Small Break Loss of Coolant Accident (SB-LOCA) fault diagnosis using Adaptive Neuro-Fuzzy Inference System (ANFIS)

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Abstract. The detection of incipient faults of the current fault diagnosis systems in Nuclear Power Plants is inherently limited. Active research in machine learning algorithms like Adaptive Neuro-Fuzzy Inference System (ANFIS) is providing promising results in the prediction of faults. This paper explored four different configurations of Adaptive Neuro-Fuzzy Inference System (ANFIS) methodology in a bid to come up with a superior model that not only had a high sensitivity in the detection of incipient faults but also had superior prediction capabilities. The data-driven ANFIS schemes were used to predict a sensitive fault signature and to evaluate the models, Small Break Loss of Coolant Accident (SBLOCA) transient events were modeled in Qinshan I Nuclear Power Plant. Coefficient of determination, normal probability plot of residuals and mean absolute percent error were used to assess the competencies of the estimation of the models.

1. Introduction

Nuclear Reactor Safety usually involves the safeguarding of humans and the environment against the massively produced ionizing radiations present in the containment of Nuclear Power Plants (NPP). Transient and accident progression and analysis form a principal part of nuclear reactor safety where the demonstration of the available safety margins is done by assessing the Design Basis Accident (DBA) boundary and triggering the response of the specific reactor type in the event of transient or accident occurring at the plant [1]. The Loss of Coolant Accident (LOCA) is an element of the DBA set of transients and it is one of the risk significant initiating events that may lead to core damage [2]. The detection of incipient faults more particularly for the case of Small Break Loss of Coolant Accident (SBLOCA) due to the current inherent limitations of the fault diagnostic systems [3] used creates a need for intelligent methods of diagnosing faults. The use of machine learning algorithms and their hybrid techniques are providing better alternatives for resolving these limitations [4]. They include the use of fault diagnosis scheme based on Deep Learning [5], [4], Artificial Neural Network (ANN) [6], Neuro-fuzzy networks [7], Support Vector Regression (SVR) [8] and Adaptive Neuro-Fuzzy Inference System (ANFIS) [9].
These applications are however limited in one way or the other. The opaque problem-solving nature of ANNs and deep learning methodologies make it difficult for the operator to know how the problem was solved. The inability of adapting of neuro-fuzzy models makes the models not fully optimized. The drawback of SVR algorithms is getting different results due to the classification of feature selection differently. On the other hand, ANFIS is a robust methodology with superior prediction features and excellent local interpolation capabilities. The applications of ANFIS scheme in the different fields have shown its competencies in classification, control and modeling. Examples of applications include: ANFIS network being used to model mixed convection of nanofluid filled branching channel [10] and Fathy et al. optimized the load frequency control of multi-interconnected plants with wind turbine and photovoltaic energy sources by ANFIS approach [11]. ANFIS scheme was utilized for classification of events in fast breeder reactors [12] while in the literature [9], ANFIS methodology was employed for energy systems optimization.

The superior competencies of ANFIS algorithm make it a good fit to be used in the early detection of incipient faults in the piping of an NPP. Additionally, no literature has compared and contrasted the different schemes of ANFIS when predicting the SBLOCA event. To bridge this knowledge gap, this research work did a comparative study of four different ANFIS frameworks to estimate a critical parameter that is sensitive to the SBLOCA signature and ascertained the most suitable model to simulate this transient event in Qinshan I NPP using RELAP5. The main objective and contribution to knowledge of this study was to develop a novel, optimized and robust ANFIS scheme capable of diagnosing incipient SBLOCA faults in Qinshan I NPP.

2. Methodology

2.1. RELAP Code

RELAP5 is a versatile, one-dimensional two-fluid flow best estimate system code used in the modeling of NPPs. It was used to simulate the thermal-hydraulic components of the reactor coolant system (RCS) of Qinshan I NPP. Qinshan I NPP is a two-looped pressurized water reactor (PWR) NPP with a capacity of 300 MW electric and thermal output of 966 MW. The complete nodalization of the RCS of Qinshan I NPP is illustrated by Figure 1. Benchmarking of the code to actual plant measurements was done to illustrate how well the model simulates the plant responses. The uncertainty analysis provided the quantification of the uncertainties of the predicted parameters [1]. These verification and validation processes as well as uncertainty analysis ensured that the code corresponded to the systems modeled and therefore it guaranteed that the code operated within the acceptable limits. It was used to simulate incipient SBLOCA events.

SBLOCA is characterized by small ruptures on the pipes of NPP resulting in the leaks of the coolant. SBLOCA is modeled by leaks of the coolant from the RCS into the containment through the break areas. In this study, incipient SBLOCA transients were simulated by small break areas appearing on the cold leg piping of the RCS. The small ruptures caused leaks of the coolant to flow from branch 216 to the containment 590 as shown in Figure 1. The calculation of six break transients was performed after 100 seconds of stable steady-state operation. With the commencement of the trip signal, simulation of each of the transient was done by adjusting the break area from 3 cm$^2$ to 13 cm$^2$ in intervals of 2 cm$^2$ to model the different conditions. Three critical variables that were sensitive to SBLOCA transients were recorded and used in the generation and evaluation of ANFIS schemes. These variables which served as input to the ANFIS schemes were secondary pressure at the steam generator U-tubes, temperature at the steam generator U-tubes and the mass flow rate at the SBLOCA breakpoint. With the system pressure of the RCS decreasing at the start of the SBLOCA event, the pressure at the pressurizer was used as the output to the predictor ANFIS algorithms.
2.2. Adaptive Neuro-Fuzzy Inference System (ANFIS)

Adaptive Neuro-Fuzzy Inference System, ANFIS, is a fusion of Fuzzy Logic (FL) and artificial neural network (ANN) with the Takagi-Sugeno fuzzy inference algorithm. It uses the advantage of FL of human reasoning to create if-then fuzzy rules with suitable membership functions and the merits of ANN of adjusting the weights of its characteristic membership function to form the optimized input-output pairs with the smallest errors. The utilization of the fuzzy concept makes it suitable for controlling uncertain circumstances as well as the connection mechanism on its structure favors it when modeling extremely complex conditions [13].

ANFIS structure consists of five layers with adjustable and fixed nodes. These layers compute normalization, multiplication, summation and linear regression as illustrated in Figure 2.

![ANFIS Structure with five layers.](image)

ANFIS modeling process entails the generation of the initial Fuzzy Inference System (FIS) architecture, tuning of FIS structure and testing of the optimized ANFIS framework. The initial architecture of FIS is derived from the training dataset. It involves the choosing of the number and shape of membership functions per input as well as the selection of the type of output membership functions. Subtractive clustering and grid partitioning are two approaches of initial architecture FIS generation. Subtractive clustering architecture FIS generation involves the selecting of data points...
with the highest density standards in specified data space to form data clusters centers. On the other hand, grid partitioning technique creates identical grids from assembling data points characterized by membership functions [14]. The tuning of the FIS structure involves the selection of the number of epochs, error tolerance and optimization technologies to determine the optimized ANFIS model. Training of the model utilizes both training and checking datasets and it usually refines the rules of optimized prediction models.

Four different models, ANFIS I - IV, based on initial FIS architecture generation, were created from RELAP5’s SBLOCA transients signatures by selecting the different configuration of critical parameters and structure. In this study, the selected input membership function of the grid partitioning was bell-shaped as it outperformed the rest of the membership functions. Hybrid learning algorithms encompassing of the back-propagation premise parameters optimization during the backward pass and during the forward cycle, least-square consequence parameters updating was chosen for tuning of the initial FIS architecture. For each training run, the number of epochs was 1000 and the error measure was selected as 0. Table 1 shows the other properties of the optimized ANFIS models.

| Properties            | ANFIS Configurations |
|-----------------------|----------------------|
|                       | I        | II       | III      | IV       |
| Initial FIS Type      | Grid Part. | Grid Part. | Sub. Clust. | Sub. Clust. |
| No of MFs             | 2 2 2    | 3 3 3    | 2 2 2    | 3 3 3    |
| No of Nodes           | 34       | 78       | 22       | 30       |
| No of Lin. Para.      | 32       | 108      | 8        | 12       |
| No of Non-Lin. Para.  | 18       | 27       | 12       | 18       |
| Total No of Para.     | 50       | 135      | 20       | 30       |
| No of Fuzzy Rules     | 8        | 27       | 2        | 3        |

The critical parameters with the SBLOCA transients signatures from RELAP5 code were used in the generation of different ANFIS models and their subsequent evaluation. Simulation of the six SBLOCA transient events produced a dataset with 11,428 entries which was used in evaluating the optimized algorithms. First and foremost, the dataset was normalized in order to reduce the range of values proportionately to fit into a common scale. The normalization function used was MinMaxScaler due to its low loss value of the results. The division of the entries was done randomly. 75% of the dataset was employed for training purposes while the remaining entries were divided equally between checking and testing datasets. This dropout method was used to prevent overfitting of the model during the training process (checking dataset) while the testing dataset was used in the evaluation of the model structure created by the training and checking datasets. The testing dataset was fed into the optimized algorithms created and the parameter prediction was obtained. The prediction accuracies of these trained networks were assessed by comparing the actual output and the ANFIS output.

3. Results and discussion

The competencies of the models were appraised by mean absolute percentage error (MAPE), normal probability plots of residuals and coefficient of determination ($R^2$). MAPE (Equation 1) computes the percentage of summation of residuals over the actual values. MAPE is appropriate for the comparison of models since it is dimensionless. The coefficient of determination ($R^2$) calculates the ratio of the variation of the predicted value described by the actual value. The computation of $R^2$ is expressed by Equation 2

\[
MAPE = \frac{1}{N} \sum_{i} \frac{|a_i - p_i|}{a_i} \times 100
\]

\[
R^2 = 1 - \left( \frac{\sum_{i}(a_i - p_i)^2}{\sum_{i}a_i^2} \right)
\]
where $a_i$ denotes the actual values, $p_i$ represents the predicted values and $N$ is the sample size. The competencies indicators for the different ANFIS configurations were given in Table 2. These statistical values were computed for the testing dataset which was not utilized during the training of the models.

| Performance Indices | ANFIS Configurations |
|---------------------|-----------------------|
| MAPE (%)            | I   | II   | III  | IV   |
|                     | 0.2444 | 0.0731 | 0.8337 | 0.4971 |
| $R^2$               | 0.9984 | 0.9998 | 0.9864 | 0.9950 |

The MAPE values, as shown in Table 2, for all the four model types showed that all the percentage errors calculated were below 1%. Model II had the smallest MAPE value followed chronologically by model I, IV and III. Nonetheless, the difference in the percentage errors was insignificantly small deducing that the algorithms used had superior prediction capabilities. Similarly, the $R^2$ values were closer to 1 for all the ANFIS networks investigated. This implied that all the models were competent at predicting the pressure at the pressurizer. However, model II generated by grid partitioning and having 27 fuzzy rules outperformed all the other models by having the lowest MAPE value and the $R^2$ value closest to 1. This was attributed to the model structure created which had a better estimation rate than the rest of the models.

Normal probability plots of residuals were used to visually determine the distribution of the residuals. Additionally, these plots displayed the magnitude and span of the residuals. Figure 3-6 shows the normal probability plots of residuals of the four ANFIS models I - IV. It was observed that the residuals were normally distributed with no particular pattern since they conformed to the diagonal normality line in their corresponding plots. This inferred that systematic errors were absent and hence, all the models had the capability of estimating the SBLOCA event. In terms of the magnitude of residuals, all the models had residuals one order of magnitude smaller than their respective range of values. This signified that the high estimation ability of all the schemes because the residuals were significantly small. Moreover, it was observed that model III had the largest span of residuals – 0.7MPa (Figure 6) while models I, II and IV had a range of residuals of 0.4MPa (Figure 3), 0.25MPa (Figure 4) and 0.6MPa (Figure 5) respectively. This means that the predicted ANFIS II values were almost similar to the actual values compared to the other models and for this reason, it had a superior predictability rate in comparison to the other models. This was in line with the results of MAPE and $R^2$ values.

![Figure 3](image1.png)  
**Figure 3.** Normal probability plot of residuals of ANFIS I model.  

![Figure 4](image2.png)  
**Figure 4.** Normal probability plot of residuals of ANFIS II model.
Ultimately, it can be concluded that model II had the best parameter estimation competency for this particular dataset as it had the lowest MAPE value, its $R^2$ value was the closest to 1 and had the smallest residual span of the four generated algorithms. This was attributed to an excellent model estimator structure that was capable of simulating the testing dataset accurately hence predicting the occurrence of the SBLOCA transient.

4. Conclusions
In this paper, four different configurations of Adaptive Neuro-Fuzzy Inference System (ANFIS) schemes were compared and contrasted while estimating the pressure at the pressurizer during a small break loss of coolant accident (SBLOCA) event. Performance indices of coefficient of determination, normal probability plot of residuals and mean absolute percent error concluded that all of the four ANFIS models displayed excellent estimation competencies and therefore makes ANFIS methodology a great choice of predictor technology that can be used in fault diagnosis systems. Nevertheless, model II with 27 fuzzy rules and generated by grid partitioning had the most optimized algorithm for predicting the SBLOCA event as it had the lowest MAPE value, the $R^2$ value closest to 1, normally distributed and smallest spanned residuals.

This study, therefore, concludes that the ANFIS algorithms are well suited for the detection of incipient faults during the SBLOCA transient event due to its superior prediction capability and its illustration of transparency and sensitivity during the decision-making process. In future research, different machine learning algorithms will be compared and contrasted and applied in the formulation of an automated NPP fault diagnostic system.

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