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Online monitoring and accident diagnosis aid system for the Nur Nuclear Research Reactor

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Abstract: This paper deals with the design of a computerized monitoring and diagnosis aid system (CMDAS) for the Nur Nuclear Research Reactor based on real-time plant-specific safety parameters. The CMDAS carries out early detection and identification of accidents that might affect this reactor using supervised neural networks. The graphical programming language LabVIEW is used for creating a human–operator interface, networking, embedding the diagnosis procedure, and handling and storing the data. The methodology presented in this paper can be adapted for any nuclear research reactor.

Key words: Accidents, artificial neural networks, computer aided diagnosis, Nur Nuclear Research Reactor, LabVIEW

1. Introduction

A nuclear process may evolve under different functioning modes, namely nominal, incidental, and accidental modes. In normal modes, the plant parameters are well within the operating limits and conditions for startup, operation, shutdown, and core configuration. In incidental modes, unplanned events might occur without producing significant damage for safety components. In accidental modes, the reactor power increases in an uncontrolled manner, possibly leading to a failure of the cooling outflow. In such severe situations a large amount of radioactivity may be released. In order to avoid human injury, environmental pollution as well as installation damage; reactor malfunctions have to be diagnosed. As classic monitoring systems consist of only one alarm system that does not permit the identification of initiating events in real time, the same alarms can be activated by different accidents but the measures to mitigate these events are different and their recognition is requisite using software tools.

In 2006, the International Atomic Energy Agency (IAEA) launched a broader agency activity on research reactors' modernization and refurbishment by including computational operation aids [1]. Therefore, computerized monitoring and diagnosis supports have been developed to be used in nuclear installations. In the literature, several approaches to solve the problem at hand have been used: [2,3] proposed different computerized tools and methods based on fast-running severe accident codes MAAP and MELCOR to analyze data and artificial neural networks (ANNs) for fast accident diagnosis. Meanwhile, [4] used ANNs and a rule-based real-time expert system to build a monitoring system, and [5] used probabilistic safety assessment techniques, a rule-based approach, and ANNs to develop operator support system.

The Nur Nuclear Research Reactor is a 1-MWth, open-pool, MTR-LEU fuel-type research reactor

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(Figure 1). The reactor core is surrounded by graphite reflector blocks and water. The water is used as coolant, moderator, and reflector. The reactivity control system of the reactor is made of five absorbing rods: four control and safety rods and one fine regulating rod [6]. Among accidents that may affect this reactor are loss of flow, loss of coolant, reactivity insertion accidents, and loss of power supply. In order to detect abnormal situations, the installation includes an alarm system that can be triggered by neutronic, thermohydraulic, and radiological parameters. However, to assist operators and provide relevant information in the case of accidental situations, including installation status, prediction of safety parameters, and corrective actions to mitigate an accident, a computerized monitoring and diagnosis aid system (CMDAS) has to be built.

Figure 1. Control room of the Nur Research Reactor (www.invap.com.ar).

In this work, accident classifiers are developed using ANNs as recommended by the IAEA [7,8] and the implementation is done using the LabVIEW platform [9,10]. Usually html, xml, or C^{++} languages are used to develop the platform, but here we propose to use the universal graphical programming language LabVIEW 10.0 (National Instruments) because the LabVIEW MATLAB script tool offers the possibility to process the acquired safety parameters with several classifiers developed with MATLAB 6.5 and implemented using this tool without any modification of the CMDAS. LabVIEW 10.0 is easy to use with a good graphic and networking capabilities.

Because of difficulties in analytically modeling a nuclear accident, the diagnosis procedure is performed by establishing the relationship between accidents and symptoms. Symptoms consisting of some characteristics obtained after establishing accident scenarios and simulating the behavior of installation affected by accidents using calculation codes [11,12]. A classification technique based on ANNs is then applied. Over the past few years, ANNs have become more popular when compared to other classification approaches [13] due to their ability to handle nonlinear relationships as well as their robustness toward modeling uncertainties and noises. The diagnosis system developed should be insensitive to measurement noises, plant parameter variations, and atmospheric conditions. The accident diagnosis is based on several neural networks; each network is trained in order to model the plant characteristics in some given accidental situation. After getting feature vectors for each accident using computing software systems, two ANN topologies are tested: radial basis functions and the multilayer perceptrons (MLPs) with different numbers of layers, neurons and transfer functions, using variant learning algorithms: gradient descent with momentum and adaptive learning backpropagation, Levenberg–Marquardt backpropagation, and resilient backpropagation. The best results of classification are obtained with the MLPs, with weights and biases adjusted with the resilient backpropagation algorithm.

2. The computerized monitoring and diagnosis aid system modules

The developed CMDAS is an informed real-time system implemented using LabVIEW toolkits on a networked supervisory PC running under Windows XP.

The LabVIEW program consists of two parts: the block diagrams, which constitute the graphical source code, and the front panel, containing the indicators, where the graphical operators interface is constructed.

The different tasks of the CMDAS are (see Figure 2):

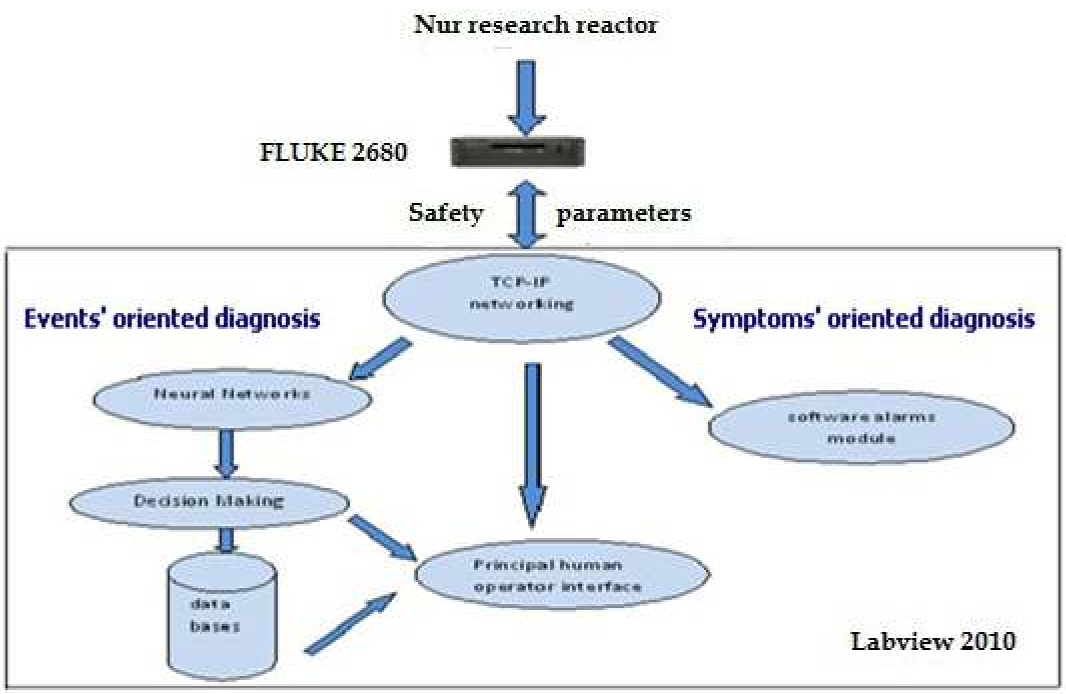

Figure 2. Computerized monitoring and diagnosis aid system (CMDAS) modules.

Task1: Collecting plant safety parameters using the LabVIEW Internet Toolkit, as depicted in Figure 3, the plant instruments are connected to an acquisition device (FLUKE 2680), which broadcasts data to the human interface on the supervisory PC via TCP-IP link across the local area network (LAN). The 2680 data acquisition system connects several networked data acquisition systems to serve 2000 channels on the LAN. Universal input modules provide precision measurement of thermocouples, DC voltages, AC voltages, RTDs, thermistors, current, and frequency with universal input conditioning on any channel any time. These measurements are read with rates from 4 readings per second up to 1000 readings per second.

Task2: Displaying the safety parameters on the user interface (see Figure 4).

Task3: Performing accident diagnosis [14], the diagnosis-based events are performed using the ANNs while the symptom-based work is done using the software alarm system.

- **Events-oriented diagnosis module:** This module not only detects but also identifies the origin of the malfunctions. Safety parameters are applied as inputs to the NI LabVIEW MATLAB script node where the modular neural networks trained and tested in MATLAB are loaded (Section 3). NI LabVIEW MathScript is a LabVIEW tool for executing textual mathematical commands (load, save, design, and execute): MATLAB m files can be integrated into the LabVIEW graphical environment. The MathScript

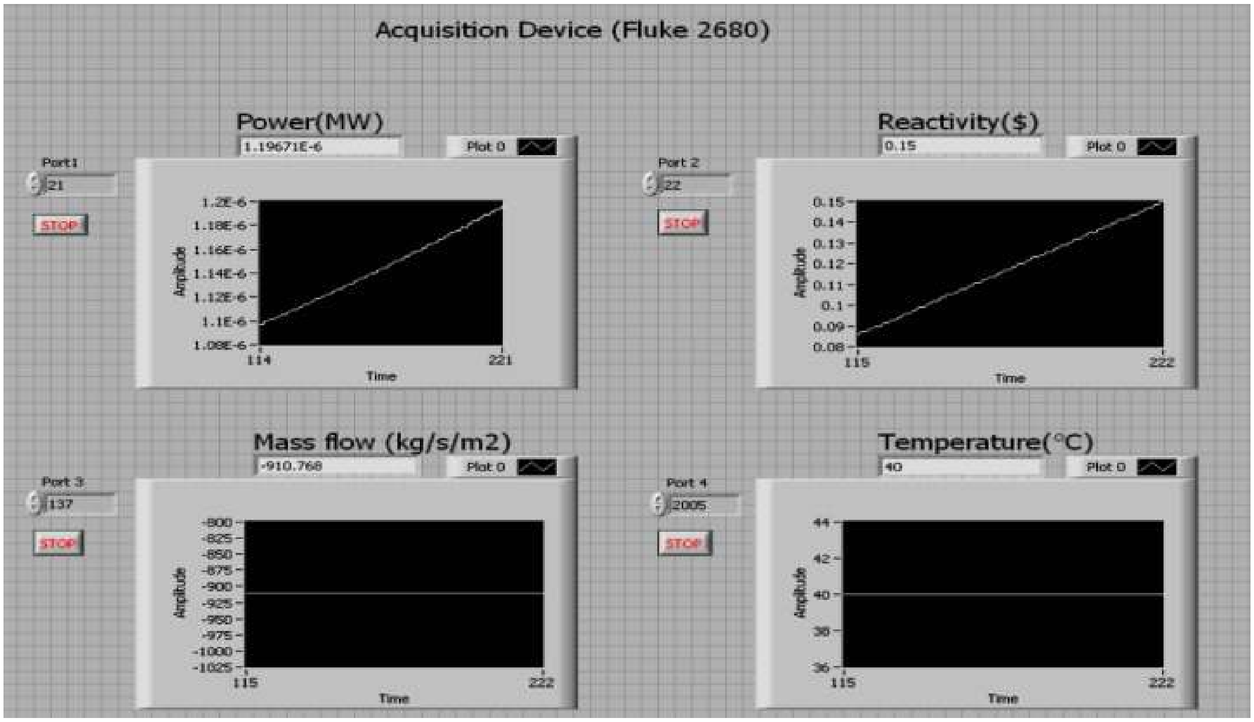

Figure 3. Measured signals displayed by LabVIEW on the acquisition PC.

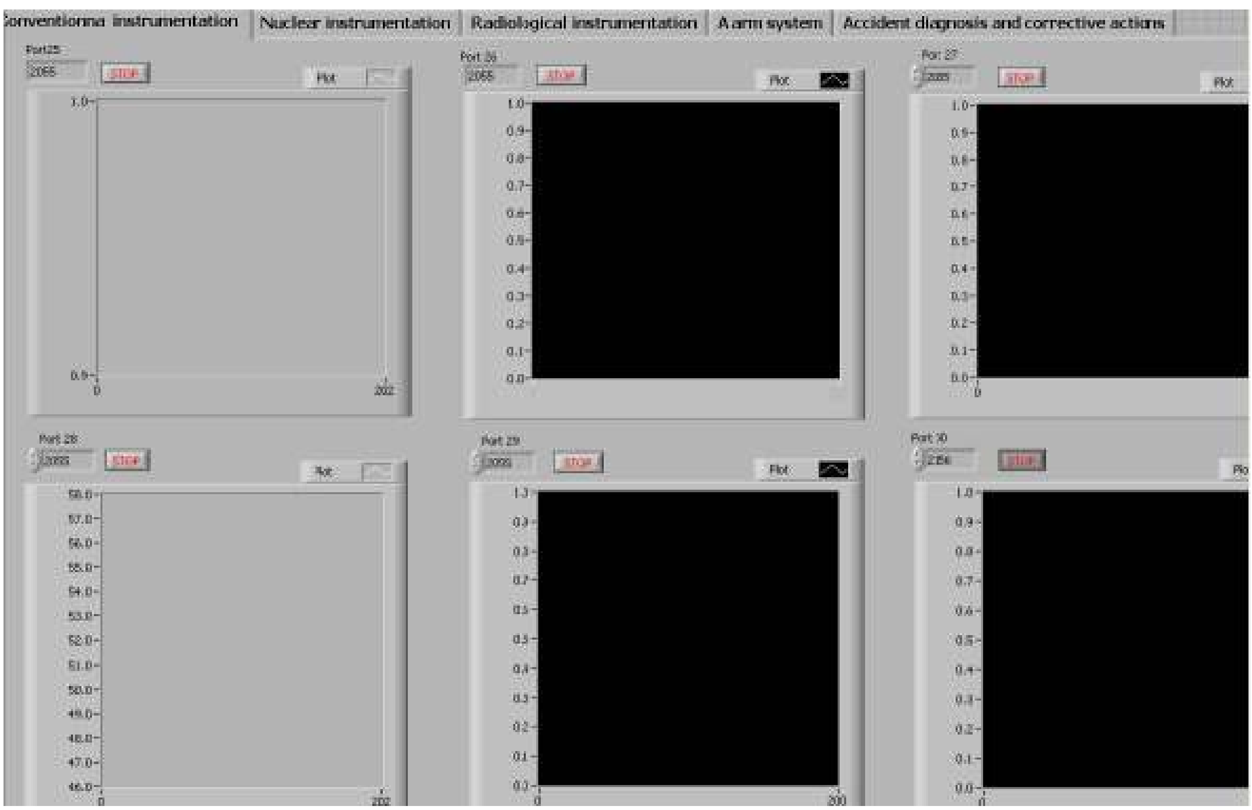

Figure 4. Main human–operator interface of the CMDAS (Windows tab control under development).

node appears as a frame inside the block diagram of a virtual instrument (VI), and then m file can be combined easily with LabVIEW graphical code.

The outputs of the loaded MLPs are then transmitted to a decision-making module to avoid misidentification; the installation status is therefore determined and the corrective actions related to the diagnosed accident are launched below the graphic interface (see Figure 4).

- **Symptom-oriented diagnosis module:** This module implements the thresholds' overshooting based on the alarm system. The safety parameters to trigger the hardware alarms are acquired and compared to the fixed thresholds. An alert is launched when the monitored signals exceed threshold levels (Figure 5).

Figure 5. CMDAS alarm system.

Task4: In archiving, the corrective actions and data are stored in a collection of Microsoft Access tables (accdb) and can be retrieved using the database connectivity toolkit.

3. Diagnosis-based classification by ANNs

The main idea to ensure diagnosis using classification is to define offline the installation classes; each class corresponds to normal or accidental behavior characterized by a collection of measured safety parameters. The online projection of the measures to these classes enables determination of the status of the installation. In this work, neural network classifiers are investigated. For each transient to be diagnosed, a set of safety parameters will act as inputs to neural networks and the type of transient will be the target [15–19].

An ANN comprises numerous interconnected processing units: the neurons, with weighted connections. The neuron calculates the weighted sum of the received signals from upriver neurons multiplied by corresponding weights, adds bias, and then passes the result through a transfer function. The result is transmitted by the unique output of the neuron to the following neurons. The weights of connections and biases are adjusted by a learning algorithm: in the case of supervised learning, the network output is compared against the objective target value and the deviation is fed back to modify the weights and bias. This process is iterated until the output approximates the target to some given accuracy. The arrangement of neurons into the network allows fulfilling the function for which the network is developed as prediction, pattern recognition, control, and diagnosis.

Numerous neural networks topologies are proposed in the literature, which are more or less used for some applications such as MLPs, radial basis functions, self-organizing maps, and probabilistic neural networks.

Among these topologies, those more frequently used in diagnosis problems are the Hopfield models, Kohonen networks, and the MLPs. The MLPs have particularly shown their performance in diagnosis because of their scalability (handling of large databases) and their generalization capacity (the ability of a network to produce a required output from an input vector, similar to its training set).

3.1. Multilayer perceptrons

The MLP is a feedforward network composed by neurons organized in layers.

Input layer: This layer consists of passive nodes, which transmit data to the following layer without any modifications.

Hidden layers: These layers consist of active nodes. The numbers of neurons and layers depend on the problem under investigation.

Output layer: The nodes in this layer are active. The number of neurons in this layer corresponds to the number of the neural network outputs.

In this work, every neuron has a sigmoid transfer function that can be written as below:

$$f(x_i) = 1/(1 + e^{-xi}). \tag{1}$$

The goal of a learning algorithm is to adapt network weights and bias in order to optimize iteratively the error function, which represents a measure of network performance. In our work, the resilient backpropagation algorithm carries out supervised learning of the MLPs.

3.2. The resilient backpropagation algorithm

The resilient backpropagation algorithm is a local adaptive learning scheme. The motivation behind this algorithm is to eliminate the influence of the magnitude of the partial derivative. Only the sign of the derivative can determine the direction of the weight update. The size of the weight changes is determined by a separate update value.

In the training phase, the P prototypes of the learning dataset are presented to the network in a sequential and iterative manner.

3.3. Results and discussion

In this work, classifier-based neural networks that can identify normal and accidental situations affecting the Nur Research Reactor are built, and the steps followed to establish diagnosis are as follows.

1st step: Selection of accidents to be diagnosed: initiating events selected from the reactor risk analysis [20] that are the most dangerous risked events that can arise due to faulty components, subsystems, and systems that insure the core cooling and control. The accidents chosen to be diagnosed are insertion reactivity accident, loss of flow accident, and blackout accident.

It is considered that accidents cannot be simultaneous and have to be diagnosed at different power levels and at different stages of operation, i.e. at startup, during operation, and at shutdown with different severity levels. Others accidental modes will be added later. The accidents not studied in the design step should not be confused with others.

2nd step: Selection of monitored variables and inputs of the neural networks: the measured variables selected to characterize the accidents are chosen among those that activate the alarms and the emergency shutdown of the reactor. The safety parameters selected are primary coolant flow rate $x_1(t)$, difference in core temperature $x_2(t)$, the difference in core pressure $x_3(t)$, reactivity $x_4(t)$, and power $x_5(t)$.

The limits of the parameter inputs of the ANNs are inferred from the safety system, which is the emergency shutdown of the reactor, which is triggered by one of the following trip signals:

- Reactor power $>$ 1.2 MW
- Primary coolant flow rate $<$ 176 m^3/h
- Maximum difference core pressure = 3.281 Pa
- Minimum difference core pressure = 1.028 Pa
- Outlet maximum temperature = 48 $^\circ$C

3rd step: Getting feature vectors for each accidental situation: the installation behaviors described by the state variables selected previously are simulated for the considered installation states. Calculation codes are used to analyze accidents caused by power excursion and reactivity change.

4th step: Preprocessing collected data using mathematical operations while it is found that the best results are obtained using nonnormalized data.

5th step: Construction (offline) of the appropriate neural networks that model the relationship between symptoms and accidents. The accidents' classification is carried out by several MLPs; each network is sensitive to one accident and robust towards the others. As the MLPs are static neural networks, the feature matrix is with moving time windows in order to consider the dynamic evolution of state variables. Feature vectors feeding each network contain three previous samples for each variable (Figure 6). After testing different architectures, the best results of classification are obtained with two hidden-layer MLPs with sigmoid functions, weights, and biases adjusted with the resilient back propagation algorithm even in a noisy environment (see the Table). The TRAINRP algorithm of the MATLAB neural network toolbox is used in the developed program. Simulation results are shown in Figures 7–10.

Table. Noises measurements.

Measurements	Random noises
Primary coolant flow rate	–1 to +1 m^3/h
Difference in core pressure	–1 to +1 Pa
Difference in core temperature	–1 to +1 °C
Reactivity	–0.05% to +0.05%
Power	–5% to +5% MW

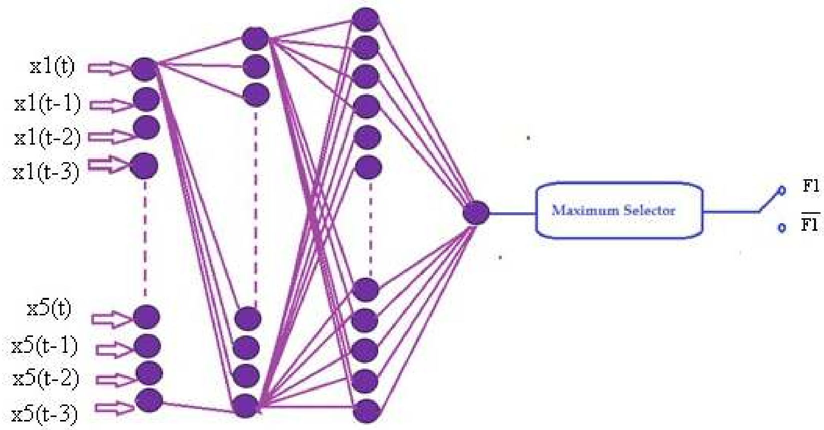

Figure 6. Architecture of one of the accident diagnosis MLPs.

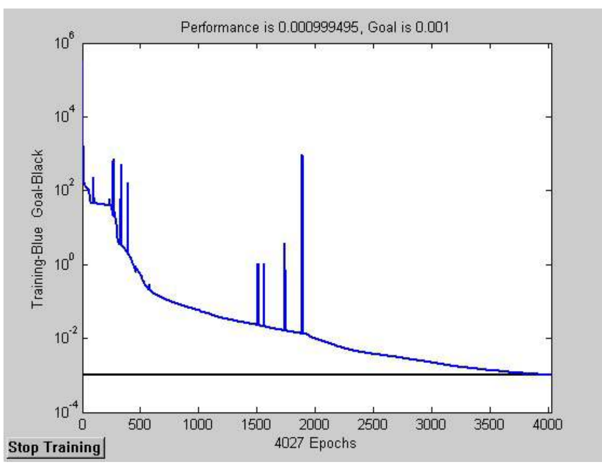

Figure 7. Convergence procedure of a MLP sensitive to a loss of flow accident.

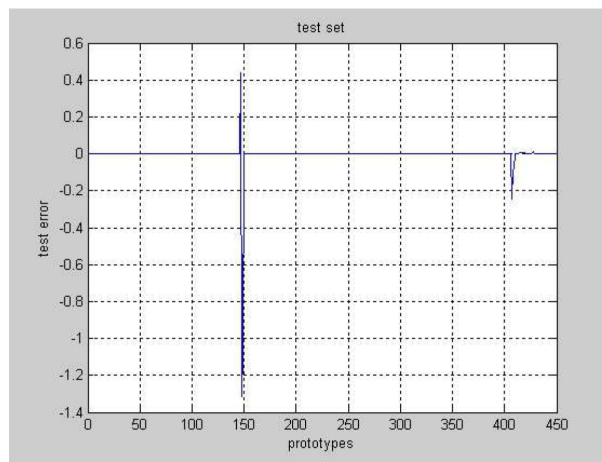

Figure 8. Test error of a neural network sensitive to a loss of flow accident.

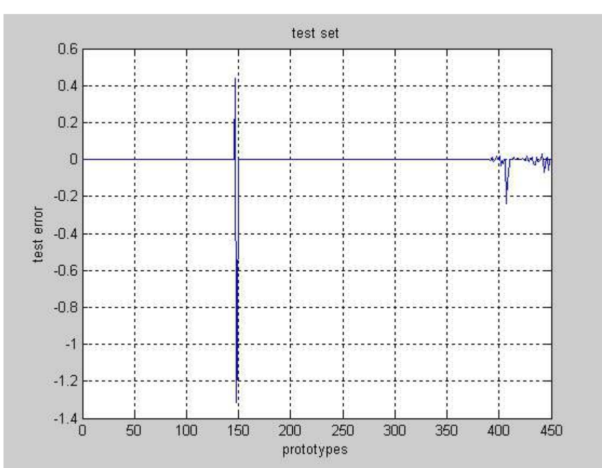

Figure 9. Test error of a neural network sensitive to loss of flow accident in noisy environment.

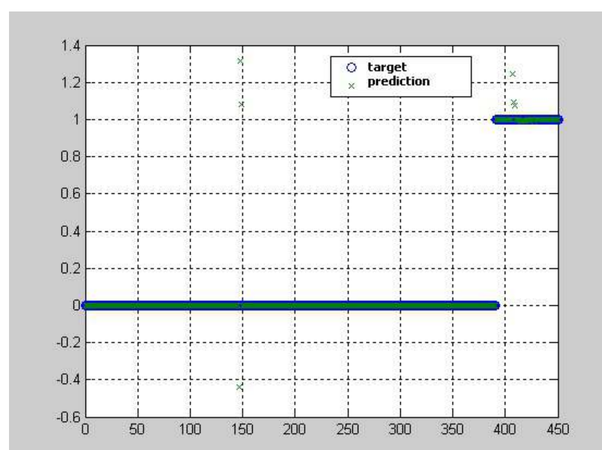

Figure 10. Classification of a neural network sensitive to a loss of flow (test set).

6th step: Testing of the neural networks and comparison with common machine learning algorithms.

Training data:

Hidden layer 1: 40 nodes Hidden layer 2: 80 nodes

Learning rate: 0.85 Momentum constant: 0.35

$\Delta_0 = 0.07; \Delta_{\max} = 50\ \eta^+ = 1.2\ ;\ \eta^- = 0.5$

Common machine learning algorithms that are used in classification in addition to MLPs are nearest neighbors, discriminant analysis, decision trees, naïve Bayes classifiers, and support vector machines. In this part, the performances of naïve Bayes classifiers and decision trees are compared with those obtained with MLPs, except that one classifier has been discussed and not dedicated classifiers because the complete transient database is not yet definitively established. This classifier permits the identification of an accident among blackout (BK), specific reactivity insertion accident (RIA), and specific loss of flow accident (LOFA). The considered RIA is a super prompt insertion of a positive reactivity of 1.5$ in 0.5 s. This transient occurs at a reactor power level of 1 MW. The considered LOFA happens at 1 MW and it is a slow loss of core coolant flow accident as a consequence of main cooling pump failure when the reactor is operating at its nominal power level; the flow decrease is modeled by the function exp (–t/25). After the simulation of these accidents, 568 samples per accident are used to assess the classifiers' performances.

A confusion matrix is used to represent misclassified data; the MATLAB commands 'confusion' (for MLPs) and 'confusionmat' (for naïve Bayes classifiers and decision trees) are used. A good classifier will yield a confusion matrix that will look dominantly diagonal.

If class1, class2, and class3 represent respectively the BK, the RIA, and the LOFA, the following confusion matrix (cm) is obtained with MLPs (details are given in Figure 11):

$$\mathrm{cm} = \begin{bmatrix} 568 & 0 & 0 \\ 0 & 556 & 12 \\ 0 & 0 & 568 \end{bmatrix}$$

This one (M) is obtained with the two other techniques:

$$M = \begin{bmatrix} 568 & 0 & 0 \\ 0 & 568 & 0 \\ 0 & 0 & 568 \end{bmatrix}$$

It can be concluded that the tested machine learning algorithms have approximately similar classification accuracy, but to overcome the weak point of the MLPs to misclassify an accident not considered in the design step to an inappropriate class, dedicated MLPs are synthesized to make decisions after calculating the mean of deviation of each neural network output from the predicted target over a given number of samples.

4. Conclusion

This paper describes the online monitoring and accident diagnosis aid system (CMDAS) proposed to assist Nur Nuclear Research Reactor operators in case of accidental situations. This system was developed using LabVIEW 10.0 and MATLAB 6.5. The advantage to this platform especially lies in the interest to process the recorded safety parameters with several diagnostic techniques elaborated with MATLAB and implemented using the Labview MATLAB script without any changes of the software tool. Moreover, it is shown that the MLP classifiers allow generalization, are easily implemented, and permit early diagnosis in the presence of modeling

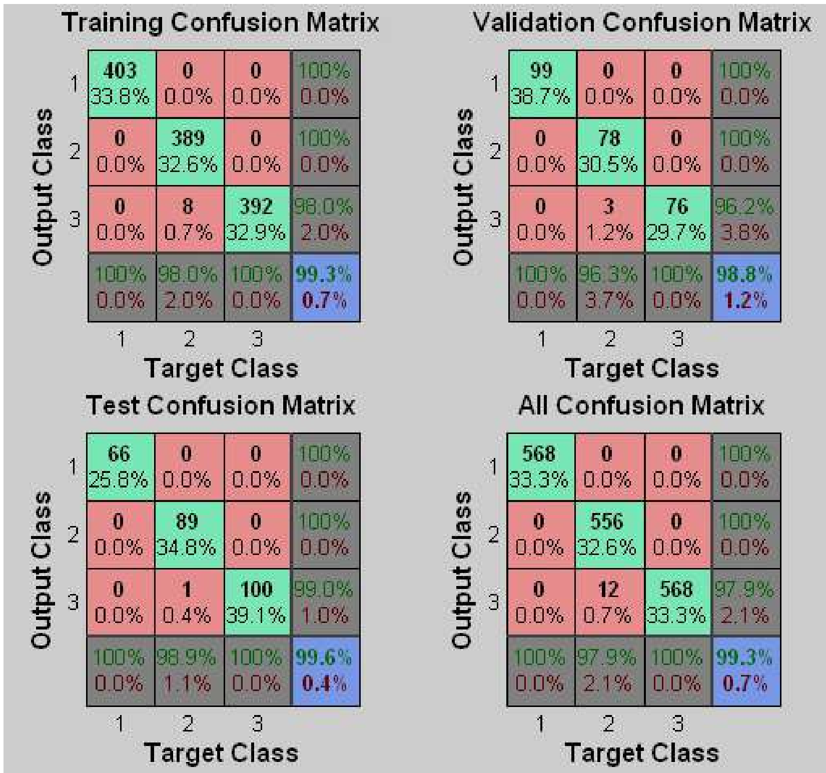

Figure 11. Multilayer perceptron confusion matrix.

incertitude and noisy environments. It is easy to retrain the MLPs in order to consider a new accident or update the networks because of installation aging.

The implemented system is specific to the installation: design specifications of the computerized tool, communication specifications, initiating events to identify, accident symptoms, and calculation codes to simulate reactor behavior. After defining these requirements, the enumerated steps in Sections 2 and 3.3 can be followed to build such a platform for any kind of reactor.

LOFA may have different origins, such as obstruction of the piping, a local power failure, or a main cooling pump failure, but the pump failure is considered among the most harmful; this failure has to be detected and mitigated in an online environment. As future work, fault diagnosis of this pump performed using wavelets and ANNs shall be added to our tool.

This CMDAS is under development; the testing has been done at module level. After building all modules and integrating them into the final software product, the final testing will be carried out. Finally, the CMDAS will be proposed to the local regulatory body to be implemented in the installation.

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