Neutron noise source reconstruction using the Adaptive Neuro-Fuzzy Inference System (ANFIS)
in the VVER-1000 reactor core

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Abstract

The neutron noise is defined as the stationary fluctuation of the neutron flux around its mean value due to the induced perturbation in the reactor core. The neutron noise analysis may be useful in many applications like noise source reconstruction. To identify the noise source, calculated neutron noise distribution of the detectors is used as input data by the considered unfolding algorithm. The neutron noise distribution of the VVER-1000 reactor core is calculated using the developed computational code based on Galerkin Finite Element Method (GFEM). The noise source of type absorber of variable strength is considered in the calculation. The computational code developed based on An Adaptive Neuro-Fuzzy Inference System (ANFIS) is used to unfold the neutron noise source. Complex neutron noise distribution (real and imaginary parts) in the detectors is considered as input data onto the developed computational code based on the ANFIS algorithm. All the characteristics of the neutron noise source, including strength, frequency and position (X and Y coordinates) are unfolded with excellent accuracy using the developed computational code.

Keywords

GFEM, neutron noise, noise source, unfolding, ANFIS.

Abbreviations

FEM Finite Element Method,

$\delta\phi(r, \omega)$ Neutron noise,

∇ The nabla operator,

1. Introduction

The neutron noise is the stationary fluctuation of the neutron flux around its mean value due to the induced perturbation in the reactor core. The noise source is considered as perturbation in material macroscopic cross section due to agents like absorber of variable strength or vibrating control rod in the reactor core. If the noise source is not identified well-timed, it may lead to a crucial event in the reactor core. From reactor safety analysis point of view, it is very important to recognize noise sources timely. The signal or neutron noise recorded by available detectors in the reactor core is usually used to reconstruct noise source. Diagnostic of neutron noise sources like the control rod vibrations via neutron noise analysis methods were the subject of a number of prior studies and experiments (Hosseini and Vosoughi, 2014; Itoh, 1986; Pázsit and Glöckler, 1983, 1984; Williams, 2013). Different methods such as inversion, zoning and scanning were used for identification and localization of various types of noise sources like the unseated fuel assemblies in reactor core, absorber of variable strength or vibrations of core internals in PWRs (Demazière and Andhill, 2005; Pázsit and Glöckler, 1984; Williams, 2013). The purpose from the noise source unfolding calculation is the solution of the inverse problem using different techniques. Since the matrix in the mentioned problems is usually singular or badly-scaled, the results obtained from the direct solution to the inverse problem is not so accurate. The other usual methods like the scanning and zoning require approximately high computational cost for noise source unfolding (Demazière and Andhill, 2005; Pázsit and Glöckler, 1984). Artificial Neural Network (ANN) is another approach that unfolds noise sources with high accuracy and approximately needs high computational cost (Hosseini and Vosoughi, 2014). It is the mathematical algorithm inspired by biological neural networks. In our previous published paper,

the developed computational codes based on the artificial neural network and its coupling with the scanning method were used to unfold noise sources of types the absorber of variable strength and vibrating absorber. The mentioned developed computational code unfolds noise source with high accuracy. The drawback of the mentioned algorithms (ANN and scanning) is that they need high running and computational cost. The literature review of the works performed in the noise source unfolding field of study shows that the neural network or combination of neural network and the scanning method is more robust in comparison to other aforementioned algorithms. In summary, the artificial neural network is proper selection to reconstruct the instability and vibration localization (Garis et al., 1998; Tambouratzis and Antonopoulos-Domis, 2002). In the mentioned studies, the neutron noise sources of type absorber of variable strength or vibrating absorber were just localized using the neural network without any attempt to reconstruct the noise source strength and/or its frequency. In the previous published paper using ANN, detailed information about noise source characteristics including, position, frequency and its strength was reconstructed with good accuracy (Hosseini and Vosoughi, 2014). The developed dynamic simulator (DYN-FEMG) (Hosseini and Vosoughi, 2012) is used for neutron noise calculations. In the present study, a new algorithm based on Adaptive Neuro-Fuzzy Inference System (ANFIS) is proposed to unfold the noise source of type absorber of variable strength in the VVER-1000 reactor core. Because of some merits of the proposed algorithm like high accuracy of the results and need for low computational cost, the developed computational code based on the ANFIS may be introduced as a reliable tool for neutron noise identification in reactor cores. An outline of remainder of the present paper is as follows: In section 2, we briefly introduce mathematical formulation used for the neutron noise calculation in the reactor core. The main specifications of the VVER-1000 reactor core is presented in Section 3. The neutron noise

distribution in the reactor core obtained from the calculation is presented in Section 4. In Section 5, the developed computational code based on the ANFIS algorithm and the unfolded noise source using the mentioned computational code are presented. A discussion on the results and the merits of the proposed method is presented in section 6. Finally, Section 7 gives the concluding remarks.

2. Neutron noise calculation

In the present study, the first order approximation of the neutron noise diffusion equation in 2-energy group is considered to calculate neutron noise distribution. The general form of the mentioned equation by considering the noise source as fluctuations in the scattering, absorption and fission macroscopic cross sections is presented as Eq. (1) (Demazière and Andhill, 2005; Hosseini and Vosoughi, 2014; Itoh, 1986; Pázsit and Glöckler, 1984; Williams, 2013):

$$\begin{aligned} \left[\nabla \cdot \bar{\bar{D}}(\bar{r}) \nabla + \bar{\bar{\Sigma}}_{dyn}(\bar{r}, \omega) \right] \times \begin{bmatrix} \delta\phi_1(\bar{r}, \omega) \\ \delta\phi_2(\bar{r}, \omega) \end{bmatrix} &= \bar{\phi}_{s,1 \rightarrow 2}(\bar{r}) \delta\Sigma_{s,1 \rightarrow 2}(\bar{r}, \omega) + \bar{\phi}_a(\bar{r}) \begin{bmatrix} \delta\Sigma_{a,1}(\bar{r}, \omega) \\ \delta\Sigma_{a,2}(\bar{r}, \omega) \end{bmatrix} + \\ \bar{\phi}_f(\bar{r}, \omega) \begin{bmatrix} \delta\nu_1 \Sigma_{f,1}(\bar{r}, \omega) \\ \delta\nu_2 \Sigma_{f,2}(\bar{r}, \omega) \end{bmatrix}, \end{aligned} \quad (1)$$

where, all quantities are defined as usual and the matrices and vectors are expressed as Eqs. (2)-(5):

$$\bar{\bar{\Sigma}}_{dyn}(\bar{r}, \omega) = \begin{bmatrix} -\Sigma_1(\bar{r}, \omega) & \frac{\nu_2 \Sigma_{f,2}(\bar{r})}{k_{eff}} \left(1 - \frac{i\omega\beta_{eff}}{i\omega + \lambda}\right) \\ \Sigma_{s,1 \rightarrow 2}(\bar{r}) & -(\Sigma_{a,2}(\bar{r}) + \frac{i\omega}{\nu_2}) \end{bmatrix}, \quad (2)$$

$$\bar{\phi}_{s,1 \rightarrow 2}(\bar{r}) = \begin{bmatrix} \phi_1(\bar{r}) \\ -\phi_1(\bar{r}) \end{bmatrix}, \quad (3)$$

$$\bar{\phi}_a(\bar{r}) = \begin{bmatrix} \phi_1(\bar{r}) & 0 \\ 0 & \phi_2(\bar{r}) \end{bmatrix} \quad (4)$$

$$\bar{\phi}_f(\bar{r}, \omega) = \begin{bmatrix} -\phi_1(\bar{r})(1 - \frac{i\omega\beta_{eff}}{i\omega + \lambda}) & -\phi_2(\bar{r})(1 - \frac{i\omega\beta_{eff}}{i\omega + \lambda}) \\ 0 & 0 \end{bmatrix} \quad (5)$$

The coefficient $\Sigma_1(\bar{r}, \omega)$ applied in Eq. (2) is defined as Eq. (6):

$$\Sigma_1(\bar{r}, \omega) = \Sigma_{r,1}(\bar{r}) + \frac{i\omega}{v_1} - \frac{v_1 \Sigma_{f,1}(\bar{r})}{k_{eff}} (1 - \frac{i\omega\beta_{eff}}{i\omega + \lambda}). \quad (6)$$

To calculate the noise source term in the right hand side of the Eq. (1) (Eqs. (3)-(5)), neutron flux distribution should be calculated from the solution of the neutron diffusion equation. To this end, the neutron flux distribution obtained from the previous developed computational code is used to calculate the neutron noise distribution (Hosseini and Vosoughi, 2012). In the present study, the neutron noise source is assumed to be an absorber of variable strength. Here, the Green's function technique is used (Demazière and Andhill, 2005) to calculate the neutron noise distribution in the reactor core. In the mentioned method, the neutron noise distribution due to unit value of the point noise source in the reactor core is calculated. The point source may be located in any considered triangle element. Therefore, the Green's components due to different positions of the unit value-point noise sources are calculated via the solution of the Eq. (7):

$$\left[\nabla \cdot \bar{D}(\bar{r}) \nabla + \bar{\Sigma}_{dyn}(\bar{r}, \omega) \right] \times \begin{bmatrix} G_{g \rightarrow 1}(\bar{r}, \bar{r}', \omega) \\ G_{g \rightarrow 2}(\bar{r}, \bar{r}', \omega) \end{bmatrix} = \begin{bmatrix} \delta(\bar{r} - \bar{r}') \\ 0 \end{bmatrix}_{g=1} \text{ or } \begin{bmatrix} 0 \\ \delta(\bar{r} - \bar{r}') \end{bmatrix}_{g=2}, \quad (7)$$

where, $G_{g \rightarrow 1}(\bar{r}, \bar{r}', \omega)$ and $G_{g \rightarrow 2}(\bar{r}, \bar{r}', \omega)$ are the Green's function components of the energy groups 1 and 2 in the position $\bar{r}$ induced by the noise source in group g located in the position $\bar{r}'$,

respectively. It is possible to consider the neutron noise source in the fast or thermal energy group.

If the noise source is considered to be in the thermal energy group (the perturbation in the thermal macroscopic cross section), the Eq. (7) can be written as Eqs. (8) and (9) using the Galerkin Finite Element Method (GFEM):

$$\sum_{e=1}^E \left[\iint_{\Omega^{(e)}} d\Omega D_1 \nabla N^{(e)}(\bar{r}) \nabla N^{(e)T}(\bar{r}) G_{2 \rightarrow 1}^{(e)} - \Sigma_1^{(e)} \iint_{\Omega^{(e)}} d\Omega N^{(e)}(\bar{r}) N^{(e)T}(\bar{r}) G_{2 \rightarrow 1}^{(e)} + \right. \\ \left. \frac{\nu_2 \Sigma_{f,2}^{(e)}}{k_{eff}} \left(1 - \frac{i\omega \beta_{eff}}{i\omega + \lambda} \right) \iint_{\Omega^{(e)}} d\Omega N^{(e)}(\bar{r}) N^{(e)T}(\bar{r}) G_{2 \rightarrow 2}^{(e)} + \int_{\partial\Omega^{(e)V}} ds N^{(e)}(\bar{r}) N^{(e)T}(\bar{r}) \frac{G_{2 \rightarrow 1}^{(e)}}{2} \right] = 0, \quad (8)$$

$$\sum_{e=1}^E \left[\iint_{\Omega^{(e)}} d\Omega D_2 \nabla N^{(e)}(\bar{r}) \nabla N^{(e)T}(\bar{r}) G_{2 \rightarrow 2}^{(e)} + \Sigma_{s,1 \rightarrow 2}^{(e)} \iint_{\Omega^{(e)}} d\Omega N^{(e)}(\bar{r}) N^{(e)T}(\bar{r}) G_{2 \rightarrow 1}^{(e)} - \right. \\ \left. \left(\Sigma_{a,2}^{(e)} + \frac{i\omega}{\nu_2} \right) \iint_{\Omega^{(e)}} d\Omega N^{(e)}(\bar{r}) N^{(e)T}(\bar{r}) G_{2 \rightarrow 1}^{(e)} + \int_{\partial\Omega^{(e)V}} ds N^{(e)}(\bar{r}) N^{(e)T}(\bar{r}) \frac{G_{2 \rightarrow 2}^{(e)}}{2} \right] = \begin{bmatrix} N_i^{(e)}(\bar{r}) \\ N_j^{(e)}(\bar{r}) \\ N_k^{(e)}(\bar{r}) \end{bmatrix}, \quad (9)$$

where, $N_i^{(e)}$, $N_j^{(e)}$ and $N_k^{(e)}$ are the components of the shape function in GFEM.

In the Eq. (8), the differential part were transformed by applying the Divergence's theorem as Eq. (10):

$$\int_{\Omega^{(e)}} d\Omega N^{(e)}(\bar{r}) (-D_1 \nabla^2 N^{(e)T}(\bar{r}) G_{2 \rightarrow 1}^{(e)}) = \int_{\Omega^{(e)}} dA \nabla N^{(e)}(\bar{r}) \cdot \nabla N^{(e)T}(\bar{r}) G_{2 \rightarrow 1}^{(e)} - \int_{\Omega^{(e)}} d\Omega \nabla \cdot (N^{(e)}(\bar{r}) \nabla N^{(e)T}(\bar{r}) G_{2 \rightarrow 1}^{(e)}) \\ = \int_{\Omega^{(e)}} d\Omega \nabla N^{(e)}(\bar{r}) \cdot \nabla N^{(e)T}(\bar{r}) G_{2 \rightarrow 1}^{(e)} - \int_{\partial\Omega^{(e)V} + \partial\Omega^{(e)R}} ds N^{(e)}(\bar{r}) \frac{\partial N^{(e)T}(\bar{r}) G_{2 \rightarrow 1}^{(e)}}{\partial n} \quad (10)$$

where, $\partial\Omega^{(e)V}$ and $\partial\Omega^{(e)R}$ refers to boundary length with vacuum and perfect reflective boundary conditions in element e, respectively.

Also,

$$\frac{\partial N^{(e)T}(\bar{r})G_{2 \rightarrow 1}^{(e)}}{\partial n} = \nabla N^{(e)T}(\bar{r})G_{2 \rightarrow 1}^{(e)} \cdot \bar{n}. \quad (11)$$

where, $\bar{n}$ is the normal unit vector on the volume V . Two types of boundary conditions (B.C.) are considered. The first B.C. is no incoming neutrons at vacuum boundaries (Marshak B.C.) which is expressed as Eq. (12):

$$\frac{\partial N^{(e)T}(\bar{r})G_{2 \rightarrow 1}^{(e)}}{\partial n} = -\frac{N^{(e)T}(\bar{r})G_{2 \rightarrow 1}^{(e)}}{2D_g}. \quad (12)$$

The second B.C. is zero net current or perfect reflective boundary condition which is described by Eq. (13):

$$\frac{\partial N^{(e)T}(\bar{r})G_{2 \rightarrow 1}^{(e)}}{\partial n} = 0. \quad (13)$$

The same procedure for applying the boundary condition is considered in the Eq. 9. The no incoming current and perfect reflective are the common boundary conditions that are used in the solution of the neutron diffusion equation.

Green's function components in each energy group in different triangle elements are calculated from the solution of the Eqs. (8) and (9). Finally, the fast and thermal neutron noise distributions are calculated by an integral over the multiplying the Green's function components and noise source in the whole domain of the reactor core as Eq. (14):

$$\begin{bmatrix} \delta\phi_1(\bar{r}, \omega) \\ \delta\phi_2(\bar{r}, \omega) \end{bmatrix} = \begin{bmatrix} \int [G_{1 \rightarrow 1}(\bar{r}, \bar{r}', \omega) S_1(\bar{r}', \omega) + \int [G_{2 \rightarrow 1}(\bar{r}, \bar{r}', \omega) S_2(\bar{r}', \omega)] d\bar{r}' \\ \int [G_{1 \rightarrow 2}(\bar{r}, \bar{r}', \omega) S_1(\bar{r}', \omega) + \int [G_{2 \rightarrow 2}(\bar{r}, \bar{r}', \omega) S_2(\bar{r}', \omega)] d\bar{r}' \end{bmatrix}. \quad (14)$$

If the thermal macroscopic absorption cross section is only perturbed, the Eq. (14) will be reduced as Eq. (15):

$$\begin{bmatrix} \delta\phi_1(\bar{r}, \omega) \\ \delta\phi_2(\bar{r}, \omega) \end{bmatrix} = \begin{bmatrix} \int [G_{2 \rightarrow 1}(\bar{r}, \bar{r}', \omega) S_2(\bar{r}', \omega)] d\bar{r}' \\ \int [G_{2 \rightarrow 2}(\bar{r}, \bar{r}', \omega) S_2(\bar{r}', \omega)] d\bar{r}' \end{bmatrix}. \quad (15)$$

Here, it is assumed that the noise source be only located in the thermal energy group and the neutron noise distribution in the reactor core is calculated using the aforementioned equations.

3. Main specifications of the VVER-1000 reactor core

The benchmark model consists of a full-size VVER-1000 core with 163 fuel assemblies(FSAR, 2003). As shown in Fig. 1, VVER assemblies are hexagonal in shape and consist of 331 lattice locations in a hexagonal array. The hexagonal lattice pitch of the assembly cell is 23.6 cm. Each assembly contains 311 fuel pins, 18 guide tubes, central tube and 1 instrumentation tube. The pins are cylindrical and clad with Zr + 1% Nb. Fuel pins contain fuel pellets with the radius 0.386 cm and fuel pin pitch is 1.275 cm. Cladding inside and outside diameters are 0.772 cm and 0.910 cm, respectively. Table 1 shows the material macroscopic cross sections and group constants used in the calculations which are obtained from cell calculation computer code, WIMS (Halsall, 1980). Fig. 2 shows the location of detectors in the reactor core.

Fig. 1

Fig. 2

Table 1

The material cross section of each assembly in VVER-1000 reactor core.

Cross section	FA16	FA24	FA36	FA24B20	FA24B36	FA36B36	Moderator
$D_1 (cm)$	1.466E+00	1.469E+00	1.474E+00	1.469E+00	1.468E+00	1.473E+00	1.486E+00
$D_2 (cm)$	5.464E-01	5.449E-01	5.448E-01	5.696E-01	5.713E-01	5.697E-01	4.112E-01
$\nu\Sigma_{f,1} (cm^{-1})$	3.699E-03	8.615E-02	5.873E-01	8.546E-02	8.521E-02	1.197E-01	0.000
$\nu\Sigma_{f,2} (cm^{-1})$	6.027E-02	8.615E-02	1.211E-01	8.546E-02	8.522E-02	1.197E-01	0.000
$\Sigma_{a,1} (cm^{-1})$	8.839E-03	7.271E-03	7.727E-03	8.375E-03	7.820E-03	7.866E-03	8.517E-03
$\Sigma_{a,2} (cm^{-1})$	4.524E-02	4.955E-02	6.139E-02	7.740E-02	6.424E-02	6.559E-02	8.159E-02
$\Sigma_{s,1\rightarrow2} (cm^{-1})$	1.240E-02	1.205E-02	1.158E-02	1.146E-02	1.140E-02	1.096E-02	2.125E-02

4. Results 1: Neutron noise distribution in the reactor core

To prepare the data for the noise source unfolding section, the neutron noise distributions in the reactor core due to the 20000 randomly generated noise sources are calculated (each data includes the randomly generated frequency, strength and X and Y coordinate of the noise source). As a sample, the magnitude and phase of the calculated neutron noise distribution due to the noise source of type absorber of variable strength located at central area of the reactor core are displayed in the Figs. 3 and 4, respectively. The validation of the calculated neutron noise distribution using the developed computational code was presented in the previous published papers through three different approaches (Hosseini and Vosoughi, 2012, 2013, 2016). The validated neutron noise distribution will be used as the input data for the noise source reconstruction.

Fig. 3

Fig. 4

5. Unfolding of the noise source

5.1. Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS is a kind of fuzzy artificial neural network which implements the Takagi-Sugeno fuzzy inference modeling algorithm when its input membership function are chosen triangle type.

Effectiveness of the ANFIS is improved via using the advantages of the both artificial neural networks structure and fuzzy inference system. The connection mechanism in ANFIS structure makes it suitable for modeling a very complex problems. Also, application of the fuzzy concept leads to control the uncertain and noisy situations. All the mentioned characteristics lead to improve the effectiveness of the ANFIS algorithm in different applications like modeling, control and classification (Johnson and Wehring, 1976; Matzke, 1994, 1997; Reginatto et al., 2002). ANFIS is considered as a universal estimator. As shown in the Fig. 5, the structure of ANFIS consists of five layers, in which the task of each layer is as follows:

Fig. 5

Layer1:

Each node in this layer consists of a membership function A_i . The input of each node in this layer is x_i (one of system input) and output is a number between 0 and 1 that shows the degree which x_i satisfies A_k . A_i is a linguistic variable like small, big and etc.

Layer2:

The output of nodes in this layer is the product of their inputs. For example $w_1 = A_1(x_1) \times A_3(x_2)$.

Actually, the output of these nodes can be the application of any T-norm operator.

Layer3:

The output of the nodes in this layer is ratio of corresponding w_i (defined in Eq. 16) to the sum of all w_k ; $k=1:n$.

$$\bar{w}_k = \frac{w_k}{\sum_{i=1}^n w_i} \quad (16)$$

Layer4:

The output of the nodes in this layer is as Eq. (17):

$$o_i = \bar{w}_i \times f_i = \bar{w}_i \times (p_i x_1 + q_i x_2 + r_i) \quad (17)$$

where $\bar{w}_i$ is the output of the previous layer and $\{p_i, q_i, r_i\}$ are the parameter set which should be computed in learning mechanism.

Layer5:

The single node in this layer, computes the overall output of the system as Eq. (18):

$$f(x_1, x_2) = \sum_i \bar{w}_i \times f_i \quad (18)$$

Computation of the parameters can be done using the various learning algorithms like gradient descent, evolutionary algorithms and other possible algorithms. For learning phase, a suitable error measure should be selected; thus, the learning algorithm should select the parameters for minimizing the error.

ANFIS algorithms is used for modeling a MISO (Multiple Input-Single Output) system. In the present problem, there is a MIMO (Multiple Input-Multiple Output) system with 108 inputs (real and imaginary parts of the neutron noise in the number of the 54 available detectors in the reactor core) and 4 outputs (including frequency, strength, X and Y coordinates of the noise source). To solve the problem, the MIMO system should be broken into some simpler MISO systems. The representation of the aforementioned description is given in Fig. 6.

Fig. 6

The MIMO system is broken to 108 MISO systems. Now, each MISO system can be modeled with the developed computational code based on the ANFIS algorithm.

For comparison and efficiency evaluation, the Fraction of Variance Unexplained (FVU) index which is defined in Eq. (19) is used:

$$FVU = \frac{\sum_{i=1}^N (\hat{y}(\vec{x}_i) - y(\vec{x}_i))^2}{\sum_{i=1}^N (y(\vec{x}_i) - \bar{y}(\vec{x}_i))^2} \quad (19)$$

In Eq. (15), $y(\vec{x}_i)$ is the real output value for the input vector $\vec{x}_i$. $\hat{y}(\vec{x}_i)$ is the output of ANFIS

model, N is the number data point and $\bar{y}(\vec{x}_i) = \frac{\sum_{i=1}^N y(\vec{x}_i)}{N}$. FVU is a kind of normalized error

index. In this index, the absolute value of error is important respect to the amount of output variable's variation. The best modeling procedure will be for FVU=0.

5. 2. Results 2: The unfolded noise source

To prepare the data needed for unfolding of the noise sources using the developed computational code based on the ANFIS algorithm, the 20000 randomly generated noise sources are considered. For each considered noise source, the strength, frequency, and position of noise sources in the reactor core are calculated via the different random numbers. The neutron noise distributions in the reactor core due to each considered noise source are calculated using the developed DYN-FEMG computational code (Hosseini and Vosoughi, 2012). The real and imaginary parts of the calculated neutron noise in the 54 available detectors in the reactor core (108 inputs for each data) are considered as inputs of the developed computational code based on the ANFIS algorithm. The position (X and Y coordinates), strength and frequency of the noise source are the outputs of the developed computational code. Fig. 7 shows the comparison between the unfolded X coordinate of the noise source and actual one for the 100 randomly considered samples. The similar comparisons for Y coordinate, strength and the frequency at which the noise source of type absorber of variable strength is happened, are given in Figs. 8-10, respectively. Table 2 shows the regression coefficient of the predicted output vs. actual one for the 4 outputs of the system computed by ANFIS algorithm. Regression coefficient is a touchstone for evaluation of any regression problem. This Criterion is used for evaluating the performance of the ANFIS algorithm. Also, Table 3 displays the average errors obtained from the calculation for each output data. As seen, there is an excellent agreement between the unfolded noise source and actual one.

Fig. 7

Fig. 8

Fig. 9

Fig. 10

Table 2. The regression coefficient of the predicted output using the developed computer code based on the ANFIS algorithm vs. actual one.

Characteristic of the noise source	Strength	Frequency	X	Y
Regression coefficient	0.9912	0.9928	0.9934	0.9937

Table 3. Average error calculated for each output using the developed computer code based on the ANFIS algorithm.

Characteristic of the noise source	Strength	Frequency	X	Y
Average error	5.471E-4	7.248E-4	1.219E-2	1.013E-2

6. Discussion

In the present study, the neutron noise source of type absorber of variable strength was unfolded using the developed computational code based on the Adaptive Neuro-Fuzzy Inference System (ANFIS). The DYN-FEMG computational code (Hosseini and Vosoughi, 2012) was used to calculate the neutron noise distribution due to the considered noise source. The 20000 randomly generated noise sources (including the number of the 20000 randomly generated location (X and Y coordinates), strength and frequency of the noise source) and the corresponding calculated neutron noise values (real and imaginary parts) in the 54 detectors in the reactor core are the outputs and inputs of the developed computational code based on the ANFIS. In the previous published papers, the unfolding of the absorber of variable strength noise source was performed using the inversion, zoning and scanning algorithms (Demazière and Andhill, 2005; Hosseini and Vosoughi, 2013). The scanning algorithm unfolds the noise source with good accuracy in the absence of the background noise in the reactor core. Therefore, the scanning algorithm is much more reliable and robust than the inversion (and to a lesser extent zoning) algorithms (Hosseini

and Vosoughi, 2013). This can be explained by the fact that no matrix inversion is needed for unfolding, whereas the inversion (and to a lesser extent zoning) algorithms rely on the inversion of a matrix that might be badly-scaled in some occurrence. The drawback of the scanning algorithm is that it needs high computational cost (Demazière and Andhill, 2005; Hosseini and Vosoughi, 2013). Also, the scanning method gives no information about the frequency at which the noise source was happen. In the previous published work by the first author, the results of the unfolded noise source using the artificial neural network were presented (Hosseini and Vosoughi, 2014). In the mentioned study, the frequency, strength and the position of the noise source was reconstructed with high accuracy using the method based on the *logsig* and *tansig* transfer functions. The motivation of the present study was the development a computational code that reconstructs the noise source with high accuracy and it requires low computational cost. As shown in tables 2 and 3, the accuracy of the unfolded noise source in the present study is more better than the similar published works (Garis et al., 1998; Tambouratzis and Antonopoulos-Domis, 2002). In fact, the noise source of type absorber of variable strength was localized with good accuracy in the present study, while the average error of the localization of the noise source in the similar published work is almost 6 cm (Tambouratzis and Antonopoulos-Domis, 2002). All the characteristics of noise source including, the strength, occurrence frequency and the position of the noise source in the reactor core were estimated with high accuracy. It should be noted that the reported results in the present study were calculated by considering the 54 active detectors in the reactor core. As described in the previous published paper, the error between the reconstructed noise source and actual one increases when the number of the active detectors in the reactor core decreases (Hosseini and Vosoughi, 2014). Also, the accuracy of the reconstruction of the noise source in the reactor core depends on the

number of the considered detectors and the arrangement of the detectors in the reactor core (Hosseini and Vosoughi, 2014). Also, the computational time of the developed computer code based on the ANFIS algorithm for the 20000 data is close to 10 min, while the same calculation using ANN computational code with *logsig* and *tansig* transfer functions takes 7 hours (Hosseini and Vosoughi, 2014).

7. Conclusion

In the present study, the neutron noise source of type absorber of variable strength was reconstructed using the developed computational code based on the Adaptive Neuro-Fuzzy Inference System (ANFIS) in the VVER-1000 reactor core. The calculation of the neutron noise distribution in the reactor core was performed using the developed DYN-FEMG computational code. Four characteristics of the noise source including, the strength, frequency and the location of the noise source were identified with high accuracy. The developed computational code based on the ANFIS algorithm requires low computational cost and may be considered as the reliable tool for identification of the noise source in the reactor core. Therefore, it may be introduced as an important computational code in the noise and safety analysis in the reactor core..

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Figure captions:

Fig. 1. A typical VVER-1000 reactor core.

Fig. 2. Distribution of detectors in the typical VVER-1000 reactor core.

Fig. 3. The magnitude of the thermal neutron noise due to noise source of type absorber of variable strength.

Fig. 4. The phase of the thermal neutron noise due to noise source of type absorber of variable strength.

Fig. 5. The structure of ANFIS consisting of five layers.

Fig. 6. The main concept used in the ANFIS algorithm.

Fig. 7. The comparison between the unfolded and actual values of the X coordinate for the number of 100 randomly considered noise source.

Fig. 8. The comparison between the unfolded and actual values of the Y coordinate for the number of 100 randomly considered noise source.

Fig. 9. The comparison between the unfolded and actual values of the noise source strength for the number of 100 randomly considered noise source.

Fig. 10. The comparison between the unfolded and actual values of the occurrence frequency for the number of 100 randomly considered noise source.