



# Real Time Accidents Diagnosis for Research Reactors using Adaptive Resonance Network

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**Abstract:** Real time locating faults in any nuclear research reactors plants are the highest importance requirements, aimed for safety of human and environmental reasons. Since a great fault can occur in a few milliseconds, accordingly, there is an increasing demand for automated systems to diagnose such failures. Adaptive Resonance network (ART) [1] is a neurofuzzy network, which is an important family of competitive neural learning model. Its memory mode is very similar to that of biological one, and memory capacity can increase while the learning patterns increase. It can perform real-time online learning, and can work under non stationary world. In this research a new proposed a neural network classifier based on ART, which achieved preferable results than several other neural algorithms will be presented. The proposed algorithm obtains and diagnosis faults accidents patterns in the Multi-Purpose Research Reactor of Egypt, to avoid the risk of occurrence of a nuclear accident.

**Keywords:** Artificial Neural Networks (ANN), Adaptive Resonance network (ART), fault diagnosis, Nuclear Reactors, Multi-Purpose Research Reactor of Egypt.

## 1. INTRODUCTION

Fault Detection and Isolation (FDI) has been considered as an important strategy to improve operational performance in a variety of industries for a long time. A fault in a process is defined as any malfunction of sensors, controllers and field devices at the initial stage, which may ultimately affect the operational performance. The most important objectives of fault detection and isolation are to prevent a sudden equipment failure, collect information on malfunctions, improve maintenance planning, and have a better plant control such that optimal operational performance can be achieved. It brings about significant benefits through minimizing the downtime, enhancing the safety and reducing the manufacturing cost [2].

A fault diagnosis system is a kind of operator support system. The objective of a fault diagnosis system is to make the task of accident diagnosis easier, to reduce human mistakes, and to ease the workload of operators by quickly suggesting likely faults based on the highest probability of their occurrence. During the first few minutes after an accident occurrence, operators in a Main Control Room (MCR) must perform highly mentally work loaded activities. The operators may be overworked and disorder may result. Information overload and stress may severely affect the operator's decision-making ability just when it is required. In such situations, using a fault diagnosis

system will be very helpful in that it will enhance operator's decision-making ability and reduce their workload. Recently many advanced intelligence systems have been developed using information and digital technologies.

Adaptive Resonance Network (ART) was developed by Carpenter and Grossberg; Allow the user to control the degree of similarity of patterns placed on the same cluster; Solution to the stability-plasticity dilemma; Plasticity: the ability of a net to respond to (learn) a new pattern equally well at any stage of learning; Stability: remember memorized patterns. ART1 is binary input classification and ART2 is continuous-valued input classification [3].

The ART has the advantage that it is able to deal with several of data types in testing process [4]. In this paper, ART1 is used to propose a real time fault diagnosis algorithm for learning new status of other faults keeping the preserved learning faults by using the stability and plasticity characteristics.

The new algorithm considered as, the feasibility study of the ART1 on the recognition of multiple faults alarms in Egyptian research reactor has been introduced. When a plant disturbance occurs, sensors outputs or instruments may trigger firing of alarms and form a different alarm pattern that represents different faults. The diagnosis of faults is approached from a pattern matching perspective in that an input pattern is constructed from multiple alarm symptoms and that



symptom pattern is matched to an appropriate output pattern that corresponds to the fault occurred. In the new algorithm ART1, where the rules are applied to check whether the input pattern is known else it acknowledges unknown alarm pattern.

The performance of the proposed algorithm is tested with K-means and PCA clustering algorithms. The results distinctly indicate that the proposed algorithm is quite flexible, fast and efficient in computation for fault diagnosis system of a nuclear power plants.

The paper is organized as follows: After the introduction, the Egyptian Second Nuclear Research Reactor is presented in section 2. Section 3 represents ART1 and its basic fundamentals; The Proposed Algorithm is explained in section 4, the results are represented in section five. Finally the conclusion and the future work are explained in section 6.

## 2. EGYPT'S SECOND RESEARCH REACTOR (MPR) OPENED

Nuclear research reactors are essential facilities in the development of nuclear technology for peaceful applications. In research reactors, where the controlled nuclear fission and release of neutrons and radiation take place, basic R & D in nuclear science and engineering can be conducted, radioisotopes and gamma radiation sources are produced. Moreover several applications related to R & D in power reactor simulation and fuel reactor structural materials performance can also be conducted. Research reactors may also be utilized in applications related to human health and electronic industry [5].

The 22 Mw open pool Multi-Purpose Reactor MPR at Inshas, aims at producing radioisotopes for industrial and medical applications, research on neutron physics and personnel training. The reactor features several beam tubes, hot cells, high pressure test loops and other research equipment. The reactor is located at the Inshas site of the Atomic Energy Authority, 60 km from Cairo-Egypt. The reactor building has four levels. The building is seismically qualified and features a massive block built in heavy concrete containing the reactor and auxiliary pools.

A Neutron House is connected to the reactor building through a corridor designed to contain the neutron guide. The reactor pool is cylindrical, has a diameter of 4.5 meters and is built in stainless steel. An auxiliary pool for fuel storage and radioactive materials handling is connected to it.

The core is configured in a 5 x 6 grid surrounded by a Zircaloy chimney, 10 meters below the pool surface. The fuel elements are low enriched uranium type with aluminium cladding. (19.75% Uranium 235). Each fuel element has 19 flat plates. Beryllium

reflectors are positioned around the core outside the reactor chimney.

The core reactivity is controlled six Ag-In-Cd alloy control plates. The plates are driven by mechanisms located beneath the reactor pool. The core is cooled by demineralized water in a forced upwards flow. After shutdown, the decay power is removed by natural circulation of the reactor pool water.

### A. Waste management

Irradiated fuel elements are stored in baskets at the auxiliary pool. The basket design and coolant conditions ensure that integrity of the fuel cladding is preserved. The radioactive liquid waste management system classifies, collects and temporarily stores liquid waste originated during operation of the reactor. The system also includes a LOC drainage system, with enough capacity to store all the water contained in the reactor and auxiliary pools.

### B. Instrumentation & Control System

The reactor is monitored, controlled and managed by the Instrumentation and Control Systems.

### C. Reactor Protection System - RPS

The Reactor is protected by the Reactor Protection System, which monitors roughly 5 safety parameters and signals to detect any potentially unsafe condition, automatically triggers the safety systems.

The plant construction is very sturdy and its safety margins are ample. The plant complies with all Safety Standards and Guides of the International Atomic Energy Agency (IAEA) on Research Reactors Safety.

### D. Reactor Facilities

MPR has Facilities for R&D and radioisotopes production.

### E. Neutron beam facilities

From the beryllium reflector, one tangential tube with two openings and two radial tubes, leave the reactor tank for neutron beam uses. The tangential tube leads towards a tunnel that leads to the Neutron House building. A neutron guide will be used to send the neutron beams to the different instruments to be placed in the Neutron House. A graphite-filled thermal column covers one of the sides of the core. This column ends in a radial channel leading to a hot cell for Neutron Boron Capture Therapy Development.

### F. Neutron radiography system

One radiography system is placed outside one of the radial tubes. Another such system is located inside the reactor tank for underwater radiography of highly activated samples.

### 1. Material Science

A hot cell at the auxiliary pool top, is provided for lodging different material testing equipment. Samples can be easily transported from the reactor pool to this cell.

#### G. Activation analysis

There are two pneumatic transport systems, enabling fast and safe transference of capsules between the reactor core and the end stations at radiochemical hoods in the hot laboratory. This system is especially suited for neutron a activation analysis.

The operation of the reactor is controlled and monitored using: the suspension and control system (SCS) and the Reactor Protection System (RPS). The SCS provide process information to the operator in charge allowing to control the process systems evolution and reactor power. The RPS is basically a control system that generates the signals for the protective functions to be carried out by the safety systems. The RPS encloses all electrical and mechanical devices and Circuitry involved in generating those initiation signals associated with protective function carried out by the safety actuation systems [6].

The reactor protection system is based on intelligent units combined with hardware voting protective logic's are placed in the instrumentation room. The faults detectors and sensors are been placed as close as possible to the variables that they supervise. The following accidents diagnosed:

1- Loss Of Flow Accident (LOFA), 2- Loss Of Power Supply (LOPS), 3- Loss Of Heat Sink (LOHS), 4- Small Loss Of Coolant Accident (SLOCA), 5- Medium Loss Of Coolant Accident (MLOCA), 6- Large Loss Of Coolant Accident (LLOCA), 7- Uncontrolled Slow Reactivity Insertion (USRI), 8- Uncontrolled Fast Reactivity Insertion (UFRI) and 9- Normal case [6].

### 3. ADAPTIVE RESONANCE THEORY

Adaptive resonance theory allows the user to control the degree of similarity of patterns placed on the same cluster; Solution to the stability-plasticity dilemma; Plasticity: the ability of a net to respond to (learn) a new pattern equally well at any stage of learning; Stability: remember memorized patterns. ART1 is binary input classification and ART2 is continuous-valued input classification.

ART1 neural networks cluster binary vectors, using unsupervised learning. The neat thing about adaptive resonance theory is that it gives the user **more** control over the degree of relative similarity of patterns placed on the same cluster.

An ART1 net achieves stability when it cannot return any patterns to previous clusters (in other words,

a pattern oscillating among different clusters at different stages of training indicates an unstable net. Some nets achieve stability by gradually reducing the learning rate as the same set of training patterns is presented many times. However, this does not allow the net to readily learn a new pattern that is presented for the first time after a number of training epochs have already taken place. The ability of a net to respond to (learn) a new pattern equally well at any stage of learning is called plasticity (e.g., this is a computational corollary of the biological model of neural plasticity). Adaptive resonance theory nets are designed to be both stable and plastic.

The basic structure of an ART1 neural network involves:

- an input processing field (called the  $F_1$  layer) which happens to consist of two parts:
  - an input portion ( $F_1(a)$ )
  - an **interface** portion ( $F_1(b)$ )
- the cluster units (the  $F_2$  layer)
- and a mechanism to control the degree of similarity of patterns placed on the same cluster
- a reset mechanism
- weighted bottom-up connections between the  $F_1$  and  $F_2$  layers
- weighted top-down connections between the  $F_2$  and  $F_1$  layers

$F_1(b)$ , the interface portion, combines signals from the input portion and the  $F_2$  layer, for use in comparing the similarity of the input signal to the weight vector for the cluster unit that has been selected as a candidate for learning[4].

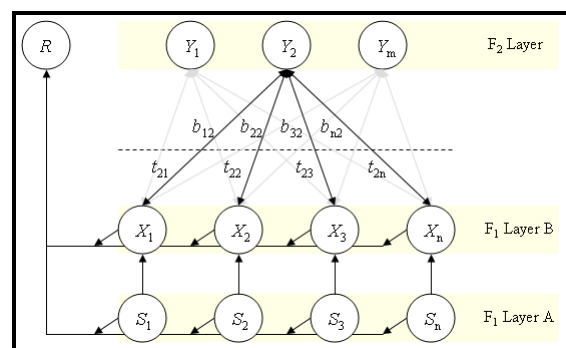


Figure 1. A simple ART1 structure.

To control the similarity of patterns placed on the same cluster, there are two sets of connections (each with its own weights) between each unit in the interface portion of the input field and the cluster unit. The  $F_1(b)$  layer is connected to the  $F_2$  layer by bottom-



up weights ( $b_{ij}$ ). The  $F_2$  layer is connected to the  $F_1(b)$  layer by top-down weights ( $t_{ij}$ ).

The  $F_2$  layer is a competitive layer: The cluster unit with the largest net input becomes the candidate to learn the input pattern. The activations of all other  $F_2$  units are set to zero. The interface units,  $F_1(b)$ , now combine information from the input and cluster units. Whether or not this cluster unit is allowed to learn the input pattern depends on how similar its top-down weight vector is to the input vector. This decision is made by the reset unit, based on signals it receives from the input  $F_1(a)$  and interface  $F_1(b)$  layers. If the cluster unit is not allowed to learn, it is inhibited and a new cluster unit is selected as the candidate. If a cluster unit is allowed to learn, it is said to classify a pattern class. Sometimes there is a tie for the winning neuron in the  $F_2$  layer, when this happens, then an arbitrary rule, such as the first of them in a serial order, can be taken as the winner [7].

During the operation of an ART1 net, patterns emerge in the  $F_1a$  and  $F_1b$  layers and are called traces of STM (short-term memory). Traces of LTM (long-term memory) are in the connection weights between the input layers ( $F_1$ ) and output layer ( $F_2$ ).

#### A. Similarity and the Vigilance Parameter

The degree of similarity required for patterns to be assigned to the same cluster unit is controlled by a user-defined gain control, known as the *vigilance parameter*. For ART1, the reset mechanism is designed to control the state of each node in the  $F_2$  layer. At any time, an  $F_2$  node is in one of three states:

- **Active**
- **Inactive**, but available to participate in competition
- **Inhibited**, and prevented from participating in competition

One problem that ART1 runs into is that the final weight values and created clusters depend, to some degree, on the order in which the input vectors are presented. The vigilance parameter helps to solve this: The higher the vigilance is raised, the less dependent the clusters become on the order of input.

In adaptive resonance theory, the changes in activations of units and in weights are governed by coupled differential equations. The net is a continuously changing (dynamic) system, but the process can be simplified because the activations are assumed to change much more rapidly than the weights. Once an acceptable cluster unit has been selected for learning, the bottom-up and top-down signals are maintained for an extended period, during which time the weight changes occur. This is the "resonance" that gives the net its name.

#### B. ART1 Learning: Fast vs. Slow

ART nets generally use one of two types of learning: Fast and Slow. In the fast learning mode, it is assumed that weight updates during resonance occur rapidly, relative to the length of time a pattern is presented on any particular trial. The weights reach equilibrium on each trial with fast learning. In slow learning mode the weight changes occur slowly relative to the duration of a learning trial; the weights do not reach equilibrium on a particular trial. Many more presentations of the patterns are required for slow learning than for fast, but fewer calculations occur on each learning trial in slow learning. Generally, only one weight update, with a relatively small learning rate, occurs on each learning trial in slow learning mode.

In fast learning, the net is considered stabilized when each pattern chooses the correct cluster unit when it is presented (without causing any unit to reset). For ART1, because the patterns are binary, the weights associated with each cluster unit also stabilize in the fast learning mode. The resulting weight vectors are appropriate for the type of input patterns used in ART1. Also, the equilibrium weights are easy to determine, and the iterative solution of the differential equations that control the weight updates is not necessary (i.e., as it is in the ART2 algorithm).

#### C. The pseudo code for ART1 algorithm

Step1. Initialization of parameters and weights

$$L=1 \ \& \ 0 \ \rho \leq 1$$

$$0 < b_{ij}(0) < \frac{L}{L-1+n}$$

Where  $n$  is the number of components in the input vector  $t_{ij}(0)=1$ . For each training input

Step2. Activation states of all  $F_2$  neurons are set to zero and all  $F_1(a)$  neurons are assigned to the input vector  $S$ .

Step3. Computation of norm of  $S = (\|S\|) \sum s_i$

Step4. Sending signals from  $F_1(a)$  to  $F_1(b)$  layer  $x_i = s_i$

For each  $F_2$  node that is not already inhibited

Step5. Calculation of net input of that particular  $F_2$  node provided the 'reset' is true.

$$y_j = \sum (b_{ij}x_i)$$

Step6. Finding highest  $y_j$  among all  $y_j$ 's.

Step7. Re-computation of  $x$  of  $F_1(b)$  layer.  $x_i = s_i t_{ij}$



Step8. Computation of the norm of vector  $x = ||X|| = \sum x_i$

Step9. Test for reset, if  $\{\frac{||x||}{||s||}\} < \rho$ , the  $j^{th}$  node is inhibited else continue from Step 5. If  $\{\frac{||x||}{||s||}\} > \rho$

Step10. Updation of weights for node  $j$ ,

$$bij = \frac{Lxi}{L-1+||x||} \& t_{ji(new)} - x_i$$

- No change in top-down or bottom up weights.
- No reset
- Maximum number of epochs exceeded

Normalization of data matrix:

All the elements in the scaled matrix are lying between 0-1.

The linear scaling function for zero to one transforms a variable  $x_k$  into  $x_k^*$  in the following way:

$$x_k^* = \frac{\min(x_k) \text{ for all } j\text{'s}}{\max(x_k) \text{ for all } j\text{'s} - \min(x_k) \text{ for all } j\text{'s}}$$

where,  $k$  and  $j$  are column and row of the data matrix respectively.

#### 4. IMPLEMENTATION OF THE PROPOSED ALGORITHM

For the diagnoses of nuclear reactor accidents, a simulation proposed computer program is developed using MATLAB environment for this purpose, ART1 algorithm program was designed and employed to construct an artificial neural fault diagnosis for second's Egyptian research reactor.

The data used in the test application were collected by the aid of reactor operation and ENRRA crew and Safety Analysis Report (SAR) of the reactor, in addition to the Atomic Energy experts. The data sets are for the eight accidental cases (Classes) listed below; plus the normal operation case as shown in Figure .2. So the total cases, which we have, are nine.

[0 0 0 0 1 1 1 1 1 1 1 1 1 1 1]
[0 0 0 0 0 1 1 1 1 1 1 1 1 1 1]
[1 1 0 1 1 0 0 1 1 1 1 1 1 1 1]
[1 1 1 1 1 1 1 0 1 1 0 1 1 1 1]
[1 1 1 1 1 1 1 0 0 1 0 0 1 1 1]
[0 0 0 0 1 1 1 0 0 0 1 0 1 1 1]
[1 1 1 1 1 1 1 1 1 1 1 0 0 0 0]
[1 1 0 0 1 1 1 1 1 1 1 0 0 0 0]
[1 1 1 1 1 1 1 1 1 1 1 1 1 1 1]

Figure .2. Sample of reactor accidents data patterns.

#### 5. RESULTS AND DISCUSSION

After a fault has been detected using the proposed algorithm, an expert system or classification algorithm is used to determine the fault type. The diagnostic system utilized in this research uses monitoring system residuals to determine fault type.

The faulted system residuals are compared to those contained in a database of historical residual signatures to determine under which fault the system is operating. Similar systems may be built using additional features, such as the results of the PCA fault detection routine including PC values or T2- and Q-statistics [8]. For the current application, the Results of K-mean, PCA and ART1 are represented in table 1 to 3 for fault classification.

TABLE 1 RESULT OF K-MEAN CLASSIFICATION

Category	class	Fault number
1	1	Fault no 1, 2,
2	2	Fault no 3, 6,
3	3	Fault no 4, 5,
4	4	Fault no 7, 8,
5	5	Fault no 9,

TABLE 2 RESULT OF PCA CLASSIFICATION

Category	class	Fault number
1	1	Fault no 1, 2, 9
2	2	Fault no 3, 6,
3	3	Fault no 4, 5,
4	4	Fault no 7, 8,

TABLE 3 RESULT OF ART1 CLASSIFICATION

Category	class	Fault number
1	1	Fault no 1,
2	2	Fault no 2,
3	3	Fault no 3,
4	4	Fault no 4,
5	5	Fault no 5,
6	6	Fault no 6,
7	7	Fault no 7,
8	8	Fault no 8,
9	9	Fault no 9,

As shown, the Results of K-mean, PCA and ART1 the ART1 gave more accurate classifications in small time are represented. The algorithms are applied on different data for the faults of the nuclear reactor in normal state and when they



contain faults patterns in order to recognize it in real time. To evaluate the performance of the proposed algorithm, Also, the same samples of faults are tested with three algorithms, K-means, PCA clustering algorithm and ART1. The results are reported in Table 4 and 5.

**TABLE 4. CPU EXECUTION TIME FOR RECOGNIZING OF PATTERNS**

Fault name	K-mean	PCA	ART1
Fault1	0.16	0.14	0.04
Fault2	0.15	0.12	0.05
Fault3	0.14	0.13	0.08
Fault4	0.15	0.12	0.08
Fault5	0.16	0.13	0.05
Fault6	0.16	0.12	0.06
Fault7	0.14	0.14	0.06
Fault8	0.14	0.13	0.06
Fault9	0.15	0.12	0.05
Average CPU	0.15	0.127	0.065

**TABLE 5 THE PERFORMANCE CPU EXECUTION TIME AND HIT RATE PARAMETERS COMPARISON.**

Algorithm name	Average CPU time Second	Hit rate for learnt Faults	Hit rate for unlearnt faults
K=mean	0.15	88%	60%
PCA	0.127	90%	50%
ART1	0.065	100%	90%

From tables 4 and 5, ART1 is much better than the K-mean, PCA from two aspects, CPU execution time and Hit rate. When the Fault is not learnt before (unsupervised learning), the ART1 method has high performance since it can classify or cluster any new pattern or the new fault with new classification and recognize it with high Hit rate

## 6. CONCLUSION AND THE FUTURE WORK

The proposed algorithm is tested with various patterns of for different faults. The results are compared with the solutions obtained from K-means clustering, PCA and ART1. The proposed ART1 exhibits its superiority over PCA and K-means in terms of CPU time or number of iterations. Since the algorithm uses simple network architecture, the results are obtained in a single iteration whereas more number of iterations is required both in PCA and K-means clustering depending on the learning faults. Therefore, the ART1 is found to be computationally efficient for real time fault diagnosis with quick solutions in our applications. This new algorithm was designed to diagnosis and to predict the Multi-Purpose Research

Reactor of Egypt accidents, to avoid the risk of occurrence of a nuclear accident.

In the future, a sequential Hardware ART1 neural Network can be implemented using Xilinx FPGA family [9]. The implementation on FPGA provides the higher benefits of lower costs and higher results, since, FPGA can be reprogrammed for an unlimited number of times [10]; they can be used in innovative designs where hardware is always in dynamic change. In addition, we can implement the new hybrid algorithm as neural network's hardware model that can be integrated within the Reactor Protection System (RPS) as a future work, where valuable interesting results will obtain.

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