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Agent Based Fuzzy ARTMAP Neural Network for Classifying the Power Plant Performance

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Abstract

In this paper, we present a "Fuzzy ARTMAP" neural network model on a power station in Al-Daura Refinery for the multi-agent process as a classifying system to improve the process real-time performance. The proposed model is a combination of the Adaptive Resonance Theory (ART) neural network and fuzzy logic control, a supervised model having high on-line classifying accuracy learning mechanism with superior performance. The model has been applied for each agent autonomously according to agent's behaviour and standard level (S.L.) control. Results have shown that the "Fuzzy ARTMAP" neural network is able to precisely learn to classify the data fusion from the multi-agent process to three classes: class (S) when the data fusion are within the (S.L.), class (H) when the data fusion are higher than the (S.L.) and class (L) when the data fusion are under the (S.L.). Also, the "Fuzzy ARTMAP" is able to learn the rules and the parameters accurately with low cost, high performance and less effort.

Keywords: Adaptive Resonance Theory; Neural Network; Fuzzy Logic Control; Fuzzy ARTMAP; Power Plant Performance

1. Introduction

Recently, the agent technology has been considered as an important approach for developing the intelligent systems that shows promises for improving their performance under real-time distributed environment. The agent technology is the fundamental cell of the distributed intelligence that provides many different solutions to commonly known problems faced in many fields. Hence, its artificial intelligence (AI) can be built by using all (AI) implementation technology currently known and it can compute regardless of its current location. However, the primary feature of agent technology is the agent's ability to communicate with each other. This enables the agents to unite their efforts to become a collective of working individuals who are aware of each other's goals. The neural network (NN) is one of the popular (AI) techniques, widely used in many applications. [1].

The ARTMAP is a class of neural network architecture that performs incremental supervised learning recognition to the input vectors. The first ARTMAP system was used to classify inputs by the set of features (also called pattern or vector) they possess of a binary values representing the presence of absence of each possible feature [2]. A new system, more general is called the fuzzy ARTMAP was developed to classify the inputs by a fuzzy set of features, or patterns of fuzzy memberships values between 0 or 1 indicating the extent to which each feature is presented[3-4].

A verity of fuzzy ARTMAP on a cluster of workstations learns the required tasks fast and has the capability for on-line learning was implemented. It has the ability to provide the learning structure that allows explaining the answers that the neural network produces [5].

In this paper, a Fuzzy ARTMAP neural network model is proposed to classify the process performance of the multi-agent's behaviors in Al- Daura Refinery power station.

2. The Agent Definition

“The term agent can be defined as "anything that can be viewed as perceiving its environment through sensors & acting upon that environment through effectors"[6]. Alternatively, are software entities that carry out some set of operations on behalf of a user or another program with some of independence or autonomy and in so doing, employ some knowledge or representation of the user's goals or desires? “[7].

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3. The Multi-Agent Systems

Multi-agent system can be used not only in distributed environment but in centralized system as well. For instance, having multiple agent could speed up systems operation by providing means for parallel computing Particularly situations where the system design are highly modular, meaning that separate tasks are clearly divided and could be delegated to agents. The parallelism of the multi-agent systems can help to deal with limitations imposed by time-bounded reasoning requirements [6]. Generally, the term multi-agent system covers all types of systems composed of multiple autonomous components showing the following characteristics: [1].

- Each agent has incomplete capabilities to solve a problem and the data is decentralized.
- There is no global system control and the computation is asynchronous.

Figure (1) illustrates that each agent is part of the environment and modeled as a separate entity .There may be any number of agents, with different degree of heterogeneity and with or without the ability to communicate directly.

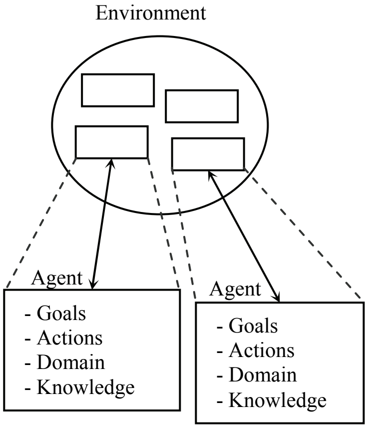

Figure 1: A General Multi-Agent framework [1].

4. The Fuzzy logic control

The basic idea behind Fuzzy Logic Control (FLC) is to incorporate the "expert experience" of a human operator in the design of the controller in controlling a process whose input–output relationship is described by a collection of fuzzy control rules (e.g., IF-THEN rule) involving linguistic variables rather than a complicated dynamic model. This utilization of linguistic variables, fuzzy control rules, and approximate reasoning provides a means to incorporate human expert experience in designing the controller [7]. In figure (2), a fuzzy controller is shown embedded in a closed-loop control system. The plant output is denoted by y (t), its input is denoted by u (t), and the reference input to the fuzzy controller is denoted by r (t).

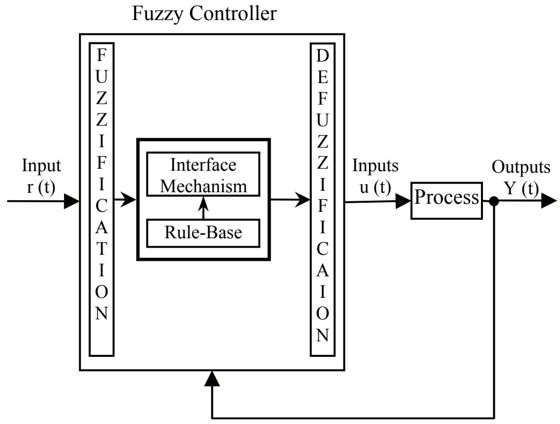

Figure 2: Fuzzy controller architecture [7].

5. The (ARTMAP) Neural Network

The ARTMAP stands for the Adaptive Resonance Theory with mapping. An ARTMAP network consists of two side-by-side ART models as shown in figure (3), the first ART is ARTA, which processes the input to detect categories of inputs. The second ART is ARTB, which examines the set of known outputs for output categories. The expectation or winning pattern from each ART is compared in a Mapping Field for a match.

The network processes the input and selects the appropriate category in the layer F_2^A based on the setting of the vigilance parameter ρ_A. The pattern associated with the winning F_2^A category is presented to the Mapping Field, which is labeled on the diagram as Inter- ART Associative Memory. Similarly, the paired output vector associated with the input vector is applied to the input of the ARTB network (right). The ART network then determines an appropriate output category for the ARTB input. The pattern associated with the winning F_2^B category is also presented to the Mapping Field. The two patterns are then compared with each other in the Mapping Field and held up against the Inter-ART vigilance parameter. If the match between the ARTA and ARTB output vector is suitable, then the weights between the layer F_2^A and the Mapping Field are adjusted to match the pattern presented by layer F_2^B. Simultaneously, the ARTA network resonates and learn its input pattern.

When the patterns at the Mapping Field do not meet the vigilance criterion, an Inter-ART reset is issued. During the Inter– ART reset, the vigilance parameter of the ARTA network is raised just far enough so that the winning neuron of ARTA no longer wins the competition. This causes the ARTA network to seek or create a new category in layer F_2^A . This particular feedback ensures that a new category is selected for data that does not fit the current pattern set. By dynamically adjusting the ARTA vigilance, the ARTMAP network ensures that there will be just enough categories created to cover all possible input-output pairs [10].

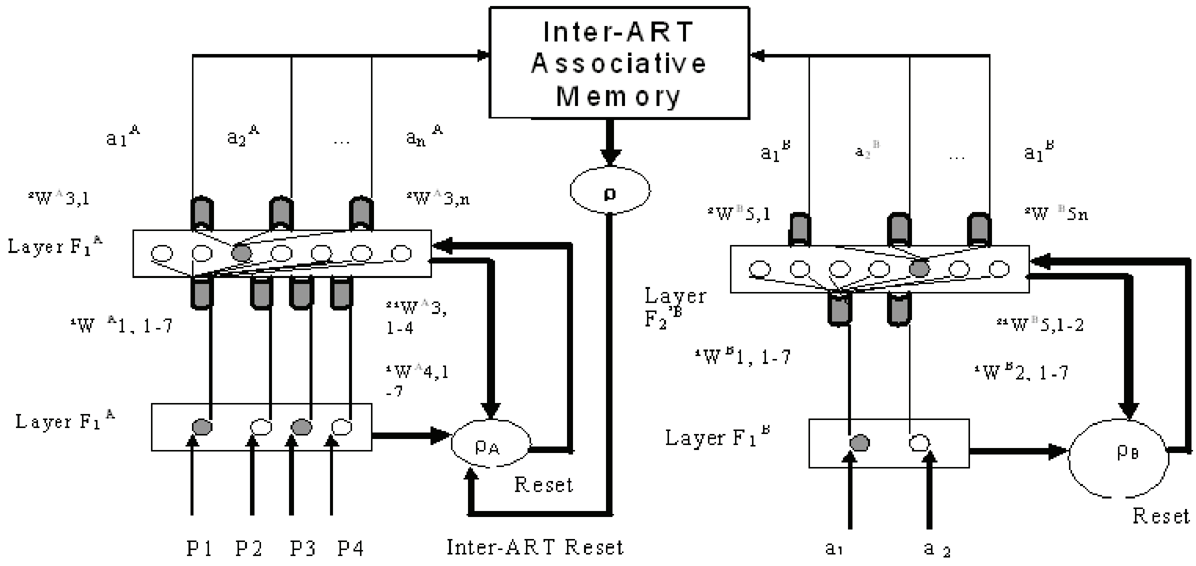

Figure 3: Block diagram of ART architecture [10].

6. Al-Daura Refinery Multi-agent Process

In general, the boiler is a device for generating a steam, which can be used for the production of power or for the heating purpose. The thermal power station boiler usually consists of different equipments working together with the aim of converting chemical energy of fuel in to heat energy in the steam, which is generated at certain pressure and temperature. The energy stored in the steam is converted to kinetic energy in the turbine then in to electrical energy in the power generator .For this reason, it is obviously clear that the performance of the boiler will directly affect the whole power system. Therefore, it is logical to seek better conditions for improving the performance of the power plant station.

In Al-Daura Refinery, the boiler shown in figure (4) has been selected as a prototype for this research. The boiler has a performance of 310 KW; its continuous operating rate for steam is 142 ton/hr at a temperature and pressure of 260 °c and 20 bar at full load. The feed water is fed in to the boiler by the feed water pumps to the economizer tubes. In the economizer, the water absorbs heat from the flue gases leaving the boiler and its temperature increases to a certain value, which is below the saturation temperature corresponding to the drum pressure. From the economizer, water flows in to the drum from which the water flows to the water walls through the down comer in a natural circulation mode. In this circulation, a great amount of heat will transfer to the water so that boiling takes place, and the motion of fluid is setting up resulting from the density difference caused by the temperature difference in the fluid. As the water from the bottom of the water walls flows upward, the process of heat transfer takes place, and at the top of the water walls, a certain percentage of the water may be vaporized. When the water-steam mixture flows back to the drum, condensation and vaporization take place simultaneously.

The water, which separates from the water-steam mixture, will mix with the water at the bottom of the drum. This water has a temperature slightly below the saturation temperature and flow in the down comer with the water coming from the economizer for the next circulation. The separated steam leaves the drum and enters the super heater section.

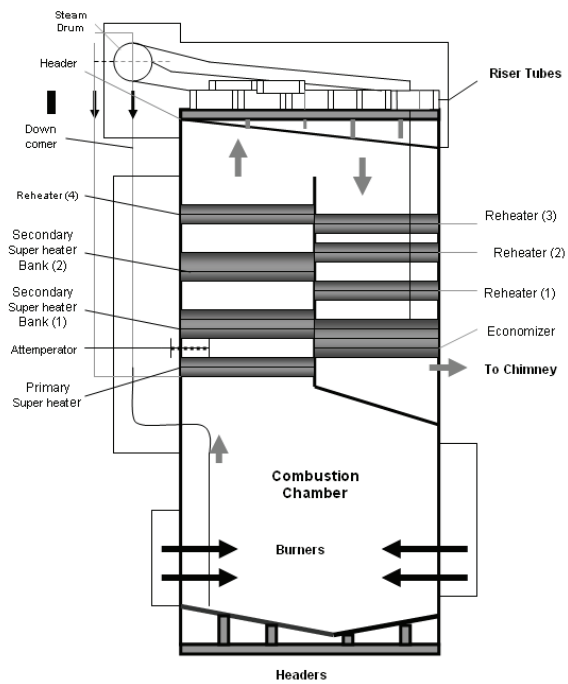

Figure 4: The Boiler System.

In the super heater section, the steam passes through various tube banks. These tubes are mounted in the horizontal position and some are vertical .This super heater is divided to primary super heaters and secondary super heaters, each consists of two bank tubes .There is a spray attemperator between the outlet of the second bank of the primary super heaters and the inlet of the secondary super heater. The attemperator is used only for controlling the temperature of the steam flowing to the high-pressure turbines. The exhausted steam from the high-pressure turbine is reheated in the four reheaters mounted in the convection section in order to raises its temperature to be used in the driving of the intermediate pressure turbine [11].

To extend life and managing operations and control activities of the power generation unit, information and network technologies have to play an important role to ensure the safety functioning and controlling the unit operations. The data and knowledge basis will be used for the analytical methods as inputs-outputs database in the construction of the agent – based genie project. Table (1) illustrates the multi agent process of the boiler hardware.

Table 1: illustrates the Boiler control system items.

No.	Items	Units	Tags (Agents)	Standard Level
1.	Steam Drum Level	mm	LRCA-1355	+50 to +200
2.	Boiler Feed Water Flow	Ton/hr	FRC-1357	70 to 110
3.	Boiler Feed Water Pressure	Bar	PI-1360	33 to 40
4.	Boiler Feed Water Temperature	°C	TR-1352	115 to 125
5.	Boiler Feed Water Level	mm	LIC-1351	+100 to +200
6.	Main Steam Flow	Ton/hr	FR-1356	50 to 110
7.	Main Steam Temperature	°C	TRCA-1353	260 to 280
3.	Main Steam Pressure	Bar	PICA-1361	19 to 20
9.	Fuel Oil Pressure	Bar	PIA-1356	6.8 to 15
10.	Fuel Oil Flow	m^2/hr	FRC-1351	3 to 7.5
11.	Oil/Steam Diff. Pressure	Bar	PDICA-1354	1.5 to 3
12.	Fuel Oil Temperature	°C	TAR-1351	90 to 110
13.	Low Pressure Steam	Ton/hr	PI-1351	1 to 3

7. The Implementation Methodology

7.1. The Agent Configuration Management

The behavioral agents combine to give an overall configuration management system for the complete product lifecycle. This system has been developed to support earlier work on change propagation in an integrated design environment where the behavioral agents define the rules for co-operation and change management also it has the knowledge about the design entities and their relationships. The first aspect of the configuration management scheme is the labeling of the design model and hence the process of change is represented within our labeling scheme as referring to Table 2. The agents are labeled as shown in Table 2

7.2. The Behavioral Agents

The behavioral of agents is the representation of each design discipline in the agent structure, which contains the rules about the co-operation and negotiation with other agents and uses these to control the final output. Its goal is the global consistency of data and the ability to reflect the change in all the models of a disparate design process. The rules for controlling these agents depend on the relationships between them. Figure 5 describe the relationship between these agents.

Table 2: The Labeled Agents.

No.	Agents	Label	No.	Agents	Label
1.	LRCA-1355	A	8.	PICA-1361	H
2.	FRC-1357	B	9.	PIA-1356	I
3.	PI-1360	C	10.	FRC-1351	J
4.	TR-1352	D	11.	PDICA-1354	K
5.	LIC-1351	E	12.	TAR-1351	M
6.	FR-1356	F	13.	PI-1351	Q
7.	TRCA-1353	G			

1	Agent (A.) → Agent (B.)		7	Agent (G.) → Agent (M.)	
2	Agent (B.) → Agent (A.)		8	Agent (H.) → Agent (K.)	
3	Agent (C.) → Agent (J.)		9	Agent (I.) → Agent (J.)	
4	Agent (D.) → Agent (Q.)		10	Agent (J.) → Agent (C.)	
5	Agent (E.) → Agent (B.)		11	Agent (K.) → Agent (I.)	
6	Agent (F.) → Agent (J.)		12	Agent (M.) → Agent (Q.)	

Figure 5: The Relationship between the Agents

8. The Fuzzy "ARTMAP" Algorithm

The Fuzzy ARTMAP Algorithm is used for each agent in the boiler for classifying. This algorithm is summarized as follows:

Step 0: Let m be the number of input units, n be the number of output units, M be the number of units on F_2^a, and N be the number of the units on F_2^b. Initially, all the adaptive weights W_j^a, W_k^b and W_{jk}^{ab} are set equal to 1.

$$W_{j1}^{a}(0) = \ldots = W_{j2m}^{a} = 1 \tag{1}$$

$$W_{k1}^{b}(0) = \ldots = W_{j2n}^{b} = 1 \tag{2}$$

$$W_{jk}^{ab}(0) = 1 \tag{3}$$

Where j=1,…, M and k=1, …, N

Initialize all category nodes of ART modules, ART_a & ART_b then set the parameters: The choice parameter $\alpha > 0$. The learning rate parameter $\beta \in [0, 1]$. The vigilance parameters ρ_a, ρ_b, $\rho_{ab} \in [0, 1]$. Set the ART_a vigilance parameters, ρ_a, to the baseline vigilance, ρ_a.

Step 1: Present a binary or analogue vector **a** and the corresponding class vector **b**. The vector **a** is input to the model ART_a and the vector **b** is input to the model ART_b. All input values of vector **a** must be with the range [0, 1]. If not, the inputs to the ART_a are analogue, then the input vector **a** should be normalized. The component coding is also required to preserve amplitude information, then the component coded for input vector A is input to the field F_1^a. While the component coded for input vector B is input to the field F_1^b.

$$A = (a, a^c) = (a_1, ..., a_m, a_1^c, ..., a_m^c) \quad (4)$$

$$B = (b, b^c) = (b_1, ..., b_m, b_1^c, ..., b_n^c) \quad (5)$$

Step 2: For each input vector **A** and **B**, the j^{th} node in the layer, F_2^a, and k^{th} node in the layer, F_2^a, are given by:

$$T_j(A) = \frac{|A \Lambda W_j^a|}{\alpha + |W_j^a|} \quad (6)$$

$$T_j(B) = \frac{|B \Lambda W_k^b|}{\alpha + |W_k^b|} \quad (7)$$

Where the fuzzy MIN operator $\wedge$ is defined to be $(x \wedge y)_I = (x_I, y_I)$, α is a choice parameter, and the norm $|\,.\,|$ Is defined to be: $|x| = \sum |x_i|$ for any vector x and y.

Step 3: Use a winner-take-all rule to select the winner. This yields the maximum weighted sum. The winner of ART_a and ART_b are indeed by j and k respectively where:

$$J = \max\{T_j(A) : j = 1, ..., M\} \quad (8)$$

$$K = \max\{T_k(B) : k = 1, ..., N\} \quad (9)$$

If more than one node is maximal on each module, the node with the smallest index is chosen to break the tie.

Step 4: Check the vigilance criteria. If nodes j and k satisfy the conditions.

$$\frac{|A \Lambda W_J^a|}{|A|} \geq \rho_a \quad (10)$$

$$\frac{|B \Lambda W_k^b|}{|B|} \geq \rho_b \quad (11)$$

The nodes j and k are chosen to represent the input pattern **A** and **B**, and proceed to **Step 5**. After the categories represented by nodes j and k are selected for learning, they become committed. If they violate the above condition, then node j and k are reset and move back to step 3. Search for another node in the F_2^a and F_2^b that satisfies vigilance criterion respectively.

Step 5: Check to see whether the match-tracking criterion is satisfied .If

$$\frac{|y^b \; \Lambda \; W_J^{ab}|}{|y^b|} \geq \rho_{ab} \quad (12)$$

Then we have achieved the desired mapping and continue to **step 6** for LTM (Long Term Memory) learning. If

$$\frac{|y^b \; \Lambda \; W_J^{ab}|}{|y^b|} < \rho_{ab} \quad (13)$$

Then the mapping between J and K is not the desired one. In this case, the vigilance parameter ρ_a is increased until it is slightly larger than $|A \wedge W_J^a| / |A|$;this leads to an immediate reset of node J in ART_a and a move to Step 3 with the new vigilance parameter for the selection of another node in F_2^a that will achieve the desired mapping.

Step 6: The weights $\mathbf{W}_j^a$ and $\mathbf{W}_k^b$ are updated by the equations.

$$W_j(t) = \beta\,(A \; \Lambda \; W_J(t\text{-}1)) + (1\text{-}\beta)\, W_J\,(t\text{-}1) \quad (14)$$

$$W_k(t) == \beta\,(A \; \Lambda \; W_K(t\text{-}1)) + (1\text{-}\beta)\, W_K\,(t\text{-}1) \quad (15)$$

Where the learning rate β is chosen in the range [0, 1]. In the fast learning mode, β is set to 1. The weights W_j^a, $j \neq J$ and W_k^b, $k \neq K$ of non-winning nodes are not updated. For efficient coding of noisy input sets, fast-commit and slow recording, which is to set $\beta < 1$ after the category committed, is normally being used. The Map Field weights with fast learning are determined by:

$$W_{jk}^{ab}(t) = 1 \quad \text{if } j = J,\ K = k \quad (16)$$

$$W_{jk}^{ab}(t) = 0 \quad \text{if } j = J,\ K \neq k \quad (17)$$

$$W_{jk}^{ab}(t) = W_{jk}^{ab}(t\text{-}1) \quad \text{otherwise} \quad (18)$$

Step 7 Go to **Step 1** and present a next pattern pair.

Tables 3 illustrate the fuzzy ARTMAP parameters used for the simulation. To perform useful functions in these environment agents, the agents must be both pro-active and reactive. To be pro-active it must be able to choose actions directed towards achieving specific goals or specific tasks. To be reactive it must be able to respond in a timely manner to unexpected changes in the environment.

Table 3: The Fuzzy ARTMAP parameters

Parameters	Description
$\epsilon = 0.001$	Match tracking parameter (increase ART_a vigilance).
$\alpha = 0.001$	Choice parameter for search order of fuzzy ART modules.
$\beta_a = 0.001$	Fuzzy ART_a learning rate.
$\beta_b = 1.0$	Fuzzy ART_b learning rate.
$\beta_{ab} = 1.0$	Map field learning rate.
$\rho_a = 0.0$	Baseline Fuzzy ART_a vigilance.
$\rho_b = 1.0$	Baseline Fuzzy ART_b vigilance
$\rho_{ab} = 1.0$	Map field vigilance

The exploration of the network variations begin by varying the baseline vigilance. The selection of the proposed Fuzzy ARTMAP decision thresholds for the output class is divided to three classes as the following:

A) (L) class: which means that the data received from the environment is less than the standard level.

B) (H) class: which means that the data received from the environment is higher than the standard level.

C) (S) class: which means that the data received from the environment is at the standard level (the desired situation) then it will switch out to the environment and will not enter to the LCS systems. Figure (6) shows the architecture of the fuzzy ARTMAP for each agent.

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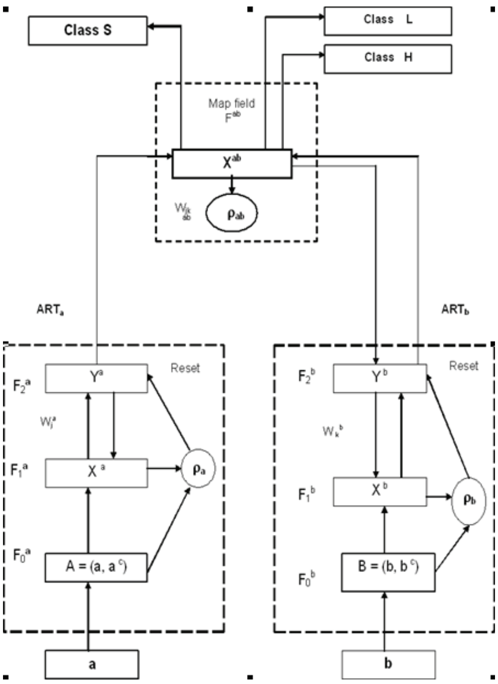

Figure 6: The Fuzzy ARTMAP Architecture

9. The Model Implementation

The proposed software model for the multi-agent process is designed to train the fuzzy ARTMAP neural network for each agent separately depending on each specification and according to its procedures, the training data must be prepared previously. The data were extracted from the position every one hour according to the boiler practical situation for ten days from 1-9-2005 to 10-9-2005. Figure (7) shows the software framework of the model. Table (4) shows a sample of the running model.

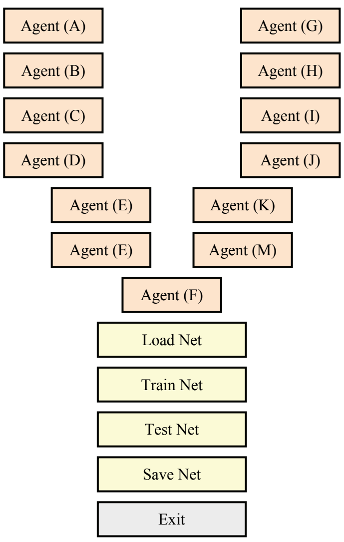

Figure 7: The Fuzzy ARTMAP Software Model

Table (4): A Sample of Agent (A) running

Agent (A)	Level	Agent (A)	Level	Agent (A)	Level	Agent (A)	Level
0.744396	S	0.858539	S	156.3232	S	180.2932	S
0.062749	S	0.421835	S	13.17725	S	88.58543	S
0.63739	S	0.179003	S	133.8519	S	37.59062	S
0.390038	S	0.50259	S	81.90791	S	105.5439	S
0.254596	L	0.081625	L	53.4651	S	17.14123	L
0.239384	S	0.673162	S	50.27063	S	141.3641	S
0.647367	S	0.789433	S	135.9472	S	165.781	S
0.495934	S	0.088526	S	104.1462	S	18.5905	S
0.711368	S	0.933985	S	149.3873	S	196.1369	S
0.694442	S	0.852391	S	145.8327	S	179.0021	S
0.504162	S	0.291228	S	105.8739	S	61.15791	S
0.270286	S	0.828359	S	56.76009	S	173.9553	S
0.851376	S	0.858949	S	178.7889	S	180.3792	S
0.027961	L	0.29293	L	5.87174	L	61.51524	L
0.245269	S	0.769304	S	51.50646	S	161.5537	S
0.270299	S	0.454756	S	56.76278	S	95.49866	S
0.386139	S	0.509952	S	81.08924	S	107.0898	S
0.455443	S	0.31024	S	95.643	S	65.15031	S
0.208302	S	0.655997	S	43.74339	S	137.7595	S
0.574673	S	0.115217	S	120.6812	S	24.19567	S
0.219899	S	0.594284	S	46.17871	S	124.7995	S
0.713845	S	0.599868	S	149.9075	S	125.9722	S
0.639814	S	0.32645	S	134.361	S	68.55455	S
0.374743	L	0.006961	L	78.69595	L	1.461829	L
0.933769	S	0.221965	S	196.0914	S	46.61265	S
0.802363	S	0.165468	S	168.4963	S	34.74826	S
0.099974	L	0.166485	L	20.99444	L	34.9618	L
0.872549	S	0.679405	S	183.2354	S	142.675	S
0.247839	S	0.928698	S	52.04625	S	195.0267	S
0.053878	S	0.687809	S	11.31435	S	144.44	S
0.340041	S	0.685062	S	71.40856	S	143.8629	S
0.849493	S	0.911357	S	178.3935	S	191.3849	S
0.40166	S	0.739697	S	84.34867	S	155.3364	S
0.076722	L	0.06972	L	16.11169	L	14.64119	L
0.373449	S	0.146526	S	78.42431	S	30.77039	S
0.490832	S	0.016048	S	103.0747	S	3.370002	S
0.656086	S	0.739813	S	137.778	S	155.3608	S
0.085137	S	0.796391	S	17.87885	S	167.2422	S
0.736338	S	0.370583	S	154.6309	S	77.82237	S
0.788468	S	0.029144	S	165.5782	S	6.120259	S
0.325551	S	0.705109	S	68.36575	S	148.0729	S
0.263995	S	0.229709	S	55.43899	S	48.23896	S
0.153648	S	0.824593	S	32.26615	S	173.1646	S
0.511195	S	0.21376	S	107.351	S	44.88963	S
0.439011	S	0.707089	S	92.19228	S	148.4888	S
0.116731	L	0.091639	L	24.51352	L	19.24409	L

10. Conclusions

The "Fuzzy ARTMAP" neural network has an on–line fast learning mechanism and has the superior performance for classifying, with very low computing costs for learning strategy. The experiments emphasize that the boiler performance has been classified to three classes: class (S) when the data fusion is within the standard level (S.L.), class (H) when the data fusion are higher than the standard level (S.L.) and class (L) when the data fusion are under the standard level (S.L.). This finding emphasizes that the dynamic fuzzy neural network has a potential for mapping the error and detecting the class's deviation with less efforts and low cost. The effectiveness of using the dynamic fuzzy ARTMAP is confirmed by the simulation results in which three typical levels has been present

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