CTH-RF-117 August 1996

The feasibility of using neural networks for determination of control rod elevation in a PWR

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ISSN 0281-9775

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ABSTRACT

This paper presents the results of a preliminary study on using neural networks for determination of the axial position of control rods in PWRs. The method is based on the dependence of the axial flux profile on control rod elevation in a reactor. This flux profile can be measured by e.g. a movable detector in an operating plant. However, in this preliminary study the flux profile is only calculated using an advanced core code for several axial positions of a partially inserted control rod. The calculated fluxes with corresponding positions of the control rod are used for training a neural network. Using the trained network it is then possible to determine the unknown axial position of a control rod elevation from the corresponding axial flux profile.

1. INTRODUCTION

In PWRs of a 3-loop Westinghouse type, the control rods are divided into six groups where each group consists of 8 control rods. For a 17x17 lattice type, each control rod in turn consists of 24 pins as shown in Fig. 1. During operation of such a reactor at full power,

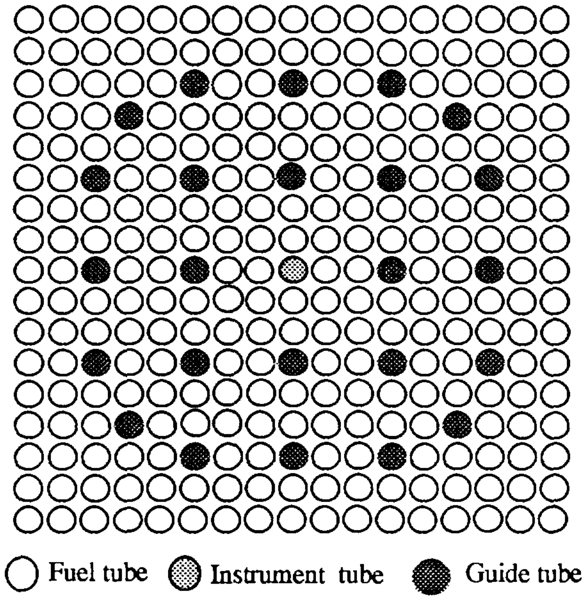

Fig. 1. 17x17 lattice assembly in a PWR of Westinghouse type.

usually only one control rod group is used for control. The control rod group is moved in an interval of 35 steps where one step is around 2.5 cm. Because of mechanical problems, the moving of control rods up and down may cause an uncertainty of the position of its edge in the reactor. The uncertainty may in a worst case be as much as 20 cm.

It is obvious that a control rod which is partially inserted will strongly affect the axial neutron flux in the vicinity of the control element. In Fig. 2, the axial neutron flux profile is calculated for a partially inserted control rod both within the assembly (point-dashed line) and from a neighbouring (solid line) one. The latter flux might be of interest in the case when it is possible to do a measurement only in a neighbouring assembly. The flux profile (solid line) for a withdrawn control rod is also included. From the figure it is clearly seen that the elevation of the control rod is highly connected to the point where the gradient of flux has a significant change. Therefore, by studying the flux profile it is possible to determine the elevation of the control using methods based on the gradient.

However, for a control rod which is inserted only in the upper quarter part of the core, the change of the gradient around the elevation of the control rod is not as clear as for other cases, see Fig. 2. From the figure it is seen that it may still be possible to obtain a rough estimate of the position for at least the control assembly. In the case of using the flux profile from a neighbouring assembly on the other hand, it is not possible to get a sufficiently accurate estimate.

A solution to the problem can be obtained by using artificial neural networks. This is possible since insertion of control rods at different axial positions results in different axial

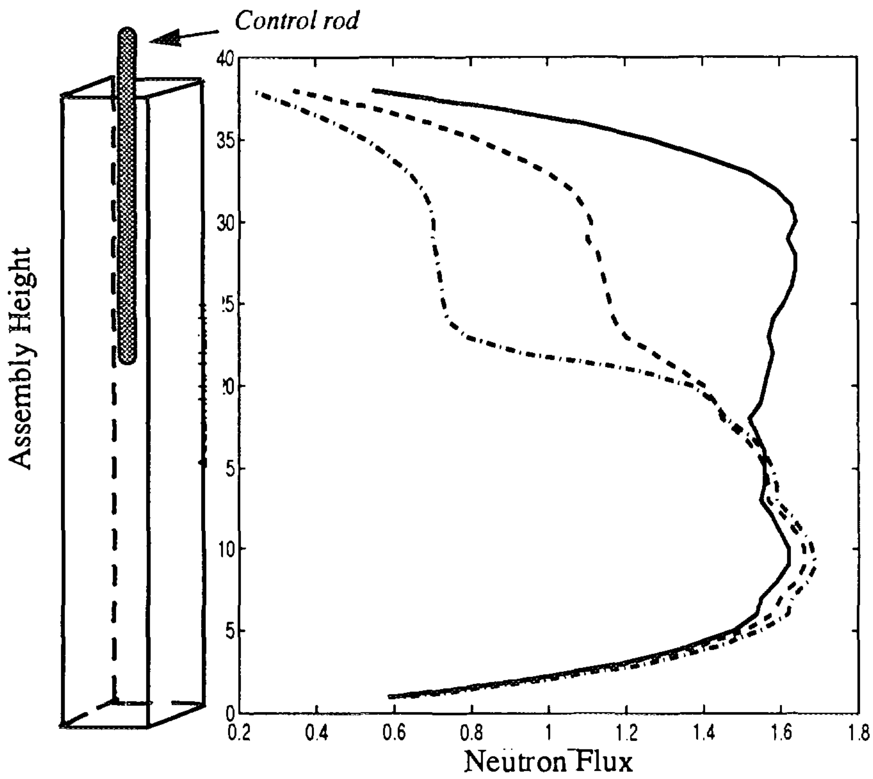

Fig. 2. The neutron flux profile for a partially inserted control rod both within the assembly (point-dashed line) and from a neighbouring assembly (dashed line). The flux profile for the fully withdrawn control rod is also included (solid line).

neutron flux profiles which generate a pattern appropriate for training neural networks. The calculated profile together with the corresponding control rod position, which is known, can be used to train a neural network. After successful training of the neural network, it is then straightforward to determine the unknown position of a control rod from a calculated or measured axial flux profile.

In Section II the principles of neural networks are described while in Section III the neural network is applied and some results are presented.

2. PRINCIPLES OF NEURAL NETWORKS

The use of neural network (NN) techniques represents a very powerful method for complex problems. Neural networks have been used extensively in the nuclear engineering field for both parameter estimation and diagnostics. Successful applications or pilot studies include diagnostics of steam generators, vibration properties, sensor validation, valves, feedwater flow [1], estimation of moderator temperature coefficients [2], BWR stability margins [3], detection of anomalies [4], localisation of vibrating control rods [5] and noise spectra analysis [6]. A review of principles and nuclear applications is found in Ref. [7].

One type of neural networks which has become popular is the so called standard three-layered feed-forward network with backward error propagation. The advantages of this type are that it is relatively simple to realize and any continuous function can be modelled if

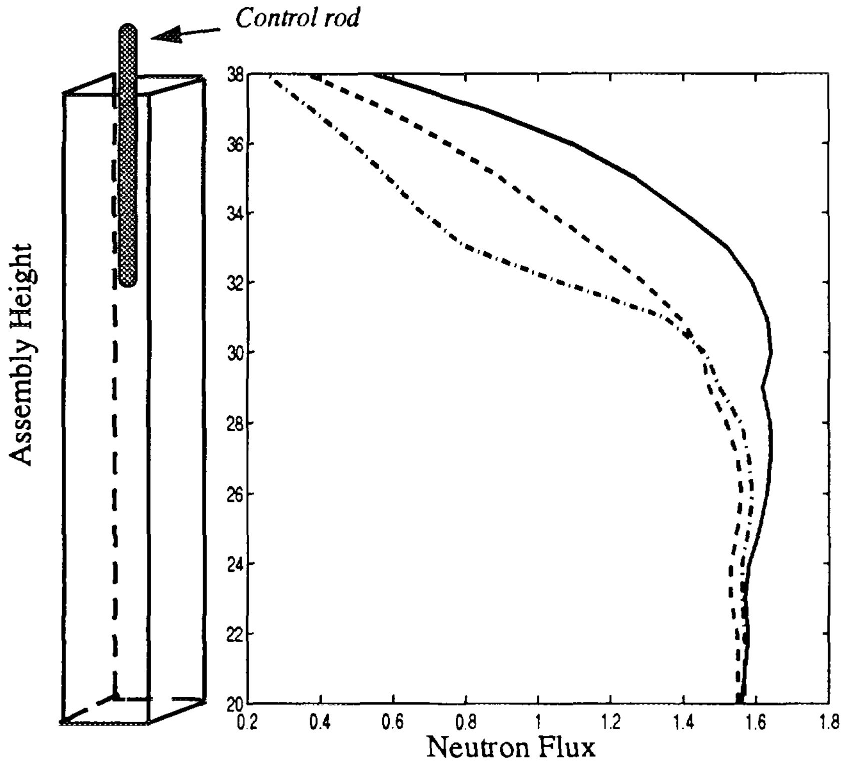

Fig. 3. .The neutron flux profile for a partially inserted control rod in the upper quarter part of the core both within the assembly (point-dashed line) and from a neighbouring one (dashed line). The flux profile for a withdrawn control rod is also included (solid line).

certain conditions are fulfilled. The structure of the neural network used in the present paper is shown in Fig. 4.

The network consists of an input layer, a hidden layer, and an output layer. Each layer is fully connected with the next layer except the output layer. The connection between two nodes is described by a connection weight which determines the amount of effect that one node can have on the other. Each node except those in the input layer is provided with a threshold (or bias) which acts like an offset. The weights and thresholds are usually initialized to small random values.

The input data, which in this case consist of axial neutron flux values, are first normalized such that they all lie between 0.1 and 0.9. They are then propagated in one direction (feed-forward) from input nodes via the hidden nodes to the output. The output layer is supposed to give the position of the control rod edge.

Before using the network, it has to be trained using input data with known output. During the training, the weights and thresholds are adjusted using the backpropagation algorithm. The network is fed with each input data while its output values are compared with desired output values, see also Fig. 5. This procedure is repeated for all input data used for training, whereafter one training iteration (cycle) is completed. After each iteration, the total root mean square (rms) output error is computed by

$$\text{total rms output error} = \left[\frac{1}{N}\sum_{k=1}^{N}(T_k - Y_k)^2\right]^{1/2} \tag{1}$$

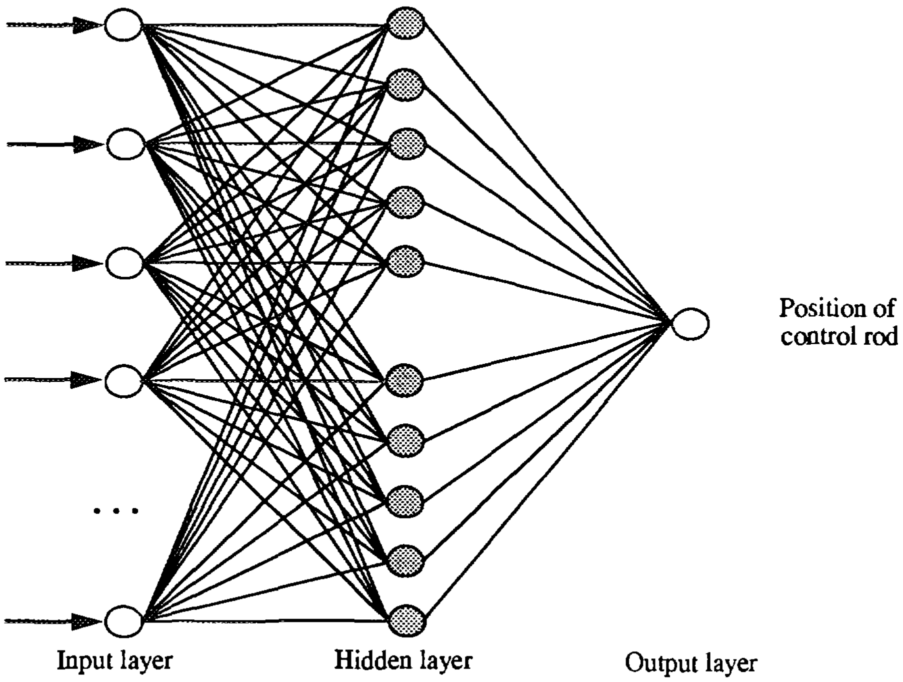

Fig. 4. The structure of a standard three-layered feed-forward neural network.

where N is the number of input data used for training, and T_k and Y_k are desired (target) and actual outputs, respectively. Using the backpropagation algorithm it is then possible to update the weights and thresholds. The idea of the backpropagation algorithm is to minimize the error function between the desired and actual output values using a variant of the gradient descent technique. Iterations are repeated until the total root mean square (rms) output error is less than a specified tolerance. After successful training of the network, the weights and thresholds are fixed, and the network is ready for recalling, i.e. producing output data when fed with input data.

There are however some parameters which have to be optimized. Two parameters, the learning rate η and the momentum rate α, are used in connection with update of weights and thresholds. Other parameters are e.g. the number of input-output pairs used for the training, the number of nodes in the hidden layer.

The learning parameter is used to increase the speed of convergence and determines the length of the step size along the gradient. A small value means that the network will have to make a large number of iterations. The momentum rate is used to avoid stagnancy at local minima. The number of input-output pairs has to be chosen so that all possible cases are covered. The reason is that networks are extremely poor in extrapolating. It is also important that during the training, input-output pairs are randomly selected. Another parameter is the number of nodes in the hidden layer where there is no general rule for how many nodes are necessary. However, if one studies how the weight values to each node in the hidden layer are changed during the training, then it is possible to eliminate nodes whose values change slightly.

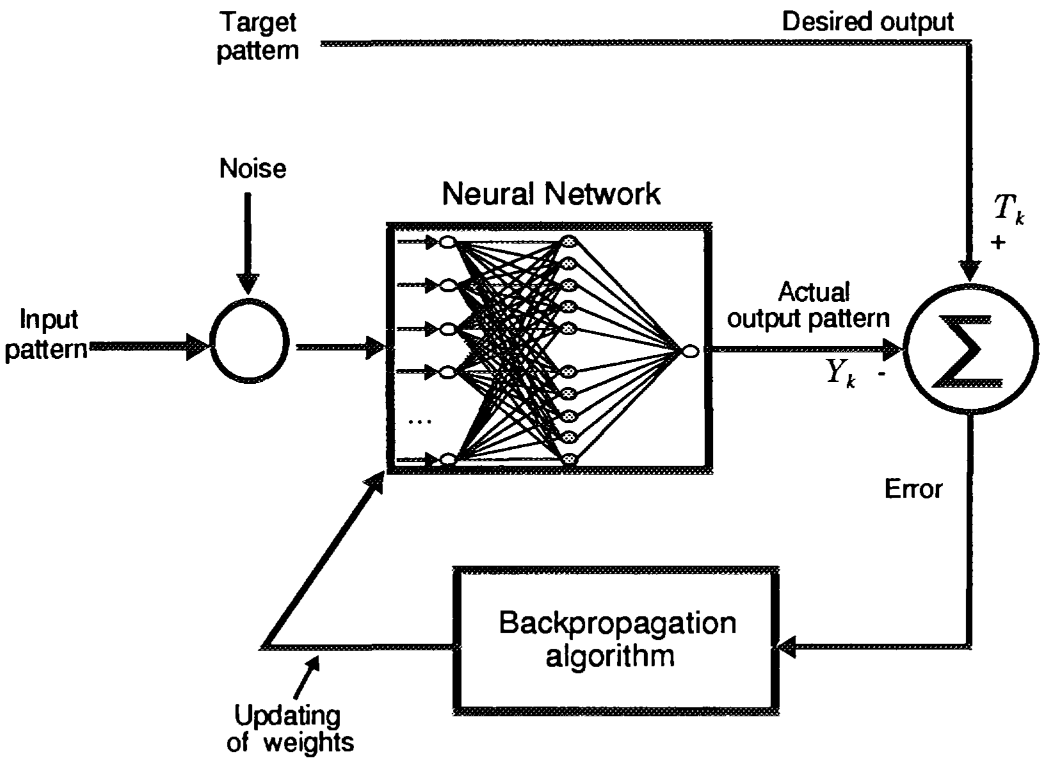

Fig. 5. The training phase of the neural network.

3. RESULTS

The generation of input data is done by calculating the axial neutron flux for different positions of the control rod considered. The simulation of background and measurement noise is possible by adding a Gaussian random number to each input data.

The flux profiles have been obtained from the generic model described in Ref. [8] where a 3-loop Westinghouse PWR reactor is considered. The reactor consists of 157 assemblies with 17x17 array of fuel pins per assembly. For modelling of the reactor, the Studsvik Core Management System (CMS) has been used. The system consists in principle of two codes: CASMO and SIMULATE. CASMO is an assembly spectrum/depletion transport code which is used to generate few-group data for most nodal diffusion codes, see Ref.[9]. Such a diffusion code is SIMULATE which is a three-dimensional (steady-state) two-group advanced nodal code, see Ref.[10]. SIMULATE can be used to perform fuel management, core design calculations, and safety analysis. Using the CMS system, three subsequent cycles were designed. For the present study, the middle of cycle 2 was found to be an appropriate candidate for calculations.

In Fig. 6, the location of control rod group which is used for control is shown. Of 8 positions, the assembly denoted F-10 was selected for simulation of control rod insertion and withdrawal.

In the present paper, mainly five simulation tests have been investigated. In the first test, the control rod is moved in the whole core and corresponding flux profile is calculated. The second test deals with a control rod which is moved only in the upper half of the core.

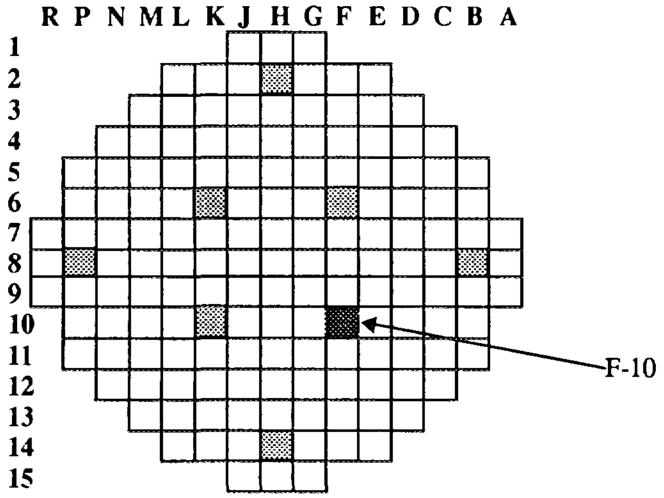

Fig. 6. Location of control rod group used for control. For simulation, the assembly denoted F-10 was selected.

In the third test, the control rod is again moved in the upper part but this time only in the upper quarter region of the core. This is also the region where the control rod group used for control is moved. In the last two tests, the control rod is moved in the same region as for the second and third test but here the control rod elevation is determined using the flux profile from a neighbouring assembly. This might be of interest because in some cases it is not possible to do a measurement in the control assembly, only in a neighbouring one.

In order to investigate the effect of the background noise, for each test three cases of different background noise have been considered. In the first case, no background noise was added while in the other two cases Gaussian noise of ±3 % and ±5 % were added to all calculated input data.

In Table I, the tests are compared quantitatively with respect to training cycles (iterations), CPU time and standard deviation for different values of added Gaussian noise. All numerical work was done on a SUN-20 Sparc Server and the times shown in the table include only the time for training of the neural network.

Test 1: Control rod moving in the whole core

In this test, the flux profile was calculated at 87 different axial positions of a partially inserted control rod into the assembly denoted F-10. Of these, 60 cases were used for training the neural network while the rest were used for testing. The number of nodes in the input layer has been set equal to 38 since this was the limited number of axial levels at which the neutron flux for each assembly was calculated. This number is also equal to the number of axial node cells used in the nodal solution. For an assembly with an active fuel height of 365.76 cm, this means that the distance between two axial flux points is ~ 9.5 cm. Comparing this distance with ~ 6 cm which is usually used during a measurement with movable detectors, the number of flux points calculated in this investigation was less than the number obtained from a measurement due to the limited number of axial levels. Of course this will affect both the training and performance of the neural network.

For the present test, the following choice of the adjustable parameters has been found as optimal. The number of nodes in the hidden layer has been set equal to 10, the learning rate to 0.9 and the momentum rate to 0.6. The training was stopped when the total root mean square (rms) output error of the algorithm reached a pre-defined value of $1 \cdot 10^{-3}$. The necessary number of iterations, CPU time and standard deviation for different values of Gaussian noise are shown in Table I.

Table I. Results of the efficiency of the trained network for various tests with different Gaussian noise.

Test	User-defined value of the rms error	Gaussian noise [%]	Training cycles	CPU [s]	Standard deviation [cm]
1	$1 \cdot 10^{-3}$	0	22779	384	0.66
		3	38794	659	1.80
		5	39156	661	2.75
2	$1 \cdot 10^{-3}$	0	127299	458	0.47
		3	186353	680	1.05
		5	114361	412	1.31
3	$3 \cdot 10^{-3}$	0	252787	135	0.20
		3	125373	67	0.90
		5	93507	50	1.73
4	$3 \cdot 10^{-3}$	0	56285	202	0.72
		3	64527	231	2.16
		5	68334	245	3.52
5	$5 \cdot 10^{-3}$	0	238809	127	0.66
		3	212731	113	2.75
		5	118992	64	3.78

After the training, the rest of input data were given to the network in order to investigate the success rate, that is the performance, of the trained network. The results of the test are shown in Fig. 7 for all three cases. In the figure, the positions for both training data and testing are shown. It can be seen that the deviation (error) of network output and correct values for the case with no background noise is around ± 1 cm, see Fig. 7a. The results for cases with background noise on the other hand show that the deviation (error) increases when more noise is added.

Test 2: Control rod moving only in the upper half of the core

In this test, only input data corresponding to control rod positions above the upper part of the core were used, i.e. the core part above the axial height of 200 cm. 30 input-output pairs were used for the training of the network and 10 for testing. The number of nodes in the input layer was reduced to 18 instead of 38 while the adjustable parameters used were same as before. The necessary number of iterations for reaching an rms output error less than $1 \cdot 10^{-3}$, CPU time and standard deviation for different values of Gaussian noise are shown in Table I. It should be mentioned that the CPU time for an iteration here is shorter despite the much larger number of iterations. The reason is that the number of input nodes is less, resulting in a fewer number of weights to update after each iteration.

The results of the success rate of the network are shown in Fig. 8. In comparison with the case of moving the control rod in the whole core, it can be seen that the performance of the neural network is better. This is due to the fact that as long as only slightly inserted rods are to be identified, the input nodes that were omitted contain less useful information on the searched rod position than those that were kept. Moreover, each weight updating related to deeply inserted rods leads to a certain "forgetting" of how to identify slightly inserted rods. Thus omitting training patterns belonging to low rod elevations enhances the ability to identify high rod elevations.

For the case of no background noise, the deviation is at most ±0.8 while for other cases the deviation is around ±2 cm. The advantage here is that the neural network does not require the flux in the whole core.

Test 3: Control rod moving only in the upper quarter of the core

In this test, only input data corresponding to control rod positions above the upper part of the core were used, i.e. the core part above the axial height of 300 cm. 12 input-output pairs were used for the training of the network and 4 for testing. The number of nodes in the input layer has been set equal to 8 and the number of nodes in the hidden layer to 6. The other adjustable parameters used were same as before. The number of iterations necessary for reaching an rms output error less than $3 \cdot 10^{-3}$ are shown in Table I.

The results of the success rate of the network are shown in Fig. 9. In comparison with the results obtained for the second test, it can be seen that the performance of the neural network is somewhat better for almost all cases. Despite the large number of iterations, the CPU time for training of the neural network is superior compared with previous tests.

Test 4: Determination of the elevation from a neighbouring assembly for a control rod moving in the upper half of the core

As in the second test, the neutron flux was calculated at 40 axial positions of partially inserted control rod but this time the axial flux profile of a neighbouring assembly was selected. 30 input-output pairs were used for the training of the network and 10 for testing. Same number of input nodes as well as adjustable parameters were used as in the second test. The number of iterations necessary for reaching an rms output error less than $3 \cdot 10^{-3}$ are shown in Table I.

The results of the performance of the network are shown in Fig. 10. Comparing to the results for the second test, it can be seen that the performance of the neural network for the case with no background noise is almost the same. For the cases with background noise on the other hand the performance is somewhat deteriorated.

Test 5: Determination of the elevation from a neighbouring assembly for a control rod moving in the upper quarter of the core

This test is similar to the fourth one only with the difference that the control rod is moving in the upper quarter of the core. 12 input-output pairs were used for the training of the network and 4 for testing. The number of nodes in the input layer has been set equal to 8 and the number of nodes in the hidden layer to 6. The number of iterations necessary for reaching an rms output error less than $5 \cdot 10^{-3}$ are shown in Table I.

The results of the success rate of the network are shown in Fig. 11. In comparison with the previous test, it can be seen that the performance of the neural network is better.

4. CONCLUSIONS AND FUTURE WORK

The above results show that use of a neural network for determination of position of control rod can be an effective method to reduce the uncertainty which may occasionally arise during the control of a PWR reactor at full power. The best result was obtained when only the upper quarter region of the core was considered. It has been shown that the deviation between network output and original values are around ± 1 cm. In the case of using the flux profile from a neighbouring assembly, the performance of the neural network is somewhat deteriorated.

However, since the objective of the present study is to use measured signals for determination of the control rod elevation, it is more appropriate to calculate the reaction rates obtained by a neutron detector. This will be investigated in a future work.

ACKNOWLEDGEMENTS

This work was supported by a research grant from Ringhals Vattenfall AB, Grant No. R53060-YVDI. ET wishes to thank Chalmers University for kind hospitality and the Swedish Institute for financial support.

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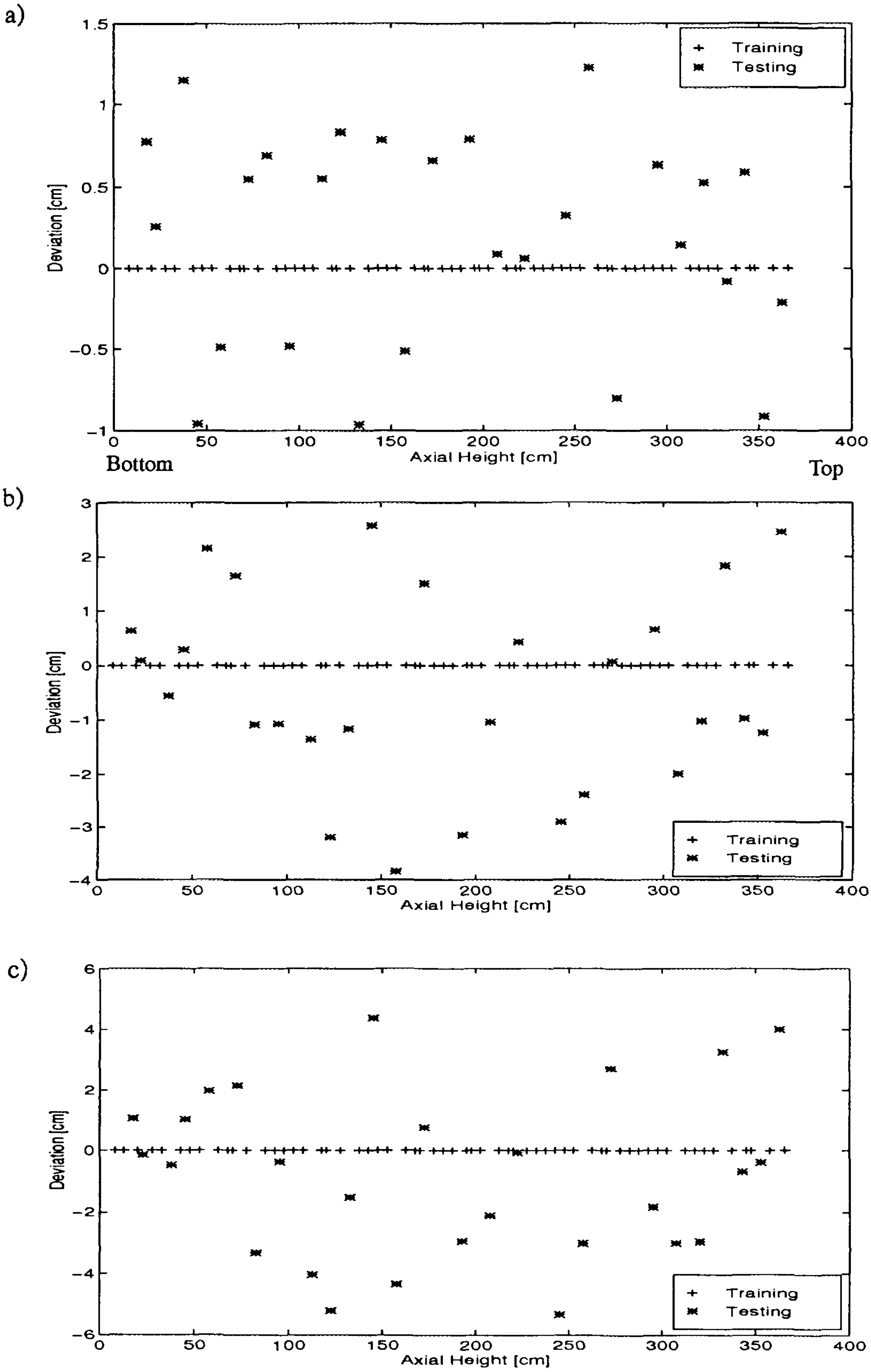
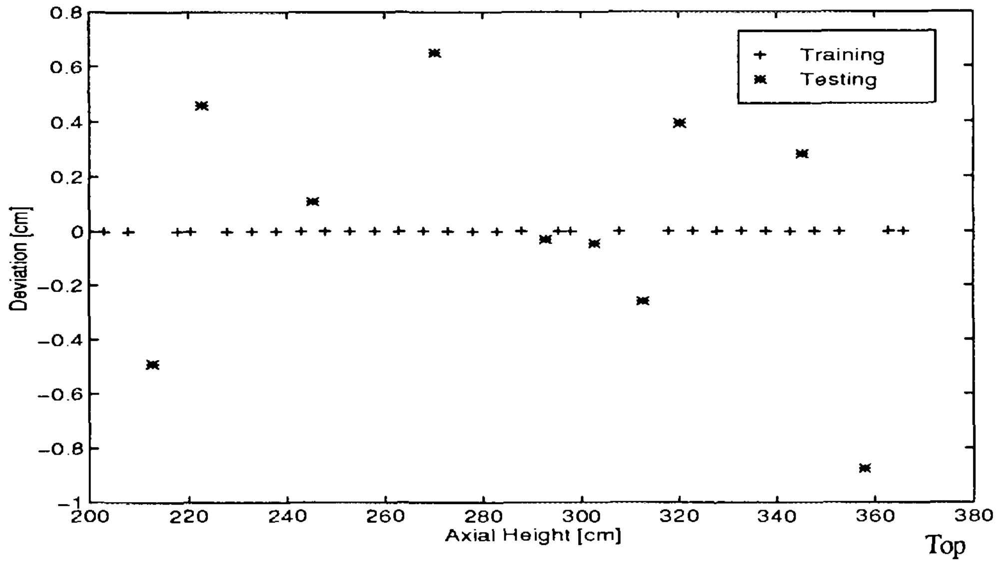
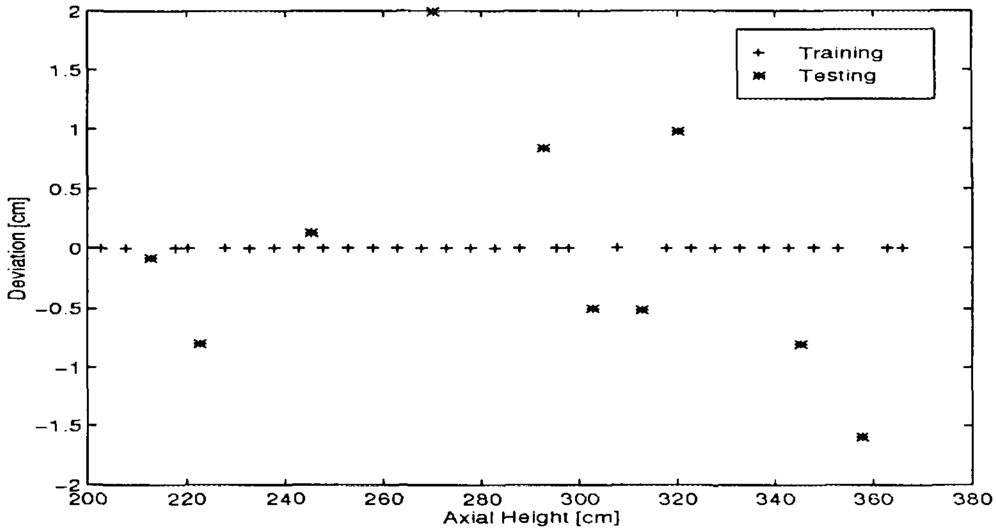


Fig. 7. Deviation (error) of network output and original values for a control rod moving in the whole core with a) 0 %, b) ±3 % and c) ±5 % Gaussian noise.

a)



b)



c)

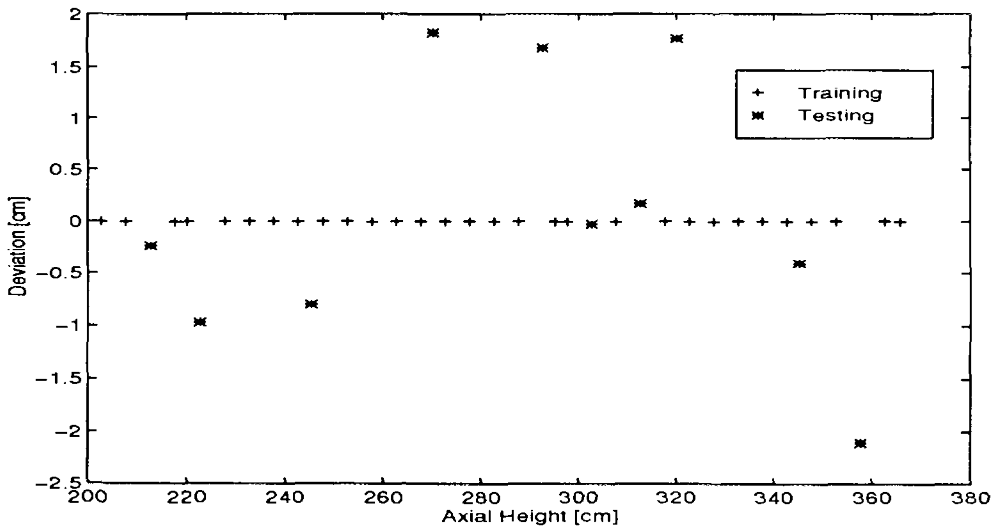


Fig. 8. Deviation (error) of network output and original values for a control rod moving in the upper half of the core with a) 0 %, b) ±3 % and c)±5 % added Gaussian noise.

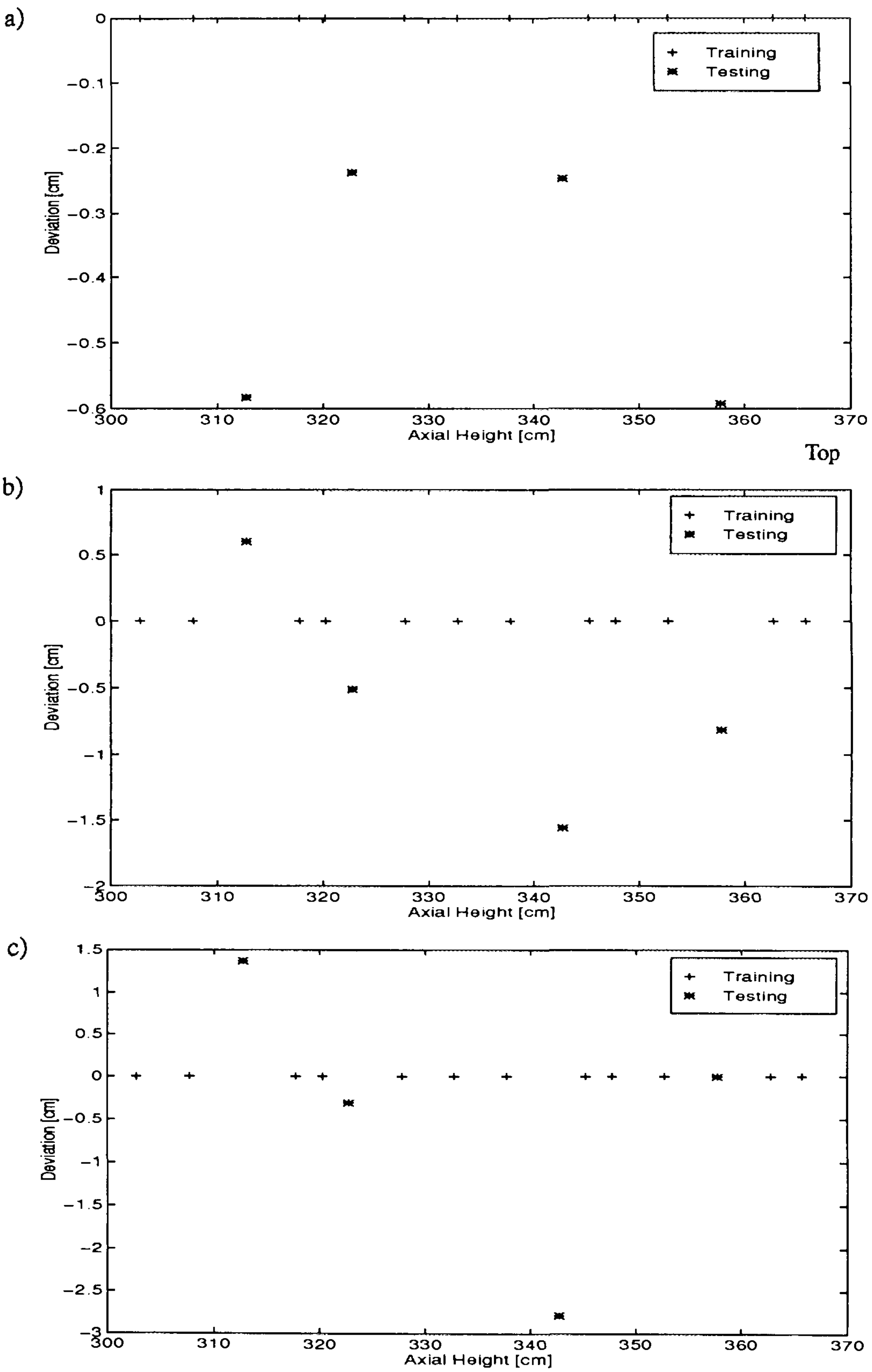


Fig. 9. Deviation (error) of network output and original values for a control rod moving in the upper quarter of the core with a) 0 %, *b)* ±3 % *and c)* ±5 % *added Gaussian noise.*

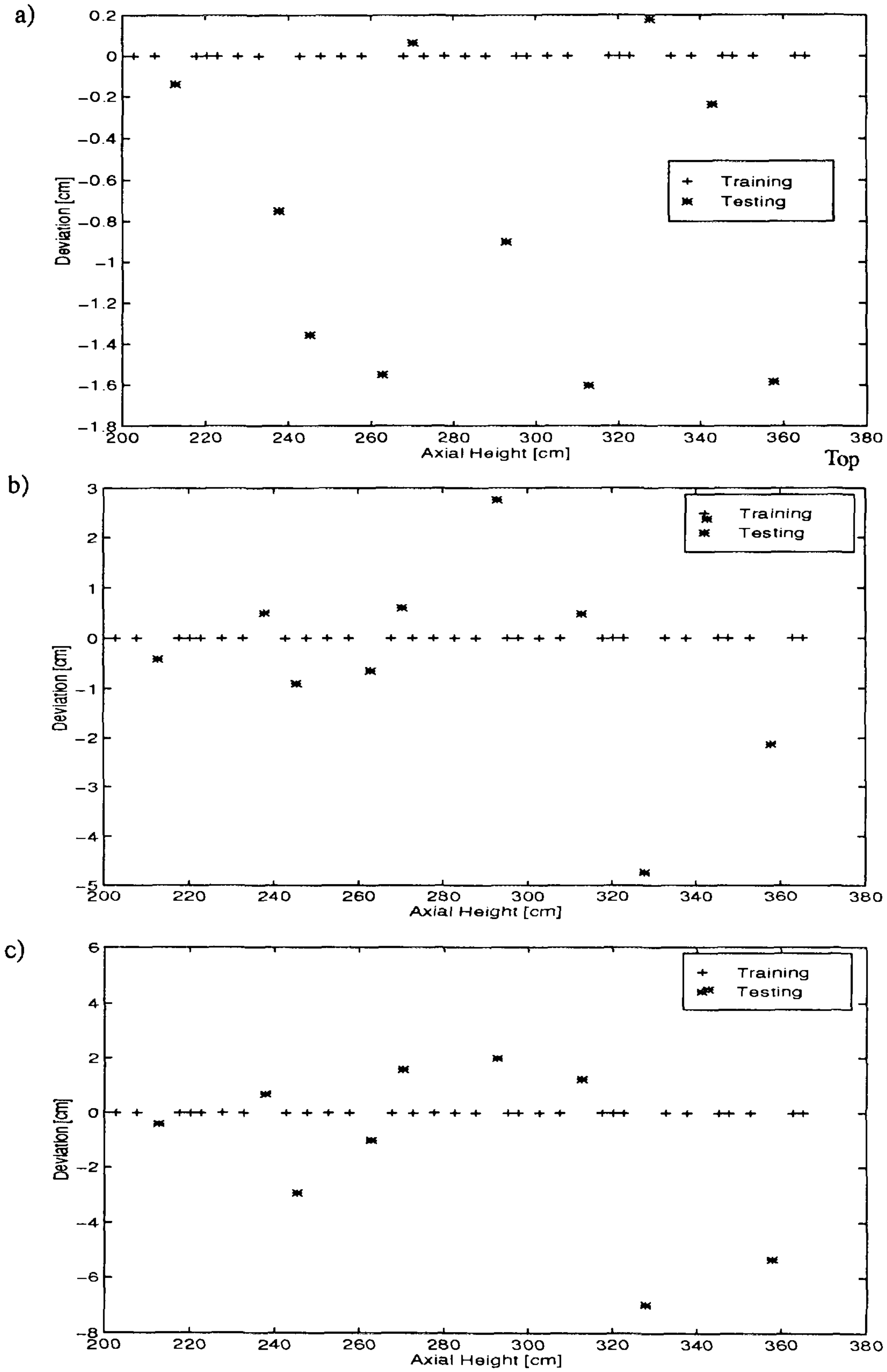


Fig. 10. Deviation (error) of network output and original values for a control rod moving in the upper half of the core and neighbouring assembly with a) 0 %, b) ±3 % and c) ±5 % added Gaussian noise.

a)

b)

c)

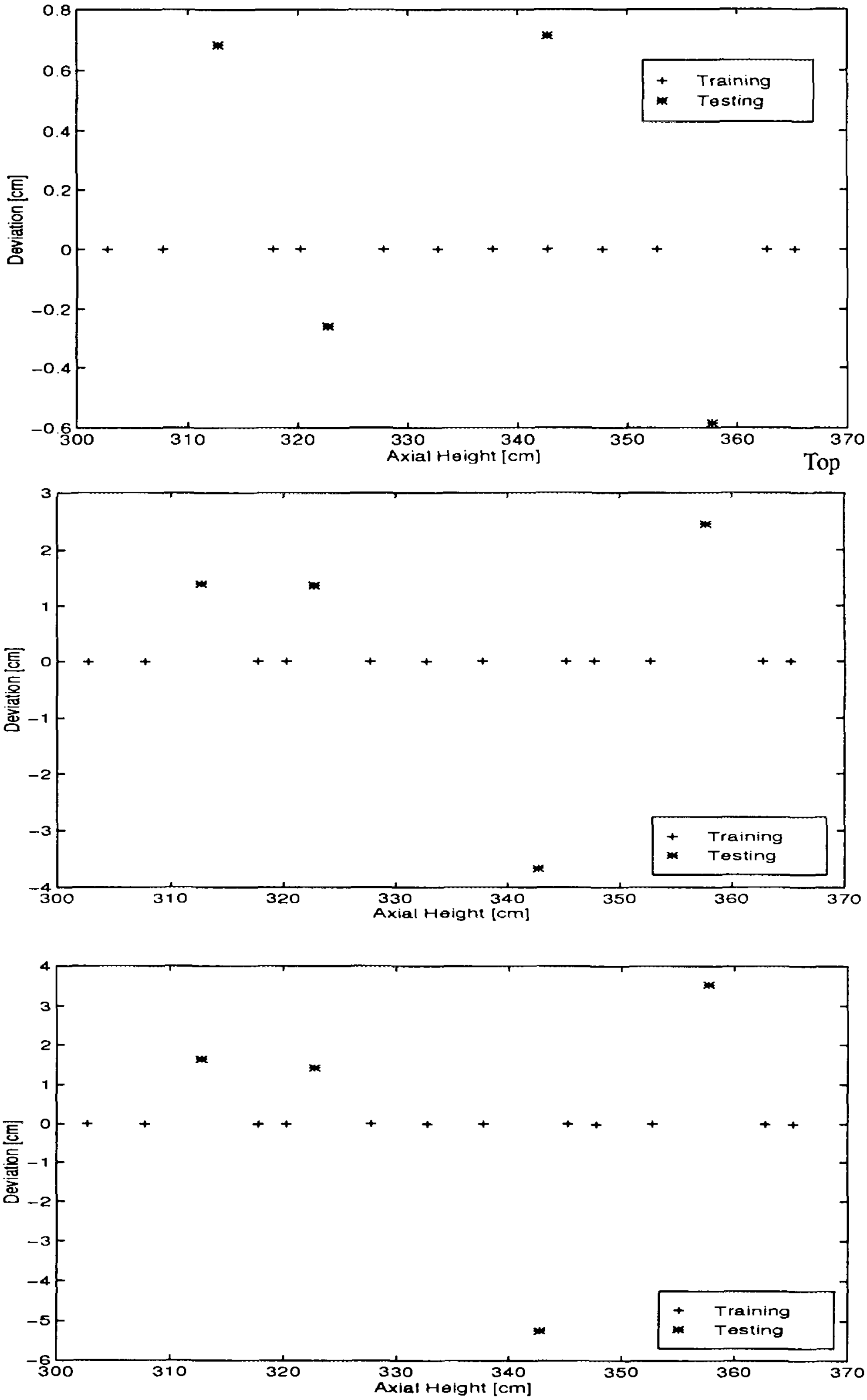


Fig. 11. Deviation (error) of network output and original values for a control rod moving in the upper quarter of the core and neighbouring assembly with a) 0 %, b) ±3 % and c) ±5 % added Gaussian noise.