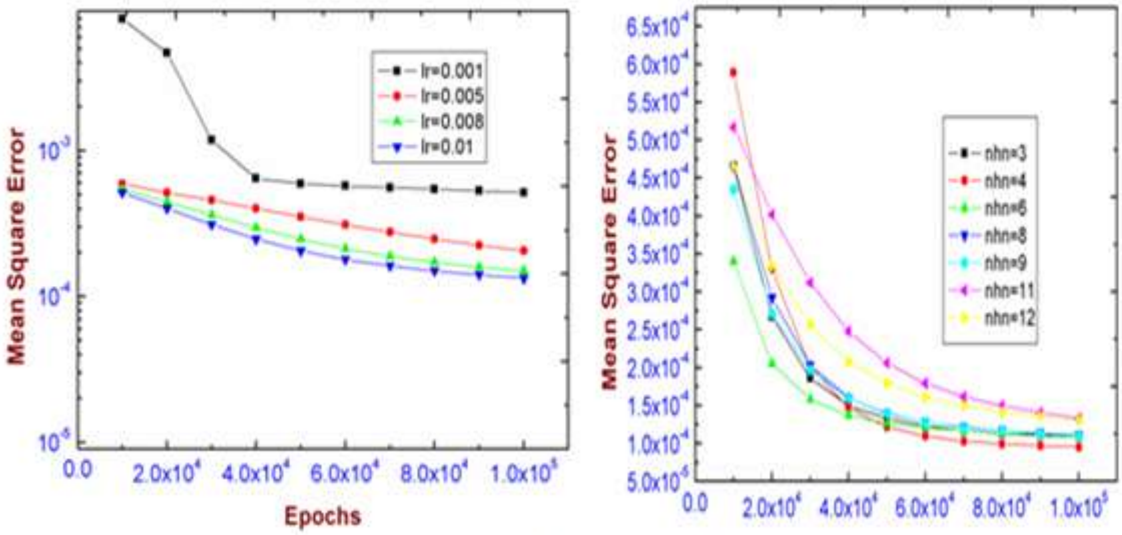


Fig 5 Epochs Vs Mean Square Error

After repeating the above process Q times the mean MSE (mMSE) and standard deviation of MSE sdMSE) were calculated respectively:

$$m\text{MSE} = \frac{\sum_{i=1}^{Q} \text{MSE}_i}{Q} \qquad (2)$$

$$sd\text{MSE} = \sqrt{\frac{1}{Q}\sum_{i=1}^{Q}(\text{MSE}_i - m\text{MSE})^2} \qquad (3)$$

The difference between mean MSE values for training and validating were compared.

IV. SIMULATED RESULTS

ARMAX structure estimates different set of zeros but same set of poles for the system and the noise model. This structure is especially suitable when the stochastic dynamics are dominating in nature and the noise enters early into the process e.g. load disturbances [17].

$$A(z)y(t) = B(z)u(t) + C(z)e(t) \qquad (4)$$

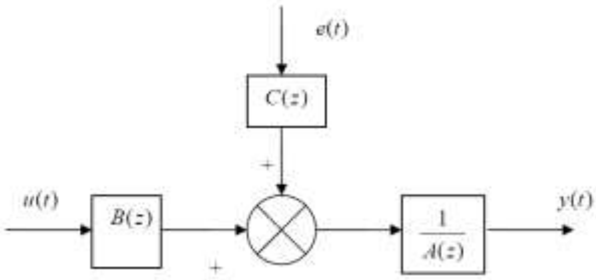
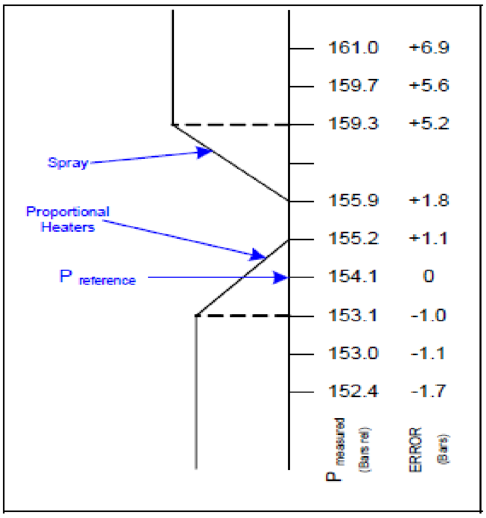


Fig 6 ARMAX Structure

For identification, the reactor is visualized as a system with fraction of total drop as input and the global power (in percentage of maximum power produced) as output. From the simulator it is known that the set point is 15.51MPa.The main pressuriser heaters are switched on at about 15.51MPa and increase linearly to about 15.41MPa where the main heaters maximum power of 315kW is reached. The pressuriser spray valves are opened at a minimum value and increase linearly to a maximum value. In none of the simulated data sets could a maximum value for the spray mass flow be reached [21].

TABLE 2 Simulated Pressurizer data sets



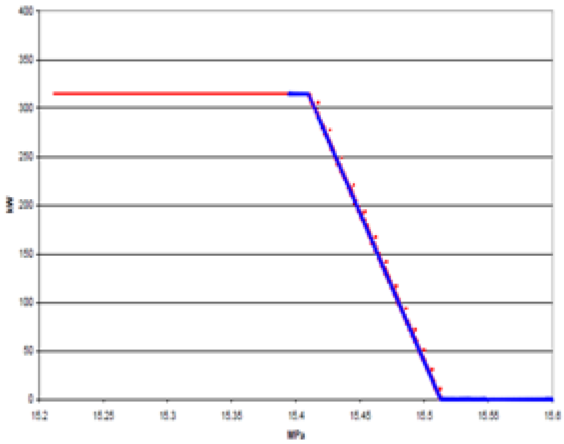


Fig 7 Heater Power Vs Pressure

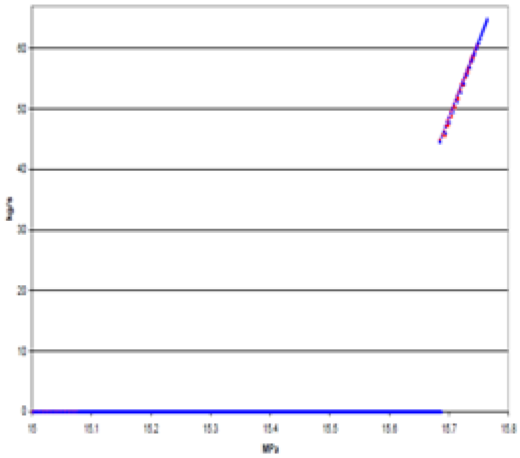


Fig 8 Mass Flow rate Vs Pressure

The identification is carried out using the *arx()*, *armax()*, *bj()*, *oe()* functions of System Identification Toolbox of MATLAB and higher order discrete transfer function models have been estimated from the measured input output data [24]. Now, the most appropriate model structure can be judged from the prediction error of the models. The statistical measure of the quality of the identified model can be judged using Akaike's Information Criterion (AIC)

$$AIC = \log\left\{\det\left[\frac{1}{N}\sum_{t=1}^{N}\varepsilon(t,\theta_N)\varepsilon^T(t,\theta_N)\right]\right\} + \frac{2d}{N} \qquad (5)$$

where, N is the number of measurement points

θ is the identified system parameters and

d is the number of parameters to be identified.

V. CONCLUSION

Fuel criticality due to loss of pressure control and cooling malfunction makes the reactor unstable. CFD Model analyses the pressure distributions and flow patterns in the assembly. Nodes representing fluid volumes or thermal masses are connected with one-dimensional heat and fluid flow elements to represent a thermal system. The type of element determines the pressure drop; mass and heat flow characteristics. Thus the flow distribution at the core inlet is influenced by the flow field in the reactor pressure vessel and the flow distribution between the loops. The calculated pressure loss coefficients can be used to increase accuracy of severe accident analysis with core meltdown. CFD validates and evaluates the pressure loss coefficient Neural networks can capture complex dynamics of the system like hindered lower plenum geometry yielding satisfactory predictions. Selected model structures available in the MATLAB System Identification Toolbox with validation techniques are used for the verifying the system model. Partition coefficients at higher pressure, improved numerical stability can be worked on for more improved performance.

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