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BHABHA ATOMIC RESEARCH CENTRE

# USE OF ARTIFICIAL NEURAL NETWORK IN ESTIMATING CHANNEL POWER DISTRIBUTION OF A 220 MWe PHWR

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Reactor Control Division
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V. Jagannathan
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| 21 | *Affiliation of author(s) :* | (1) Reactor Control Division, Bhabha Atomic Research Centre, Mumbai<br>(2) Theoretical Physics Division, Bhabha Atomic Research Centre, Mumbai<br>(3) Electronics Division, Bhabha Atomic Research Centre, Mumbai |
| 22 | *Corporate author(s) :* | Bhabha Atomic Research Centre, Mumbai - 400 085 |
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60 Abstract : Knowledge of the distribution of power in all the 306 channels of a Pressurised Heavy Water Reactor (PHWR) as a result of the movement of one or more of the four regulating rods is important from the operation and maintenance point view of the reactor. Conventional computer codes available for this purpose take several minutes to calculate the channel power distribution on PC-AT/486. An Artificial Neural network (ANN), based on the RPROP algorithm has been developed and employed in predicting channel power distribution of a 220 MWe Indian PHWR as a result of a perturbation caused by the movement of one or more of the four regulating rods of the reactor. The ANN based system produces the result of an analysis much faster than that produced by a conventional computer code usually employed for this application. The ANN based system is rugged, accurate and fast, and therefore, has potential to be used in real-time applications.



70 *Keywords/Descriptors :* PHWR TYPE REACTORS; POWER RANGE 100-1000 MW; POWER DISTRIBUTION; POWER DENSITY; NEURAL NETWORKS; REACTOR CONTROL SYSTEMS; COMPUTER ARCHITECTURE; REGULATING RODS; REACTOR CHANNELS; C CODES; NEUTRON FLUX; PERFORMANCE TESTING; ERRORS; DATA COVARIANCES.

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# Use of Artificial Neural Network in Estimating Channel Power Distribution of a 220 MWe PHWR

B. P. Dubey, A. K. Chandra and G. Govindarajan
Reactor Control Division, Bhabha Atomic Research Centre, Mumbai - 400 085

V. Jagannathan
Theoretical Physics Division, Bhabha Atomic Research Centre, Mumbai - 400 085

S. K. Kataria
Electronics Division, Bhabha Atomic Research Centre, Mumbai - 400 085

## I. Introduction

Complex computer codes have been developed for a large variety of reactor states involved in design, commissioning and operational stages of a nuclear power plant. For example, the CEMESH[1] code has been developed for design and operational analyses of Indian Pressurised Heavy Water Reactors (PHWRs). CEMESH code simulates the reactor core by diffusion theory in two energy groups with the help of a parameterised lattice data base generated by PHANTOM code system[2]. A single 3-D simulation by CEMESH takes about 4 minutes on a PC-AT/486 computer. Even if a single parameter, like the position of a regulating rod is altered, CEMESH requires the same computational time to determine the new power distribution. Computer codes designed or being designed for 500 MW reactors take even more time for similar analyses. Therefore, it is difficult to use these codes for real time analyses purposes.

Michel De Vlamink[3] et. al have developed an operator advisor to help deal with emergencies in nuclear power plants using expert system techniques. In an earlier study, Dubey[4] et. al. also have developed a knowledge based operator support system for nuclear reactors using the techniques of expert system. Rule based expert systems can provide accurate results of an analysis but they also require significant computation time and resources to progress through many decision levels. Rule based systems need the knowledge of the domain of application to be formulated in the form of *if - then* rules. For a nuclear power plant, it is extremely difficult to envisage and conceive all the possible scenarios and formulate them in the form of *if - then* rules. Even if such a huge rule base is formed, an expert system containing such a huge rule-base may undergo a combinatorial explosion and thus may be unable to produce the result of an analysis in reasonable time, leave alone in real time. In addition, the temporal behaviour of all the important variables is also required at various levels of decision making. Noise can degrade input signals and cause these systems to deviate from the desired path at critical decision levels. Because of these limitations, the expert systems have not yet become as popular as expected earlier.

It is hoped that neurocomputing, as the science of ANNs is sometimes called, will be successful in the development of a computer code for real-time analysis of reactor states. In the last few years, several applications of ANNs have been reported in the field of nuclear reactors. Basu and Bartlett[5-6] have used ANNs in the development of a nuclear power plant fault diagnostic advisor. This ANN based system monitors 97 important parameters of a nuclear power plant on-line and can detect and identify 43 different scenarios representing 27 distinct transients. The system is able to detect a vast majority of transients within 20 seconds. Kim[7] et. al. have used ANN for estimating error bounds while diagnosing fault in a nuclear power plant. Reifman[8] et. al. selected 40 process parameters from 8 subsystems of a nuclear power plant to detect the occurrence of 3 different transient types in the plant. In yet another application Reifman[9] et. al. followed a hybrid approach using expert system and ANN in diagnosing the faulty components of a nuclear power plant. At the first level, an expert system is used to narrow down the diagnostic focus to a particular set of possible faulty components. At the second level, trained ANNs are used to further narrow down the diagnosis and identify the faulty component. B. R. Upadhayaya[10] has used ANN in sensor validation in a nuclear power plant. He used the control rod position, core exit temperature and the intermediate heat exchanger secondary outlet temperature as inputs to an ANN to predict the reactor power. The ANN predicted power is then compared with the measured reactor power for the sensor validation. Horiguchi[11] et. al. have also used ANN for diagnosis of a nuclear power plant. An ANN diagnoses and identifies a failed equipment by recognising patterns of main plant parameters. Howell[12] have used ANN in developing a system for performing anomaly detection and consistency checking in safeguards and security data of a nuclear power plant.

Encouraged by the use of ANN in the field of nuclear power plants, a feasibility demonstration of the application of ANNs was undertaken to predict the channel power distribution in a PHWR due to changes in the position of regulating rods.

## II. The Aim

Indian PHWRs consider 4 control elements called regulating rods for auto regulation purposes. In the present discussion, the 4 regulating rods are referred to as LE(Lower East), UE(Upper East), LW(Lower West) and UW(Upper West). Figure 1-A gives the lateral and fig. 1-B gives the cross-sectional view of these rods in the reactor. The fully inserted and fully withdrawn positions of a regulating rod is represented by 1 and 0 respectively. An intermediate position of a regulating rod is represented by linearly mapping its position in the range 0 to 1. The distribution of the channel power in all the 306 channels in kW is obtained by running the 3-D diffusion simulation code (CEMESH program) for a specified combination of the regulating rod positions. All other parameters like the fuel type, moderator level, fuel burn-up, refuelling, reactor geometry etc. were fixed to constant values for all the calculations mentioned in the following discussion. Only the regulating rod positions are considered as variables. The distribution of power in all the 306 channels of the reactor, calculated by CEMESH is taken as the desired output for the ANN training. A particular combination of the positions of the 4 regulating rods form an input pattern for the CEMESH as well as the ANN. A particular combination of the positions of the 4 regulating rods and the corresponding channel power distribution in all the 306 channels, generated by the CEMESH is called an *input+desired output* pattern for training the ANN.

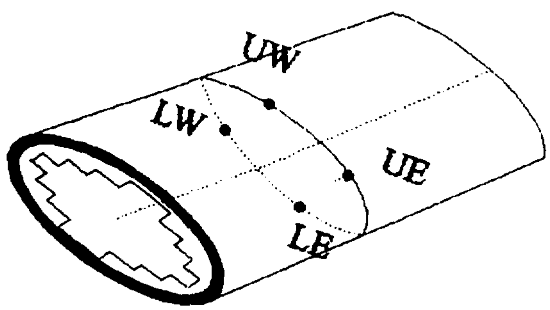


Fig. 1-A : Schematic Diagram of the Lateral View of the Reactor and the Position of the 4 Regulating Rods.

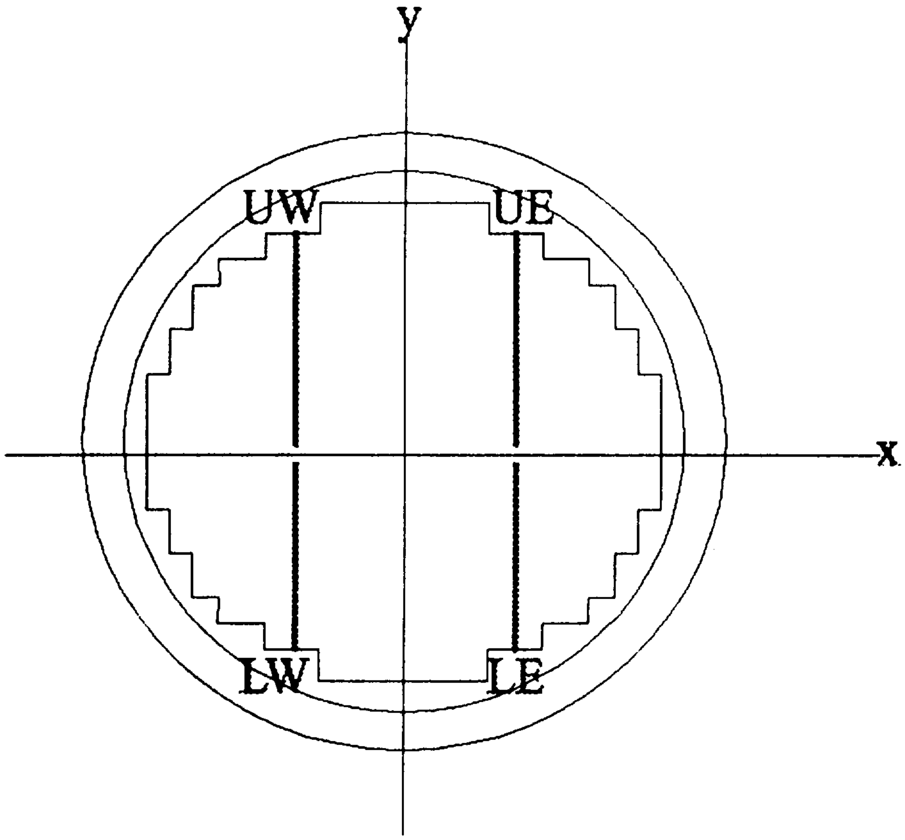


Fig. 1-B : Schematic Diagram of the Cross-sectional View of the Centre of the Reactor and the Position of the 4 Regulating Rods.

A study has been carried out to choose a suitable ANN architecture for analysing channel power distribution of an Indian PHWR. The chosen ANN was trained using several *input+desired output patterns*. After the training, the ANN is able to predict the distribution of the power in 306 channels of the reactor as a result of a perturbation caused by the movement of one or more of the 4 regulating rods of the reactor with reasonable accuracy. The ANN calculations are much faster than those of the CEMESH code. These features are discussed in Sections V and VI.

## III. Neural Network Methodology

The evolution of ANNs is highly influenced by biological neural systems[13-14]. An ANN consists of one or more layers of simple processing elements called neurons, neurodes or simply nodes. A neuron has an output and several inputs. Each input of a neuron is assigned an adjustable weight. The neuron calculates the weighted sum of its inputs and passes the weighted sum through a transfer function to generate an output. The most widely used transfer function is the sigmoid function defined as follows.

$$f(I) = \frac{1}{1+e^{-I}} \tag{1}$$

where I is the weighted sum of all the inputs to a neuron.

Depending upon the architecture in which the individual neurons are connected, there are several types of ANNs. But the most widely used architecture is the feed forward. A feed forward ANN consists of an input layer, an output layer and one or more layers in between the input and output layers, called hidden layers. Fig. 2 shows a 4 layered feed forward ANN, similar to the one used for the work presented here.

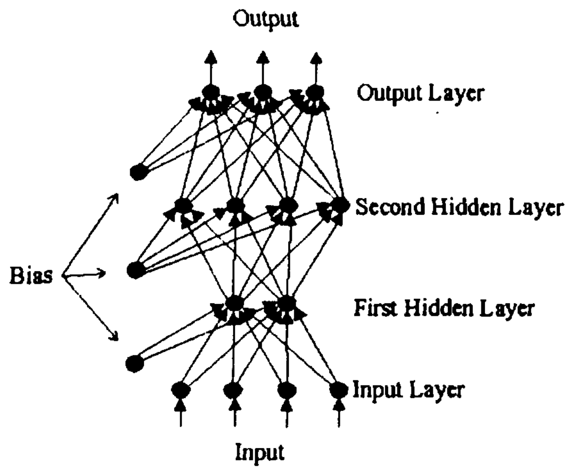


Fig. 2 : A 4 layer Feed Forward ANN

The first layer, i.e. the input layer contains neurons which are inactive, i.e. these neurons don't do any processing on their inputs. They simply collect the inputs and pass it on to the neurons of the next layer as it is. Neurons of the other layers process their inputs as described above.

To train an ANN, initially all the neurons of the ANN are assigned random weights and the input and the desired output vectors are presented to the ANN. The

ANN uses the input vector to produce an output vector. The output vector is compared with the desired output vector to calculate the error vector E.

$$E = \frac{1}{2}\sum_{p=1}^{p=P}\sum_{n=1}^{n=N}(d_{pn} - c_{pn})^2 \qquad (2)$$

Where P is the number of patterns in the set and N is the number of neurons in the output layer. $d_{pn}$ and $c_{pn}$ are the desired and the ANN generated outputs respectively. The ANN learns by adjusting its weights such that in the next iteration the net error produced by the ANN is smaller than that in the current iteration. The most popular algorithm which is used in training an ANN for a large variety of applications is the *backpropagation* algorithm. The net error generated by the neurons of the $i^{th}$ layer depends upon the connection weights $w_{ij}$, where j = 1, 2, ... k; k being the number of neurons in the previous layer i.e. $(i-1)^{th}$ layer. The back propagation algorithm finds out the values of the corrections in the weights $w_{ij}$ viz. $\Delta w_{ij}$ so that it can be added to $w_{ij}$ to reduce the net error in the next iteration. Simple backpropagation uses learning constants $\beta$ and momentum factor $\alpha$ to hasten learning as follows.

$$\Delta w_{ij}(t) = \beta\frac{\partial E(t)}{\partial w_{ij}} + \alpha\Delta w_{ij}(t-1) \qquad (3)$$

$$w_{ij}(t+1) = w_{ij}(t) + \Delta w_{ij}(t) \qquad (4)$$

where t is the iteration index. The backpropagation algorithm is very popular because of its robustness. But the weakness of it is that it takes very long time to converge. The convergence depends upon the problem, selection of network architecture and selection of parameters $\alpha$ and $\beta$. In some cases it may not converge at all.

Recently a number of researchers have made interesting improvements in the backpropagation algorithm. Reifman[15] et. al have used the method of conjugate gradient to expedite the learning of a backpropagation ANN. In standard backpropagation algorithm $\alpha$ and $\beta$ are kept constant during a particular learning session. In the method of conjugate gradient, $\alpha$ and $\beta$ are also changed in each iteration to achieve the convergence faster. Riedmiller[16-17] have proposed the

**RPROP** ( Resilient backpropagation ) algorithm for faster convergence of a backpropagation ANN. According to the **RPROP** algorithm

$$\Delta w_{ij}(t) = \begin{cases} -\Delta_{ij}(t) & \text{if} \quad \dfrac{\partial E(t)}{\partial w_{ij}} > 0 \\ +\Delta_{ij}(t) & \text{if} \quad \dfrac{\partial E(t)}{\partial w_{ij}} < 0 \\ 0 & \text{if} \quad \dfrac{\partial E(t)}{\partial w_{ij}} = 0 \end{cases} \tag{5}$$

$$\Delta_{ij}(t) = \begin{cases} \eta^{+}\Delta_{ij}(t-1) & \text{if} \quad \dfrac{\partial E(t-1)}{\partial w_{ij}} * \dfrac{\partial E(t)}{\partial w_{ij}} > 0 \\ \eta^{-}\Delta_{ij}(t-1) & \text{if} \quad \dfrac{\partial E(t-1)}{\partial w_{ij}} * \dfrac{\partial E(t)}{\partial w_{ij}} < 0 \\ \Delta_{ij}(t-1) & \text{if} \quad \dfrac{\partial E(t-1)}{\partial w_{ij}} * \dfrac{\partial E(t)}{\partial w_{ij}} = 0 \end{cases} \tag{6}$$

Where $\Delta_{ij}$ are called update values. The weights are adjusted by calculating $\Delta w_{ij}$ using equations (5) and (6) and then substituting them in equation (4).

At the beginning, all update values are set to an initial value $\Delta_0$ and weights are randomised. Values of $\eta^+$ and $\eta^-$ are fixed to be 1.2 and 0.5 respectively for optimum performance. Though Riedmiller suggests the values of $\Delta_0$ = 0.1, and $\Delta_{max}$ = 50, he has compared several algorithms and found **RPROP** to be relatively insensitive to the initial selection of the parameters $\Delta_0$, $\Delta_{max}$ and the network architecture whereas the standard backpropagation algorithm is quite sensitive to the selection of the initial values of the parameters $\alpha$, $\beta$ and the network architecture. Because of this **RPROP** algorithm have been adapted for doing this work.

## IV. Selection of Training and Test Data

The 4 regulating rods mentioned above (figs. 1-A and 1-B) control the powers in 4 quadrants of the reactor. In order that all the 4 quadrants generate nearly the same power, the regulating rod positions are normally kept equal. However, when it is difficult to keep all of them at equal positions, their positions may be kept nearly equal at least pair-wise. For the purpose of the present study the 2 lower rods LE and LW form one pair and the 2 upper rods UE and UW form another pair. The two rods of the LE-LW pair are generally inserted or withdrawn together by an equal amount. Similar is the case with the UE-UW pair. Table 1 contains 25 combinations of the 4 regulating rod positions at 25% intervals. Corresponding to each combination of the 4 regulating rod positions listed in table 1, i.e. corresponding to each row of the table 1, CEMESH generated 306 numbers, representing powers in kW in 306 channels of the reactor. A pattern containing a row of the table 1 and the corresponding CEMESH generated 306 outputs form an *input+desired output pattern* in ANN training. A set containing 25 *input+desired output patterns* (let us call it set SY25) is used in the training of the ANN. Each *input+desired output pattern* of the training set SY25 contains two parts - the input pattern and the corresponding (CEMESH generated) desired output pattern. The input part of the set SY25 is listed in table 1. A sample of the 306 channel powers obtained by CEMESH (the desired output) and the corresponding ANN output is given in table 2 for one *input+desired output pattern.*

Table 1 : Adjuster Rod Positions in set SY25; Step Size = 25 %

| LE-LW Pair | | UE-UW Pair | | LE-LW Pair | | UE-UW Pair | | LE-LW Pair | | UE-UW Pair | | LE-LW Pair | | UE-UW Pair | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| LE | LW | UE | UW | LE | LW | UE | UW | LE | LW | UE | UW | LE | LW | UE | UW |
| 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.25 | 0.25 | 0.00 | 0.00 | 0.50 | 0.50 | 0.00 | 0.00 | 1.00 | 1.00 |
| 0.25 | 0.25 | 0.00 | 0.00 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.50 | 0.50 | 0.25 | 0.25 | 1.00 | 1.00 |
| 0.50 | 0.50 | 0.00 | 0.00 | 0.50 | 0.50 | 0.25 | 0.25 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 1.00 | 1.00 |
| 0.75 | 0.75 | 0.00 | 0.00 | 0.75 | 0.75 | 0.25 | 0.25 | 0.75 | 0.75 | 0.50 | 0.50 | 0.75 | 0.75 | 1.00 | 1.00 |
| 1.00 | 1.00 | 0.00 | 0.00 | 1.00 | 1.00 | 0.25 | 0.25 | 1.00 | 1.00 | 0.50 | 0.50 | 1.00 | 1.00 | 1.00 | 1.00 |

**Table 2** : Comparison of CEMESH and ANN generated Channel Power Distribution. The channels are numbered as 1, 2, 3 ... , 20 horizontally and A, B, C, ... , T vertically. The following display mimics the face of the reactor in 2-D. CEMESH and ANN calculated power in kW and the corresponding percentage difference between the two is given for each channel. The Legend CEMESH, ANN and Dev(%) is written only for channel A1.

Set No. = 55 : Input = UE = 0.40, UW = 0.40; LE = 1.00, LW = 1.00

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A CEMESH | | | | | | | | 1653 | 1742 | 1801 | 1802 | 1744 | 1655 | | | | | | | |
| A ANN | | | | | | | | 1676 | 1756 | 1812 | 1816 | 1759 | 1677 | | | | | | | |
| A Dev(%) | | | | | | | | -1.37 | -0.78 | -0.62 | -0.78 | -0.87 | -1.32 | | | | | | | |
| B | | | | | | 1738 | 1900 | 2086 | 2217 | 2283 | 2284 | 2220 | 2089 | 1903 | 1741 | | | | | |
| B | | | | | | 1785 | 1946 | 2109 | 2234 | 2295 | 2291 | 2237 | 2113 | 1945 | 1788 | | | | | |
| B | | | | | | -2.68 | -2.43 | -1.10 | -0.75 | -0.55 | -0.30 | -0.75 | -1.15 | -2.21 | -2.69 | | | | | |
| C | | | | 1715 | 1957 | 2078 | 2258 | 2477 | 2605 | 2666 | 2668 | 2609 | 2481 | 2262 | 2082 | 1960 | 1717 | | | |
| C | | | | 1730 | 1978 | 2113 | 2288 | 2495 | 2611 | 2671 | 2672 | 2618 | 2497 | 2295 | 2111 | 1981 | 1731 | | | |
| C | | | | -0.86 | -1.05 | -1.68 | -1.33 | -0.74 | -0.22 | -0.19 | -0.15 | -0.35 | -0.63 | -1.48 | -1.39 | -1.09 | -0.83 | | | |
| D | | | 1756 | 2037 | 2280 | 2418 | 2577 | 2765 | 2871 | 2920 | 2924 | 2877 | 2771 | 2582 | 2422 | 2282 | 2037 | 1754 | | |
| D | | | 1759 | 2040 | 2285 | 2428 | 2586 | 2768 | 2870 | 2916 | 2921 | 2879 | 2779 | 2594 | 2431 | 2293 | 2045 | 1760 | | |
| D | | | -0.18 | -0.15 | -0.23 | -0.41 | -0.37 | -0.11 | 0.03 | 0.13 | 0.11 | -0.06 | -0.29 | -0.45 | -0.36 | -0.48 | -0.38 | -0.35 | | |
| E | | | 2064 | 2341 | 2557 | 2664 | 2789 | 2944 | 3019 | 3047 | 3057 | 3029 | 2952 | 2795 | 2668 | 2558 | 2339 | 2059 | | |
| E | | | 2067 | 2338 | 2559 | 2666 | 2788 | 2944 | 3016 | 3037 | 3051 | 3021 | 2948 | 2796 | 2672 | 2561 | 2343 | 2060 | | |
| E | | | -0.14 | 0.12 | -0.06 | -0.07 | 0.02 | 0.02 | 0.11 | 0.34 | 0.20 | 0.27 | 0.14 | -0.03 | -0.16 | -0.12 | -0.18 | -0.07 | | |
| F | | 1943 | 2279 | 2567 | 2754 | 2823 | 2911 | 3028 | 3061 | 2903 | 3078 | 3071 | 3036 | 2917 | 2825 | 2752 | 2561 | 2269 | 1932 | |
| F | | 1940 | 2272 | 2562 | 2749 | 2820 | 2906 | 3023 | 3055 | 2897 | 3069 | 3064 | 3028 | 2912 | 2826 | 2751 | 2557 | 2266 | 1929 | |
| F | | 0.14 | 0.31 | 0.18 | 0.17 | 0.11 | 0.16 | 0.16 | 0.18 | 0.22 | 0.31 | 0.24 | 0.28 | 0.18 | -0.04 | 0.03 | 0.14 | 0.15 | 0.17 | |
| G | | 2114 | 2458 | 2724 | 2885 | 2911 | 2961 | 3040 | 2883 | 3040 | 2854 | 2867 | 3043 | 2966 | 2911 | 2877 | 2709 | 2439 | 2095 | |
| G | | 2110 | 2450 | 2721 | 2883 | 2907 | 2958 | 3031 | 2879 | 3029 | 2843 | 2861 | 3036 | 2960 | 2908 | 2876 | 2706 | 2436 | 2092 | |
| G | | 0.19 | 0.32 | 0.11 | 0.08 | 0.12 | 0.12 | 0.28 | 0.15 | 0.35 | 0.40 | 0.21 | 0.24 | 0.21 | 0.10 | 0.04 | 0.11 | 0.12 | 0.15 | |
| H | 1811 | 2214 | 2572 | 2820 | 2997 | 2947 | 2958 | 3011 | 2917 | 2823 | 2993 | 2836 | 3019 | 2965 | 2941 | 2980 | 2790 | 2537 | 2183 | 1786 |
| H | 1808 | 2208 | 2561 | 2810 | 2994 | 2947 | 2953 | 3005 | 2913 | 2812 | 2982 | 2830 | 3018 | 2967 | 2942 | 2975 | 2786 | 2533 | 2181 | 1784 |
| H | 0.19 | 0.28 | 0.43 | 0.35 | 0.11 | -0.00 | 0.16 | 0.19 | 0.13 | 0.38 | 0.36 | 0.20 | 0.03 | -0.07 | -0.02 | 0.16 | 0.13 | 0.18 | 0.08 | 0.09 |
| J | 1867 | 2280 | 2622 | 2841 | 2950 | 2919 | 2907 | 2792 | 2793 | 2950 | 2763 | 2791 | 2967 | 2925 | 2904 | 2903 | 2786 | 2560 | 2233 | 1834 |
| J | 1863 | 2273 | 2612 | 2834 | 2950 | 2920 | 2908 | 2794 | 2790 | 2941 | 2760 | 2788 | 2969 | 2930 | 2908 | 2904 | 2786 | 2556 | 2228 | 1833 |
| J | 0.21 | 0.32 | 0.37 | 0.25 | -0.01 | -0.05 | -0.02 | -0.07 | 0.11 | 0.31 | 0.09 | 0.10 | -0.05 | -0.18 | -0.14 | -0.02 | -0.01 | 0.15 | 0.22 | 0.07 |
| K | 1886 | 2281 | 2617 | 2823 | 2910 | 2872 | 2687 | 2912 | 2932 | 2729 | 2712 | 2909 | 2732 | 2861 | 2844 | 2682 | 2741 | 2392 | 2219 | 1847 |
| K | 1881 | 2276 | 2613 | 2819 | 2913 | 2883 | 2695 | 2918 | 2933 | 2723 | 2710 | 2908 | 2736 | 2880 | 2860 | 2695 | 2739 | 2394 | 2215 | 1843 |
| K | 0.26 | 0.24 | 0.17 | 0.15 | -0.11 | -0.39 | -0.32 | -0.22 | -0.03 | 0.20 | 0.07 | 0.02 | -0.16 | -0.65 | -0.55 | -0.47 | 0.06 | -0.06 | 0.20 | 0.22 |
| L | 1849 | 2072 | 2568 | 2776 | 2856 | 2807 | 2796 | 2708 | 2899 | 2697 | 2694 | 2872 | 2684 | 2786 | 2776 | 2798 | 2713 | 2501 | 2024 | 1814 |
| L | 1848 | 2068 | 2561 | 2778 | 2867 | 2835 | 2824 | 2722 | 2901 | 2698 | 2688 | 2878 | 2703 | 2819 | 2807 | 2811 | 2722 | 2500 | 2024 | 1814 |
| L | 0.06 | 0.21 | 0.27 | -0.08 | -0.37 | -0.99 | -0.98 | -0.53 | -0.05 | -0.03 | 0.23 | -0.19 | -0.69 | -1.19 | -1.12 | -0.45 | -0.32 | 0.03 | -0.00 | 0.02 |
| M | 1819 | 2175 | 2505 | 2709 | 2790 | 2741 | 2752 | 2752 | 2869 | 2680 | 2847 | 2668 | 2730 | 2733 | 2715 | 2752 | 2666 | 2461 | 2138 | 1790 |
| M | 1815 | 2170 | 2502 | 2711 | 2802 | 2777 | 2785 | 2768 | 2871 | 2678 | 2842 | 2675 | 2747 | 2767 | 2749 | 2769 | 2674 | 2461 | 2136 | 1789 |
| M | 0.23 | 0.24 | 0.11 | -0.06 | -0.43 | -1.31 | -1.22 | -0.58 | -0.08 | 0.09 | 0.16 | -0.28 | -0.63 | -1.26 | -1.26 | -0.62 | -0.30 | 0.00 | 0.10 | 0.04 |
| N | | 2109 | 2405 | 2615 | 2708 | 2676 | 2710 | 2814 | 2674 | 2830 | 2661 | 2828 | 2809 | 2698 | 2658 | 2682 | 2585 | 2375 | 2082 | |
| N | | 2106 | 2402 | 2615 | 2720 | 2707 | 2740 | 2826 | 2670 | 2827 | 2654 | 2827 | 2819 | 2727 | 2690 | 2697 | 2588 | 2373 | 2084 | |
| N | | 0.12 | 0.11 | -0.01 | -0.43 | -1.14 | -1.11 | -0.41 | 0.15 | 0.10 | 0.27 | 0.03 | -0.35 | -1.06 | -1.20 | -0.55 | -0.10 | 0.09 | -0.12 | |
| O | | 1943 | 2254 | 2483 | 2598 | 2592 | 2649 | 2776 | 2723 | 2653 | 2647 | 2641 | 2782 | 2645 | 2580 | 2581 | 2463 | 2233 | 1923 | |
| O | | 1941 | 2249 | 2483 | 2603 | 2606 | 2662 | 2777 | 2716 | 2646 | 2643 | 2640 | 2783 | 2659 | 2593 | 2589 | 2464 | 2235 | 1924 | |
| O | | 0.10 | 0.20 | -0.02 | -0.20 | -0.53 | -0.50 | -0.02 | 0.26 | 0.27 | 0.15 | 0.04 | -0.03 | -0.53 | -0.51 | -0.30 | -0.05 | -0.07 | -0.07 | |
| P | | 1755 | 2057 | 2305 | 2447 | 2472 | 2557 | 2712 | 2768 | 2633 | 2789 | 2788 | 2785 | 2567 | 2465 | 2435 | 2290 | 2041 | 1740 | |
| P | | 1753 | 2052 | 2300 | 2444 | 2469 | 2557 | 2706 | 2754 | 2618 | 2770 | 2774 | 2776 | 2569 | 2466 | 2432 | 2287 | 2034 | 1736 | |
| P | | 0.14 | 0.26 | 0.24 | 0.12 | 0.11 | -0.01 | 0.21 | 0.50 | 0.57 | 0.68 | 0.50 | 0.32 | -0.08 | -0.02 | 0.14 | 0.14 | 0.35 | 0.25 | |
| Q | | | 1835 | 2075 | 2244 | 2306 | 2417 | 2598 | 2687 | 2719 | 2729 | 2699 | 2614 | 2418 | 2296 | 2232 | 2062 | 1822 | | |
| Q | | | 1832 | 2067 | 2237 | 2298 | 2407 | 2579 | 2669 | 2698 | 2709 | 2679 | 2597 | 2410 | 2290 | 2225 | 2054 | 1821 | | |
| Q | | | 0.18 | 0.38 | 0.33 | 0.34 | 0.42 | 0.72 | 0.66 | 0.78 | 0.74 | 0.74 | 0.66 | 0.35 | 0.24 | 0.30 | 0.39 | 0.06 | | |
| R | | | 1540 | 1816 | 1987 | 2085 | 2216 | 2412 | 2521 | 2568 | 2568 | 2522 | 2413 | 2208 | 2063 | 1972 | 1805 | 1530 | | |
| R | | | 1536 | 1806 | 1970 | 2068 | 2197 | 2388 | 2495 | 2545 | 2543 | 2499 | 2390 | 2189 | 2049 | 1960 | 1796 | 1528 | | |
| R | | | 0.25 | 0.56 | 0.86 | 0.80 | 0.84 | 1.01 | 1.01 | 0.91 | 0.97 | 0.91 | 0.94 | 0.67 | 0.67 | 0.61 | 0.53 | 0.16 | | |
| S | | | | | 1721 | 1786 | 1938 | 2143 | 2260 | 2309 | 2300 | 2252 | 2137 | 1930 | 1773 | 1711 | | | | |
| S | | | | | 1708 | 1767 | 1916 | 2122 | 2235 | 2287 | 2278 | 2229 | 2113 | 1907 | 1757 | 1697 | | | | |
| S | | | | | 0.76 | 1.07 | 1.14 | 0.99 | 1.11 | 0.97 | 0.97 | 1.01 | 1.11 | 1.21 | 0.91 | 0.80 | | | | |
| T | | | | | | 1492 | 1636 | 1832 | 1947 | 1990 | 1863 | 1931 | 1822 | 1627 | 1484 | | | | | |
| T | | | | | | 1475 | 1615 | 1809 | 1929 | 1971 | 1844 | 1913 | 1803 | 1610 | 1470 | | | | | |
| T | | | | | | 1.14 | 1.30 | 1.23 | 0.93 | 0.98 | 1.03 | 0.92 | 1.05 | 1.04 | 0.93 | | | | | |
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 |

Min dev = 0.00% in Channel no. H6, Max dev = 2.69% in Channel no. B15, RMS dev = 0.62%.

A more detailed set of 121 *input+desired output patterns* (let us call it set SY121) was used in testing of the trained ANNs. The input part of the set SY121 is listed in table 3. The data presented in table 3 represents a situation in which the two rods of the LE-LW pair are moved together by a step size of 10% for each position of UE-UW pair and vice versa. The training set SY25 and the test set SY121 are similar except for their step sizes.

Table 3 : Adjuster Rod Positions in set SY121; Step Size = 10 %

| LE-LW Pair | | UE-UW Pair | | LE-LW Pair | | UE-UW Pair | | LE-LW Pair | | UE-UW Pair | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| LE | LW | UE | UW | LE | LW | UE | UW | LE | LW | UE | UW |
| 0.0 | 0.0 | 0.0 | 0.0 | 0.8 | 0.8 | 0.3 | 0.3 | 0.5 | 0.5 | 0.7 | 0.7 |
| 0.1 | 0.1 | 0.0 | 0.0 | 0.9 | 0.9 | 0.3 | 0.3 | 0.6 | 0.6 | 0.7 | 0.7 |
| 0.2 | 0.2 | 0.0 | 0.0 | 1.0 | 1.0 | 0.3 | 0.3 | 0.7 | 0.7 | 0.7 | 0.7 |
| 0.3 | 0.3 | 0.0 | 0.0 | 0.0 | 0.0 | 0.4 | 0.4 | 0.8 | 0.8 | 0.7 | 0.7 |
| 0.4 | 0.4 | 0.0 | 0.0 | 0.1 | 0.1 | 0.4 | 0.4 | 0.9 | 0.9 | 0.7 | 0.7 |
| 0.5 | 0.5 | 0.0 | 0.0 | 0.2 | 0.2 | 0.4 | 0.4 | 1.0 | 1.0 | 0.7 | 0.7 |
| 0.6 | 0.6 | 0.0 | 0.0 | 0.3 | 0.3 | 0.4 | 0.4 | 0.0 | 0.0 | 0.8 | 0.8 |
| 0.7 | 0.7 | 0.0 | 0.0 | 0.4 | 0.4 | 0.4 | 0.4 | 0.1 | 0.1 | 0.8 | 0.8 |
| 0.8 | 0.8 | 0.0 | 0.0 | 0.5 | 0.5 | 0.4 | 0.4 | 0.2 | 0.2 | 0.8 | 0.8 |
| 0.9 | 0.9 | 0.0 | 0.0 | 0.6 | 0.6 | 0.4 | 0.4 | 0.3 | 0.3 | 0.8 | 0.8 |
| 1.0 | 1.0 | 0.0 | 0.0 | 0.7 | 0.7 | 0.4 | 0.4 | 0.4 | 0.4 | 0.8 | 0.8 |
| 0.0 | 0.0 | 0.1 | 0.1 | 0.8 | 0.8 | 0.4 | 0.4 | 0.5 | 0.5 | 0.8 | 0.8 |
| 0.1 | 0.1 | 0.1 | 0.1 | 0.9 | 0.9 | 0.4 | 0.4 | 0.6 | 0.6 | 0.8 | 0.8 |
| 0.2 | 0.2 | 0.1 | 0.1 | 1.0 | 1.0 | 0.4 | 0.4 | 0.7 | 0.7 | 0.8 | 0.8 |
| 0.3 | 0.3 | 0.1 | 0.1 | 0.0 | 0.0 | 0.5 | 0.5 | 0.8 | 0.8 | 0.8 | 0.8 |
| 0.4 | 0.4 | 0.1 | 0.1 | 0.1 | 0.1 | 0.5 | 0.5 | 0.9 | 0.9 | 0.8 | 0.8 |
| 0.5 | 0.5 | 0.1 | 0.1 | 0.2 | 0.2 | 0.5 | 0.5 | 1.0 | 1.0 | 0.8 | 0.8 |
| 0.6 | 0.6 | 0.1 | 0.1 | 0.3 | 0.3 | 0.5 | 0.5 | 0.0 | 0.0 | 0.9 | 0.9 |
| 0.7 | 0.7 | 0.1 | 0.1 | 0.4 | 0.4 | 0.5 | 0.5 | 0.1 | 0.1 | 0.9 | 0.9 |
| 0.8 | 0.8 | 0.1 | 0.1 | 0.5 | 0.5 | 0.5 | 0.5 | 0.2 | 0.2 | 0.9 | 0.9 |
| 0.9 | 0.9 | 0.1 | 0.1 | 0.6 | 0.6 | 0.5 | 0.5 | 0.3 | 0.3 | 0.9 | 0.9 |
| 1.0 | 1.0 | 0.1 | 0.1 | 0.7 | 0.7 | 0.5 | 0.5 | 0.4 | 0.4 | 0.9 | 0.9 |
| 0.0 | 0.0 | 0.2 | 0.2 | 0.8 | 0.8 | 0.5 | 0.5 | 0.5 | 0.5 | 0.9 | 0.9 |
| 0.1 | 0.1 | 0.2 | 0.2 | 0.9 | 0.9 | 0.5 | 0.5 | 0.6 | 0.6 | 0.9 | 0.9 |
| 0.2 | 0.2 | 0.2 | 0.2 | 1.0 | 1.0 | 0.5 | 0.5 | 0.7 | 0.7 | 0.9 | 0.9 |
| 0.3 | 0.3 | 0.2 | 0.2 | 0.0 | 0.0 | 0.6 | 0.6 | 0.8 | 0.8 | 0.9 | 0.9 |
| 0.4 | 0.4 | 0.2 | 0.2 | 0.1 | 0.1 | 0.6 | 0.6 | 0.9 | 0.9 | 0.9 | 0.9 |
| 0.5 | 0.5 | 0.2 | 0.2 | 0.2 | 0.2 | 0.6 | 0.6 | 1.0 | 1.0 | 0.9 | 0.9 |
| 0.6 | 0.6 | 0.2 | 0.2 | 0.3 | 0.3 | 0.6 | 0.6 | 0.0 | 0.0 | 1.0 | 1.0 |
| 0.7 | 0.7 | 0.2 | 0.2 | 0.4 | 0.4 | 0.6 | 0.6 | 0.1 | 0.1 | 1.0 | 1.0 |
| 0.8 | 0.8 | 0.2 | 0.2 | 0.5 | 0.5 | 0.6 | 0.6 | 0.2 | 0.2 | 1.0 | 1.0 |
| 0.9 | 0.9 | 0.2 | 0.2 | 0.6 | 0.6 | 0.6 | 0.6 | 0.3 | 0.3 | 1.0 | 1.0 |
| 1.0 | 1.0 | 0.2 | 0.2 | 0.7 | 0.7 | 0.6 | 0.6 | 0.4 | 0.4 | 1.0 | 1.0 |
| 0.0 | 0.0 | 0.3 | 0.3 | 0.8 | 0.8 | 0.6 | 0.6 | 0.5 | 0.5 | 1.0 | 1.0 |
| 0.1 | 0.1 | 0.3 | 0.3 | 0.9 | 0.9 | 0.6 | 0.6 | 0.6 | 0.6 | 1.0 | 1.0 |
| 0.2 | 0.2 | 0.3 | 0.3 | 1.0 | 1.0 | 0.6 | 0.6 | 0.7 | 0.7 | 1.0 | 1.0 |
| 0.3 | 0.3 | 0.3 | 0.3 | 0.0 | 0.0 | 0.7 | 0.7 | 0.8 | 0.8 | 1.0 | 1.0 |
| 0.4 | 0.4 | 0.3 | 0.3 | 0.1 | 0.1 | 0.7 | 0.7 | 0.9 | 0.9 | 1.0 | 1.0 |
| 0.5 | 0.5 | 0.3 | 0.3 | 0.2 | 0.2 | 0.7 | 0.7 | 1.0 | 1.0 | 1.0 | 1.0 |
| 0.6 | 0.6 | 0.3 | 0.3 | 0.3 | 0.3 | 0.7 | 0.7 | | | | |
| 0.7 | 0.7 | 0.3 | 0.3 | 0.4 | 0.4 | 0.7 | 0.7 | | | | |

From mechanical constraints and also due to flux tilt control considerations, the positions of the 4 regulating rods can be quite different from each other during actual operation of the reactor. For this purpose, another set of 99 ***input+desired output patterns*** (let us call it set AS99) was also used in testing of the trained ANNs.

The input part of AS99 contains non-repeating random patterns listed in table 4. Each input pattern listed in

Table 4 : Adjuster Rod Positions in set AS99; Step Size = RANDOM

| LE-LW Pair | | UE-UW Pair | | LE-LW Pair | | UE-UW Pair | | LE-LW Pair | | UE-UW Pair | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| LE | LW | UE | UW | LE | LW | UE | UW | LE | LW | UE | UW |
| 0.2 | 0.3 | 0.3 | 0.6 | 0.9 | 0.6 | 0.3 | 0.2 | 0.8 | 0.8 | 0.1 | 0.3 |
| 0.0 | 0.1 | 0.4 | 0.5 | 0.1 | 0.5 | 0.4 | 0.4 | 0.7 | 0.5 | 0.8 | 0.0 |
| 0.0 | 0.6 | 0.2 | 0.8 | 0.0 | 0.1 | 0.6 | 0.0 | 0.6 | 0.9 | 0.0 | 0.4 |
| 0.4 | 0.8 | 0.1 | 0.1 | 0.6 | 0.2 | 0.8 | 0.4 | 0.1 | 0.1 | 0.7 | 0.4 |
| 0.7 | 0.0 | 0.0 | 0.6 | 0.3 | 0.0 | 0.9 | 0.1 | 0.1 | 0.5 | 0.6 | 0.1 |
| 0.2 | 0.8 | 0.9 | 0.4 | 0.9 | 0.2 | 0.6 | 0.0 | 0.8 | 0.4 | 0.2 | 0.3 |
| 0.8 | 0.0 | 0.5 | 0.4 | 0.6 | 0.4 | 0.6 | 0.4 | 0.0 | 0.0 | 0.5 | 0.4 |
| 0.9 | 0.2 | 0.0 | 0.8 | 0.7 | 0.6 | 0.3 | 0.2 | 0.9 | 0.9 | 0.8 | 0.9 |
| 0.2 | 0.9 | 0.5 | 0.1 | 0.9 | 0.4 | 0.1 | 0.2 | 0.1 | 0.9 | 0.3 | 0.8 |
| 0.2 | 0.5 | 0.7 | 0.8 | 0.8 | 0.9 | 0.5 | 0.3 | 0.5 | 0.5 | 0.5 | 0.8 |
| 0.0 | 0.5 | 0.4 | 0.2 | 0.1 | 0.9 | 0.0 | 0.0 | 0.9 | 0.8 | 0.7 | 0.0 |
| 0.5 | 0.3 | 0.9 | 0.3 | 0.5 | 0.2 | 0.3 | 0.7 | 0.9 | 0.8 | 0.2 | 0.4 |
| 0.1 | 0.1 | 0.1 | 0.9 | 0.4 | 0.8 | 0.3 | 0.9 | 0.3 | 0.6 | 0.9 | 0.5 |
| 0.3 | 0.2 | 0.5 | 0.7 | 0.3 | 0.4 | 0.7 | 0.6 | 0.1 | 0.8 | 0.5 | 0.8 |
| 0.8 | 0.8 | 0.3 | 0.2 | 0.7 | 0.5 | 0.8 | 0.1 | 0.1 | 0.5 | 0.6 | 0.3 |
| 0.9 | 0.2 | 0.4 | 0.8 | 0.9 | 0.5 | 0.5 | 0.1 | 0.7 | 0.5 | 0.1 | 0.6 |
| 0.8 | 0.5 | 0.1 | 0.0 | 0.6 | 0.2 | 0.4 | 0.1 | 0.1 | 0.2 | 0.9 | 0.2 |
| 0.2 | 0.7 | 0.6 | 0.8 | 0.6 | 0.7 | 0.2 | 0.8 | 0.1 | 0.5 | 0.4 | 0.5 |
| 0.0 | 0.9 | 0.6 | 0.6 | 0.3 | 0.8 | 0.9 | 0.5 | 0.0 | 0.8 | 0.9 | 0.1 |
| 0.1 | 0.9 | 0.1 | 0.8 | 0.2 | 0.7 | 0.4 | 0.7 | 0.2 | 0.7 | 0.5 | 0.1 |
| 0.7 | 0.6 | 0.2 | 0.3 | 0.9 | 0.3 | 0.5 | 0.0 | 0.0 | 0.8 | 0.1 | 0.1 |
| 0.7 | 0.6 | 0.7 | 0.7 | 0.3 | 0.4 | 0.3 | 0.2 | 0.1 | 0.0 | 0.9 | 0.8 |
| 0.8 | 0.2 | 0.2 | 0.4 | 0.3 | 0.0 | 0.8 | 0.9 | 0.6 | 0.7 | 0.1 | 0.2 |
| 0.8 | 0.1 | 0.0 | 0.1 | 0.3 | 0.5 | 0.9 | 0.3 | 0.3 | 0.7 | 0.8 | 0.2 |
| 0.2 | 0.9 | 0.6 | 0.6 | 0.5 | 0.9 | 0.5 | 0.6 | 0.2 | 0.6 | 0.5 | 0.3 |
| 0.4 | 0.4 | 0.6 | 0.9 | 0.1 | 0.9 | 0.6 | 0.9 | 0.1 | 0.1 | 0.8 | 0.1 |
| 0.6 | 0.3 | 0.8 | 0.1 | 0.4 | 0.5 | 0.2 | 0.4 | 0.4 | 0.2 | 0.9 | 0.0 |
| 0.7 | 0.8 | 0.4 | 0.5 | 0.1 | 0.9 | 0.0 | 0.5 | 0.8 | 0.2 | 0.8 | 0.8 |
| 0.4 | 0.6 | 0.0 | 0.9 | 0.9 | 0.2 | 0.4 | 0.5 | 0.6 | 0.6 | 0.0 | 0.2 |
| 0.1 | 0.9 | 0.2 | 0.1 | 0.5 | 0.5 | 0.3 | 0.9 | 0.6 | 0.1 | 0.6 | 0.0 |
| 0.3 | 0.7 | 0.6 | 0.7 | 0.5 | 0.3 | 0.0 | 0.4 | 0.6 | 0.3 | 0.0 | 0.9 |
| 0.1 | 0.2 | 0.9 | 0.6 | 0.2 | 0.2 | 0.0 | 0.2 | 0.0 | 0.6 | 0.8 | 0.9 |
| 0.1 | 0.0 | 0.4 | 0.4 | 0.1 | 0.6 | 0.9 | 0.9 | 0.1 | 0.8 | 0.0 | 0.6 |

table 4, i.e. each row in table 4, contains 4 numbers representing the position of the 4 regulating rods. Each one of the 4 numbers of a row is completely independent of the other 3 numbers. Using the set SY25 for training and SY121 for testing an ANN means that the ANN is trained and tested for pair-wise equally distributed rod patterns. That is, the situation for testing is similar to the situation for which it is trained except that the test data is more exhaustive than the training data. Using the set SY25 for training and the set AS99 for testing the ANN means that the ANN is trained using pair-wise equally distributed rod patterns but it is tested for unequally (randomly) distributed rod patterns. Obviously, the *input+desired output patterns* in the test set AS99 represent more severe test cases than that in the test set SY121 for an ANN trained with pair-wise equally distributed rod patterns.

## V. Selection of the ANN Architecture

Since there are 4 inputs and 306 outputs, the number of neurons in the input and the output layer is fixed to be 4 and 306 respectively. The number of the hidden layers and the number of neurons in each hidden layer can be chosen at will. To decide the number of

hidden layers and the number of neurons in each hidden layer, first an ANN with two hidden layers was set-up. To decide the number of neurons in the first and the second hidden layers, first the number of neurons in the first hidden layer was fixed to be 2 and the number of neurons in the second hidden layer was varied from 2 to 50. For each change in the number of neurons in the second hidden layer, the resulting ANN was trained using the training set SY25 and was tested using the test sets SY121 and AS99. The results of this study is presented in fig. 3.

Corresponding to each desired output (power) of an *input+desired output pattern* of the set SY121, the ANN calculates power in the corresponding channel. The percentage difference between the desired and the ANN generated output power is found for each of the 306 channels. The RMS value of the 306 error values and the maximum of the 306 error values is then calculated. This is done for each of the 121 *input+desired output pattern* of the test set SY121. Table 2 displays the regulating rod positions and the corresponding desired (CEMESH generated) and the ANN calculated powers in kW in all the 306 channels of the reactor for one *input+desired output pattern.* The percentage difference (error) between the CEMESH and the ANN calculated powers in each of the 306 channels and the maximum and the RMS values of these errors are also listed in

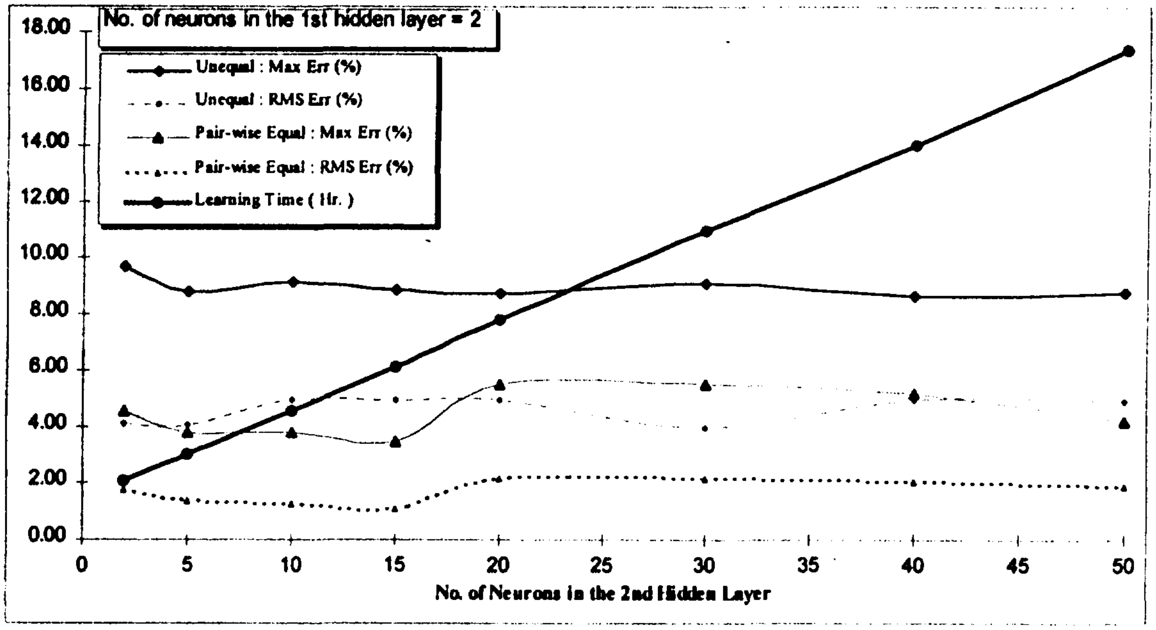


Fig. 3 : Number of Neurons in the 2nd Hidden Layer vs. Learning Time and Prediction Errors of a 4 Layered ANN. Number of Neurons in the 1st Hidden Layer = 2

table 2. For each change in the ANN architecture, there are 121 tables similar to the one shown in table 2 for the test set SY121. Thus there are 121 maximum and 121 RMS error values for the test set SY121 for each change in the ANN architecture. The largest amongst the 121 maximum error values, the corresponding RMS error values of the test set SY121 and the learning time was plotted against the changes in the ANN architecture (fig. 3). The plot of the largest amongst the 121 maximum error values and the corresponding RMS error values for the test set SY121 is referred to as *Pair-wise Equal : Max Err* and *Pair-wise Equal : RMS Err* respectively in fig. 3. Similar plots for the test set AS99 are referred to as *Unequal : Max Err* and *Unequal : RMS Err* respectively in fig. 3. It was found that as the number of neurons in the second hidden layer are increased from 2 to 50, the time of learning increases linearly but the 121 maximum error values and the corresponding RMS error values of the test set SY121 and the 99 maximum error values and the corresponding RMS error values of the test set AS99 remain more or less constant. Though the curves *Pair-wise Equal : Max Err* and *Pair-wise Equal : RMS Err* remain more or less flat, they show a broad shallow minimum in fig. 3 when the number of neurons in the second hidden layer are between 5 and 15. In other words, the performance of the ANN is slightly better when

the number of neurons in the second hidden layer are between 5 and 15 though it doesn't depend much upon the number of neurons in the second hidden layer.

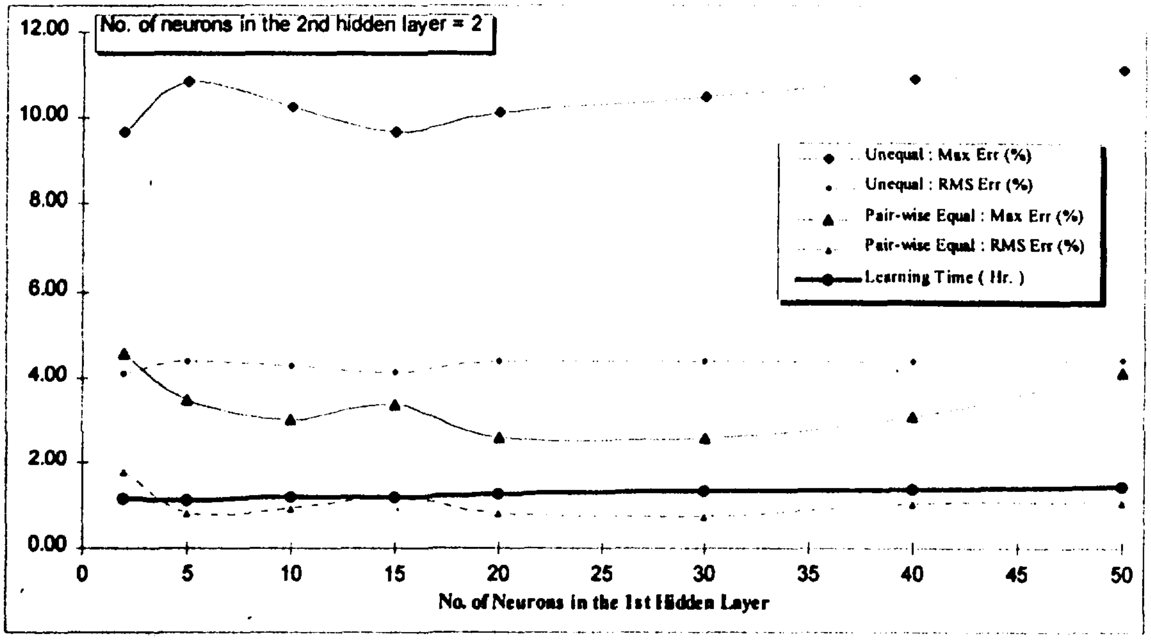


Fig. 4 : Number of Neurons in the 1st Hidden Layer vs. Learning Time and Prediction Errors of a 4 Layered ANN. Number of Neurons in the 2nd Hidden Layer = 2

Next, the number of neurons in the second hidden layer was fixed to be 2 and the number of neurons in the first hidden layer was varied from 2 to 50. Again for each change in the number of neurons in the first hidden layer, the resulting ANN was trained using the training set SY25 and tested using the test sets SY121 and AS99. Curves for this study were drawn and are presented in fig. 4. As the number of neurons in the first hidden layer are increased from 2 to 50, the time of learning increases linearly but far less rapidly than that when the number of neurons were increased from 2 to 50 in the second hidden layer (the reason is given in the last paragraph of this section). In this case the performance of the ANN is slightly better when the number of neurons in the first hidden layer are between 15 and 40 though it doesn't depend much upon the number of neurons in the first hidden layer.

After studying the performance of the ANN with two hidden layers, an ANN with one hidden layer was set-up. To decide the number of neurons in the hidden layer, the number of neurons in the hidden layer was varied from 1 to 50. For each change in the number of neurons in the hidden layer, the resulting ANN was trained using the training set SY25 and was tested using the test sets SY121 and AS99 as in the case of the 4 layered ANN. The plots of largest amongst the 121 maximum error values and the RMS error values for the test set SY121, the largest amongst the 99 maximum error values and the RMS error values for the test set AS99 and the time of learning were prepared for this study also and are presented in fig. 5. The time of learning increased linearly and rapidly like that in fig. 3 as the number of neurons are increased in the hidden layer. In this case the performance of the ANN is slightly better when the number of neurons in the first hidden layer are between 5 and 20 though it doesn't depend much upon the number of neurons in the hidden layer.

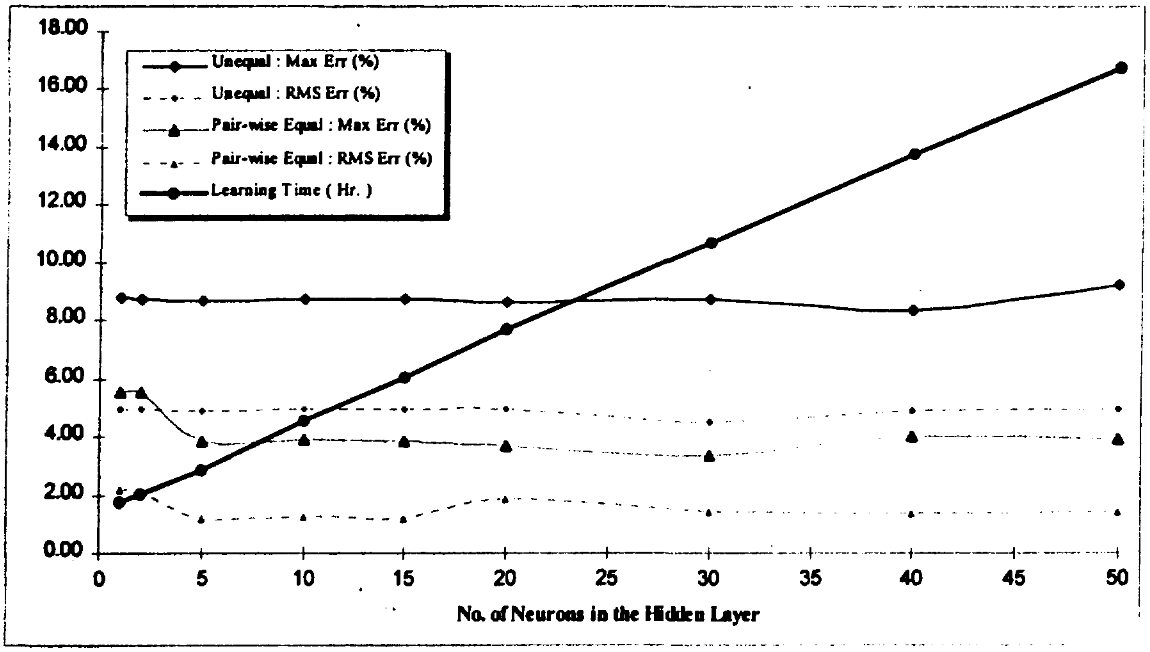


Fig. 5 : Number of Neurons in the Hidden Layer vs. Learning Time and Prediction Errors of a 3 Layered ANN.

From the above study it was concluded that the performance of a 3 and a 4 layered ANN is more or less the same. A 4 layered ANN performs slightly better when the number of neurons in its first layer is between 15 and 40 and that in the second layer is between 5 and 15. Since the output layer contains 306 neurons, addition of each neuron in the last hidden layer, increases the number of connection weights and update values each by 306, which in turn increases learning time drastically. Similarly an increase in the number of neurons in the first hidden layer also increases the learning time but relatively far less rapidly compared to that in the second hidden layer because the input layer contains only 4 neurons which increases the number of connection weights and update values each only by 4 for addition of each neuron in the first hidden layer. That is, in this study the learning time depends more on the number of neurons in that hidden layer which is closest to the output layer. This was observed clearly while studying the effect of addition of neurons in hidden layers on the maximum and RMS prediction errors. As a rule of thumb in ANN paradigm, large number of neurons in the hidden layers tend to memorise rather than generalise. It is therefore preferred to keep as small number of neurons as possible in the hidden layers. The primary aim of the study mentioned above is to tentatively select an ANN architecture which gives a reasonable performance (not necessarily the best one). The ANN architecture so selected is to be used for training with different training sets and determine the minimum number of training patterns required for training the selected ANN to give a reasonable performance. Therefore a 4 layered ANN with 4, 20, 5 and 306 neurons in the input, first hidden layer, second hidden layer and the output layers respectively was selected for studying the channel power distribution of a 220 MWe Indian PHWR as a result of the movement of the 4 regulating rods. This architecture is referred to as 4-20-5-306 architecture / configuration. Since the prediction errors are relatively insensitive to addition or deletion of a few neurons in the hidden layers, the selection of some other architecture, with a few more or less number of neurons in their hidden layers is also expected to give almost equally good result except for the time required for training.

## VI. Evaluating the Performance of the Selected ANNs

Tables 5, 6, 7, 1 and 3 show the input parts of the 5 sets of *input+desired output patterns* used in the training of the selected ANN viz. 4-20-5-306. Table 5 represents a bare minimum data that can be used for training the ANN - all the rods are either fully inserted or fully withdrawn. Table 6 shows fully inserted and fully withdrawn LE-LW pair positions for each fully inserted and fully withdrawn UE-UW pair position. Table 7 shows 50% step size for LE-LW pair positions for each 50%

step size of the UE-UW pair position. Tables 1 and 3 represent 25% and 10% step sizes respectively as explained earlier. Sets SY121 and AS99 were used for testing the performance of the ANNs as earlier. Using the 5 sets of *input+desired output patterns* whose inputs are listed in tables 5, 6, 7, 1 and 3 for training and the sets SY121 and AS99 for testing the ANNs amounts to studying the error produced by the ANNs as the step size in rod pair movement is reduced from 100% to 10% in its training.

The maximum and the RMS prediction errors for the test sets SY121 and AS99 as a function of the five training sets are plotted in fig. 6. The legend followed in fig. 6 is similar to that of fig. 3. The learning time increases linearly as the numbers of patterns increase in training sets. Fig. 6 shows that as the step size of the rod pair movement decreases in training, the prediction error decreases rapidly from the case of 100% step size with bare minimum training patterns to 25% step size of table 1. Further reduction of the step size doesn't decrease the prediction error by the ANNs. That is, if a selected ANN is trained using the training set SY25, the trained ANN is expected to give minimum prediction error. The prediction error of the ANN is not expected to reduce further even if it is trained using bigger training sets such as SY121. Similar studies were performed with ANN architectures having a few more and less neurons in their hidden layers. The performances of these ANNs were more or less the same as that of the ANN 4-20-5-306, as expected.

The maximum and the RMS prediction errors for the test sets SY121 and AS99 as a function of the five training sets are plotted in fig. 6. The legend followed in fig. 6 is similar to that of fig. 3. The learning time increases linearly as the numbers of patterns increase in training sets. Fig. 6 shows that as the step size of the rod pair movement decreases in training, the prediction error decreases rapidly from the case of 100% step size with bare minimum training patterns to 25% step size of table 1. Further reduction of the step size doesn't decrease the prediction error by the ANNs. That is, if a selected ANN is trained using the training set SY25, the trained ANN is expected to give minimum prediction error. The prediction error of the ANN is not expected to reduce further even if it is trained using bigger training sets such as SY121. Similar studies were performed with ANNs having slightly different number of neurons in their hidden layers. These ANNs also exhibited similar behaviour.

Table 5 : Adjuster Rod Positions; Step Size = 100 %

| LE-LW Pair | | UE-UW Pair | |
|---|---|---|---|
| LE | LW | UE | UW |
| 0.00 | 0.00 | 0.00 | 0.00 |
| 1.00 | 1.00 | 1.00 | 1.00 |

Table 6 : Adjuster Rod Positions; Step Size = 100 %

| LE-LW Pair | | UE-UW Pair | |
|---|---|---|---|
| LE | LW | UE | UW |
| 0.00 | 0.00 | 0.00 | 0.00 |
| 1.00 | 1.00 | 0.00 | 0.00 |
| 0.00 | 0.00 | 1.00 | 1.00 |
| 1.00 | 1.00 | 1.00 | 1.00 |

Table 7 : Adjuster Rod Positions; Step Size = 50 %

| LE-LW Pair | | UE-UW Pair | |
|---|---|---|---|
| LE | LW | UE | UW |
| 0.00 | 0.00 | 0.00 | 0.00 |
| 0.50 | 0.50 | 0.00 | 0.00 |
| 1.00 | 1.00 | 0.00 | 0.00 |
| 0.00 | 0.00 | 0.50 | 0.50 |
| 0.50 | 0.50 | 0.50 | 0.50 |
| 1.00 | 1.00 | 0.50 | 0.50 |
| 0.00 | 0.00 | 1.00 | 1.00 |
| 0.50 | 0.50 | 1.00 | 1.00 |
| 1.00 | 1.00 | 1.00 | 1.00 |

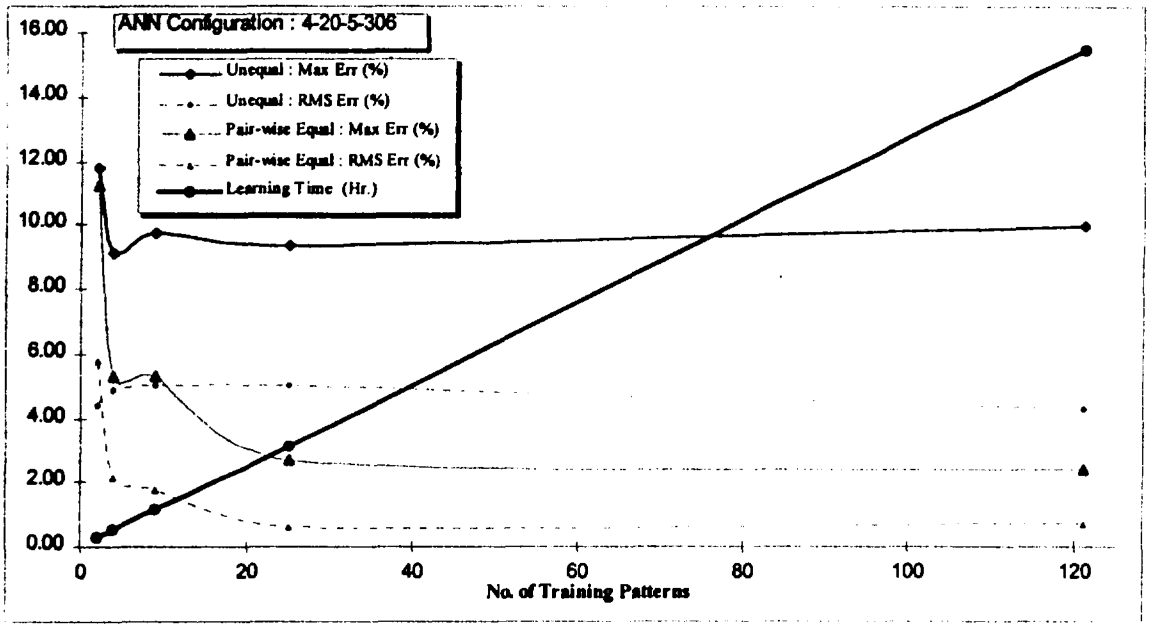


Fig. 6 : Number of Training Patterns vs. Learning Time and Prediction Errors. ANN Architecture : 4-20-5-306

From the above discussion, it is clear that the ANN architecture 4-20-5-306 is a reasonably good architecture for the channel power distribution studies and the training set SY25 is the optimum training set for training the selected ANN architecture. When this ANN is trained using the training set SY25 and is tested with the test set SY121, 121 channel power distributions are obtained - one corresponding to each of the *input+desired output pattern*. The channel power distribution for the test set number 55 is shown in table 2 as mentioned earlier. The presentation in table 2 is organised to look like one of the 2 faces of the reactor. Table 2 also shows the percentage error in ANN prediction of the channel power for each channel. The maximum and the RMS values of the errors for the test set number 55 is also displayed in table 2. There are 121 tables similar to table 2 - one corresponding to each one of the 121 test cases of the test set SY121. Each of the 121 tables has a maximum and an RMS error value. The largest amongst the 121 maximum errors appear in the test set number 55. For this reason, the set number 55 was selected to be displayed in table 2. The prediction errors shown in table 2 are graphically presented in fig. 7. It shows that the magnitude of the error is below 1.5% in most of the channels. The magnitude of the maximum prediction error is 2.69% in one of the channels (channel number B15). Only in a few channels the magnitude of the ANN prediction error is between 2% and 2.69%.

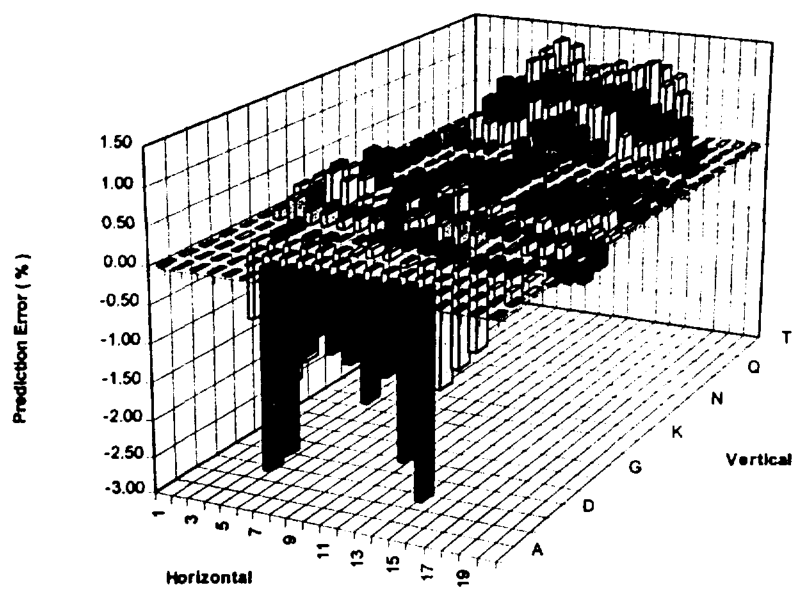


Fig. 7 : Distribution of Errors in Channel Power Calculation in all the 306 Channels of the Reactor for Pair-wise Equally Distributed Test Patterns (Set Number 55).

Though the maximum error for the test set SY121 is 2.69% in fig. 7, the corresponding RMS errors is only 0.62%. Fig. 7 shows the distribution of errors in all the 306 channels for a single *input+desired output pattern* - the one which is having the largest of the 121 maximum error values. Other test cases of the test sets SY121 produce lesser errors compared to that shown in fig. 7. To get an overall view of the ANN prediction errors, the magnitude of the 121 maximum error values for the test set SY121 are classified into several groups with a group interval of 0.5% and presented in the form of a histogram in fig. 8. Similar histogram is prepared for the test set AS99 and is presented in fig. 8 for comparison. The histograms for test sets SY121 and AS99 are marked as *Pair-wise Equal* and *Unequal* respectively. Fig. 8 shows that the maximum ANN prediction error is around 1.25% and 6.75% in most of the cases for the test sets SY121 and AS99 respectively. The mean, the variance and the maxima of the frequency distribution for the test set SY121 are 1.56%, 0.19% and 2.69% respectively. The mean, the variance and the maxima of the frequency distribution for the test set AS99 are 6.00%, 3.85% and 9.37% respectively. From fig. 8 it is clear that the ANN prediction is extremely good for the test set SY121 but relatively poorer for the test set AS99. Both the training set SY25 and the test set SY121 are similar except for the step size. It is therefore concluded that if the ANN is tested for those situations for which it was trained, its prediction is extremely good. If the ANN is tested for those situations for which it was never trained, its predictions are relatively poorer. The magnitude of the maximum errors are around 6% in majority of the cases. In a few cases, the error are in the range of 9.4%.

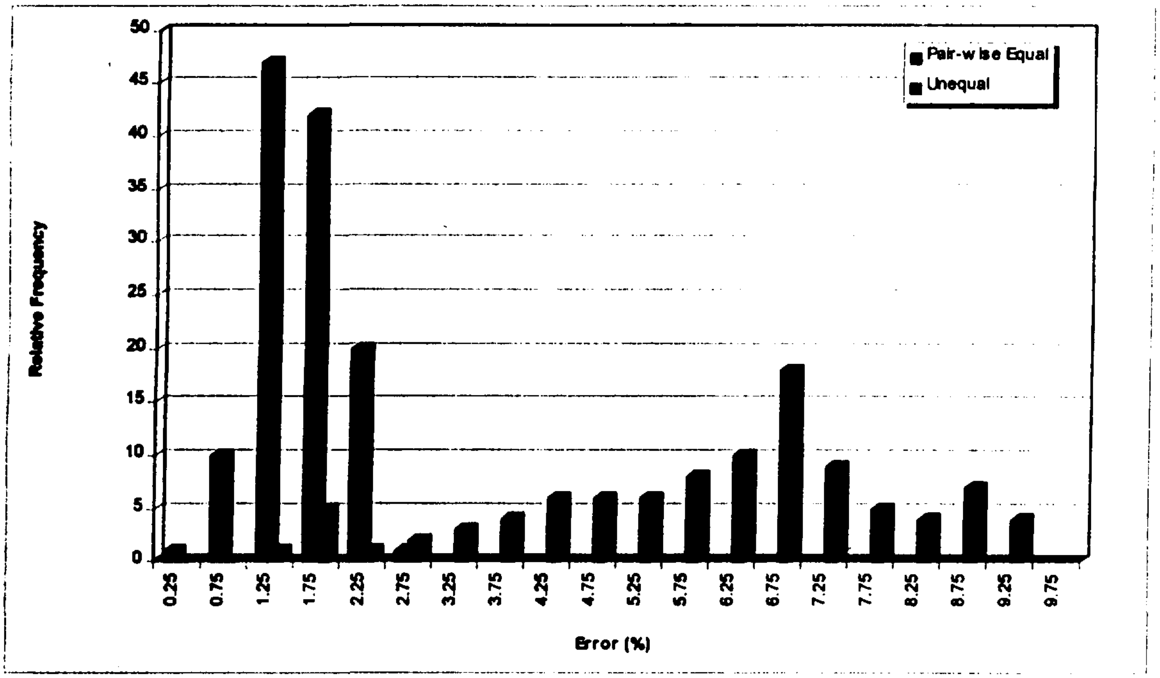


Fig. 8 : Frequency Distribution of Maximum Errors for the Test Sets SY121 and AS99. The ANN was Trained Using the Training Set SY25.

It is expected that if the ANN is trained using a good mixture of sufficiently large unequally (i.e. randomly) distributed and equally distributed training patterns, it will predict channel power distribution with smaller maximum and RMS errors in all test conditions. The sets AS99 and SY25 were, therefore, merged to form a new training set named AS124. The ANN was then trained using the training set AS124. Another test set named AS150 consisting of 150 random test patterns similar to that of AS99 was generated for testing the performance of the ANN. None of the test patterns of the set AS150 were there in the set AS99. After training the ANN with the training set AS124, it was tested using the test sets SY121 and AS150. A frequency distribution histogram similar to that of fig. 8 for this test was prepared and is presented in fig. 9. It is interesting to see that the histograms for *Pair-wise Equal* and *Unequal* test sets which are visible separately in fig. 8 have almost merged in fig. 9. In this later case, the mean, the variance

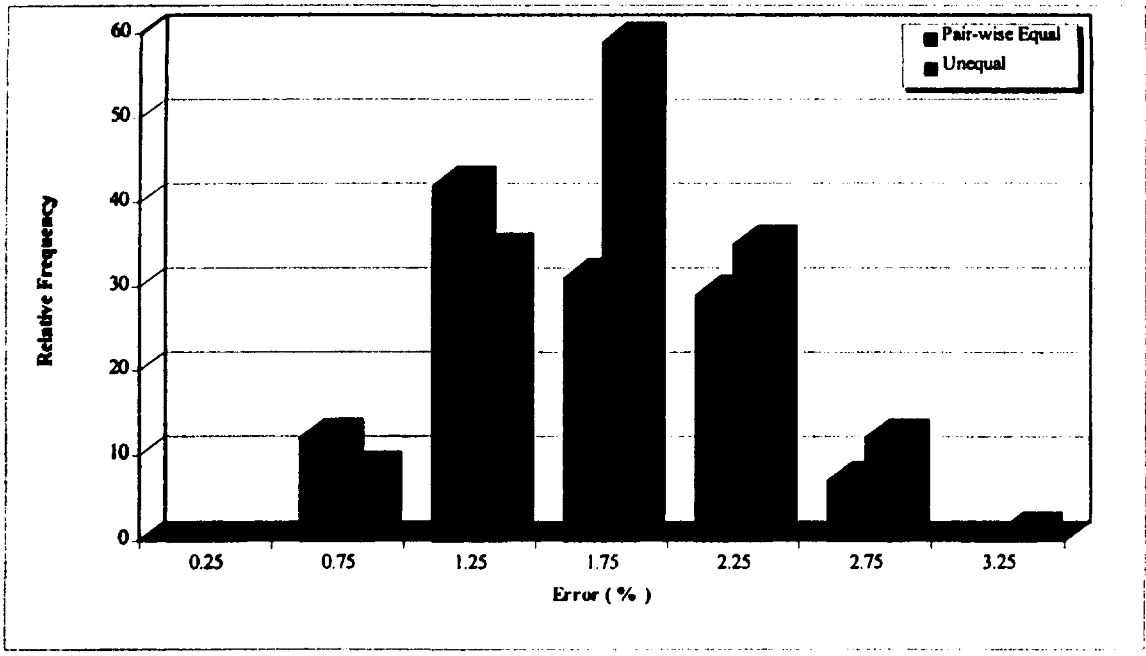


Fig. 9 : Frequency Distribution of Maximum Errors for the Test Sets SY121 and AS150. The ANN was Trained Using the Training Set AS124.

and the maxima of the frequency distribution for the test set SY121 are 1.67%, 0.26% and 2.90% respectively. The mean, the variance and the maxima of the frequency distribution for the test set AS150 are 1.80%, 0.26% and 3.46% respectively. Figs. 8 and 9 show the histograms for the maximum prediction errors. Similar histograms were prepared for the RMS errors also. The histograms for the RMS errors are not being presented here because they look similar to those of fig. 8 and 9 respectively. Table 8 summarises the mean, the variance and the maxima for the two training and the four test cases discussed above. It also shows the mean, the variance and the maxima for the RMS error distribution for comparison.

Table 8 : Comparison of the ANN performance When Trained with Pair-wise Equally Distributed and Unequally Distributed Training Patterns.

| ANN trained with | ANN Tested With | Maximum Error (% ) Distribution Parameters | | | RMS Error (% ) Distribution Parameters | | |
|---|---|---|---|---|---|---|---|
| | | Mean | Variance | Maximum | Mean | Variance | Maximum |
| SY25 | SY121 | 1.557 | 0.190 | 2.691 | 0.544 | 0.024 | 1.016 |
| | AS99 | 6.004 | 3.853 | 9.369 | 2.297 | 1.192 | 5.047 |
| AS124 | SY121 | 1.670 | 0.261 | 2.903 | 0.495 | 0.032 | 1.098 |
| | AS150 | 1.797 | 0.255 | 3.459 | 0.475 | 0.013 | 0.747 |

The conclusion of the study presented in this section is that if an ANN is trained for pair-wise equally distributed training patterns, its prediction of channel power distribution is excellent for pair-wise equally distributed test cases. If the ANN is trained for pair-wise equally distributed training patterns and is tested for unequally distributed test cases, its prediction of channel power distribution is relatively poorer but is still quite good. If the ANN is trained using a mixture of unequally (i.e. randomly) distributed and pair-wise equally distributed training patterns, its prediction of channel power distribution is very good in all test cases. The sets SY25 and AS124 are the optimum training sets for training an ANN for pair-wise equally distributed and unequally (i.e. randomly) distributed training patterns respectively.

## VII. Conclusion

The above study shows that an ANN can predict the channel power distribution of a 220 MWe PHWR accurately as a result of the movement of one or more of the 4 regulating rods of the reactor. It is also observed that the prediction of the channel power distribution by an ANN is relatively insensitive to the ANN architecture and the number of neurons in the hidden layers, which shows the ruggedness of the ANN methodology. The ANN takes about 650 milliseconds to generate the distribution of power in all the 306 channels whereas the CEMESH takes about 4 minutes for the same calculation, on the same computer. That is, the ANN prediction is about 350 times faster than the CEMESH prediction. This shows that the ANNs can be used reliably for channel power distribution analyses in real-time applications.

The scope of the present work can be further extended to the changes in channel power distribution due to core burn-up, refuelling, moderator level etc. In large PHWRs, the xenon induced transients also need quick and accurate estimate of regional average powers. The employment of ANN for such applications is expected to yield accurate results of an analysis very fast and hence is expected to be useful in the control of xenon oscillation, if any. Such studies are underway.

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