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Voting Algorithm Based on Adaptive Neuro Fuzzy Inference System for Fault Tolerant Systems

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Abstract

Some applications are critical and must design Fault Tolerant System. Usually Voting Algorithm is one of the principle elements of a Fault Tolerant System. Two kinds of voting algorithm are used in most applications, they are majority voting algorithm and weighted average algorithm these algorithms have some problems. Majority confronts with the problem of threshold limits and voter of weighted average are not able to produce safe outputs when obtaining a correct output is impossible and also both of them are not able to perform appropriately in small error limit. In the present paper, delivering a voter for safety system, Adaptive Neuro-Fuzzy Inference System (ANFIS) is proposed. The above mentioned model is trained through Hybrid learning algorithm that is effective and using basic Fuzzy inference system, subtractive clustering and fuzzy C-means method. Results show that delivered voter produced more safety outputs especially for small error amplitude.

Keywords: *ANFIS, Adaptive Neuro-Fuzzy Inference System, Voting Algorithm, Fault Tolerant Systems, Safety-Critical Systems.*

1. Introduction

Getting reliable outputs is the main goal of computer systems. In the case of human's life or human's property, this target is more important. When occurrence of any problem in a system can result in irreparable loss; these types of systems are called critical system. It is obvious that designing and modeling of these systems are different form the designing and modeling of normal systems. As the system of flight control and the system of controlling the nuclear power plant [1], [5].Such system should be more resistance against error. There are 3 general methods for overcoming the errors and keeping the system in the normal situation. These methods are:

1)Preventing the occurrence of an error
2)Covering the error
3)Resistance of the system against the errors [11].

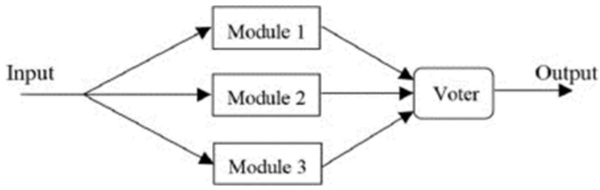


Figure 1. Triple-Modular Redundancy voting system [2],[12]

The most important method used in making the system resistant against errors is the method of redundancy. This can be used in hardware and software. One of the redundancy methods instead of using one item, n similar items that have the same synchronic effects on the inputs will be used. This type of systems called TMR. As a result, there will be n outputs while there should be only one output. So these modules submit the outputs to a voter. The voter produces one output by using a specific algorithm. Here, the voting on a redundancy system which has 3 modules will be studied (figure 1).

The main task of a voter is the selection of the most reliable and the safest output among several outputs. Each voter includes several inputs (the outputs of modules), one algorithm for the selection of the best output, one output which is the final output. The voters can be used in controlling systems, special applications, and surfaces of the sensors [1, 5]

The voting algorithms are used in the selection of the modules in a system which is resistant against errors and when the production of a correct output is not possible, they should be able to produce a secure output. Many algorithms have been suggested but each one has its specific advantages and disadvantages in the recent years, the number of using the Genetic algorithms, fuzzy logic and neural networks has increased. By using these methods, resistance against errors has progressed prominently.

According to the learning ability of the neural network which is the result of combination of the neural network and fuzzy logic, many studies have been offered [4].

The presence of weight in the algorithm and the production of weight in the weighted voting algorithm as data mining and processing of pictures is a time consuming activity in the reality.

In many algorithms, the distribution of the weighted is not justified. The present research tries to produce a suitable weight for each output of a module by studying the previous methods and using ANFIS.

2. Related Work

Among different types of voting, inexact majority has the highest level of frequency. In this algorithm, among several outputs of modules, the output of the voter is the item that most of the module's outputs have agreed on it by offering the same value if the values of module's outputs are 9, 11, 9.5 and threshold value is 0.5, this algorithm will selected 9.5 as the output weighted average voter is another type of voter which has the highest frequency. And it is used in the systems that are resistant against errors. This target includes two different types: 1) static 2) dynamic.

In the static type, according to the history of the system operation the weights are determined in advance. In the dynamic type, according to the available information about variables and the distance between inputs, the weights are determined. In the algorithm of dynamic production of weight, offered by lorczak if inputs are shown by x_i

and input weight of I is shown by w_i, the following formula is used for the calculation of the weight [3]:

$$d_{ij} = \left| x_i - x_j \right|;\ i, j = 1, 2, \ldots, n;\ i \neq j \tag{1}$$

In this formula, d_{ij} is the distance between two inputs.

In this step, difference between inputs will be calculated two by two. Here, this relation should be used in the process of the calculation of the weight:

$$w_i = \frac{1}{1 + \prod_{\substack{i,j=1 \\ i \neq j}}^{n} \frac{d_{ij}}{\alpha^2}} \tag{2}$$

In this formula, *i* and *j* are showing the number of inputs and *x* is a parameter that its value is determined by the type of the used system and *n* is number of module. The final output is calculated by:

$$z = \frac{\sum_{i=1}^{n} x_i . w_i}{\sum_{i=1}^{n} w_i} \tag{3}$$

Beside weighted algorithm, Lorczak offered median algorithm in which, among several inputs of voter, the median of them is selected as the output of the system. Here, the parameter of threshold is not needed. (For example among 10, 12, 15 then 12 is the output of median voter). A fuzzy voter algorithm has been offered in which fuzzy logic is used for the production of the suitable weights. In this algorithm, difference between the inputs of voter will be converted to fuzzy values by using fuzzification system. These fuzzy values include small, median and large by using fuzzy logic, the weights will be produced that are suit able to the differences of the distances between inputs.

The values produced by fuzzy system can be categorized in different levels: very low, low, medium, high, and very high. This categorization is based on what each pair of distance has agreement on it. When the output of an input in a fuzzy system is very high, it means that the output is heavier than its input [5]. The defuzzification systems can show the fuzzy produced weight by numeral values and finally by using formula 3, the final output can be calculated.

Another study has tried to offer suitable weights (weighted average) for the average of weight algorithm by using learning ability of the neural networks [6]. Many algorithms have been offered for the voter systems, but this article explained them briefly. Inexact majority, weighted average and median are the most useful and the most important algorithms that are used in applied systems.

And given that many voting algorithms were presented in recent years such as [12], [13], [14], new policyis presented here.

3. ANFIS Voter

ANFIS is a combination of fuzzy logic and neural networks. One of the most important features of fuzzy system is that it is a science that can be shown by logical rules and neural networks can use these experiments and knowledge. By using the combined patterns of fuzzy and neural networks, the concept of neuro-fuzzy controller has developed. The target of the fuzzy logic is the combination of the human logic inputs and voting [4]. In modeling, the physic of system can't be understood by neural network. In other word, mostly, making connection between parameters of network and parameters of the process is not possible. Beside this, combination of the abilities of neural network and fuzzy system result in the production of a more useful method. Neuro-fuzzy method is an ideal solution for the complicated problems [7].

FIS model focuses on the intelligent use of system description. This model includes logical rules as in then rules that are produced to make quality relationship between variables. By using these natural rules, information can be stated in the syntax of the natural language. As a result, an oral model of description will be produced [8]. Sometimes, this method operates weakly in regulation the linguistic knowledge with variable inputs.

FIS includes membership functions which match the rules and the structure of Inference engine should be determined in advance for the model system by regulating the expert knowledge. Because of the problem of the classification of the voter, it is suggested to pay attention to the shape of the membership function and the structure of the inference engine. So, instead of will full selection of the parameters of membership functions and the structure of FIS, because of the variability of data, input and out data will be regulated by a new optimization method which is called Anfis.[9]

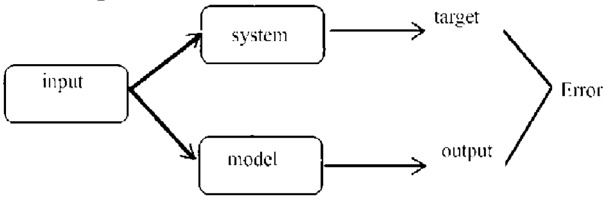


Figure 2. learning phase in a neural system

In designing the fuzzy system the behavior of the fuzzy system can be shown in quantitative values by using these data. And it can be said that if the behavior of fuzzy system is suitable or not. To improve the system behavior, it should be similar to the model behavior.

The output of the real system is called target which is shown in figure 2. The output of the model is called output. When the values of the target and the output of each input are equal, the model can describe the system precisely. The difference between the values of target and output is the error rate. By changing the model's parameters, its behavior will be similar to the system's behavior. It means that the error rate will be close to the cost function will have the lowest value. A series of operation takes place in a neural network is called learning fuzz. Cost function of the results of MSE is calculated by this Formula:

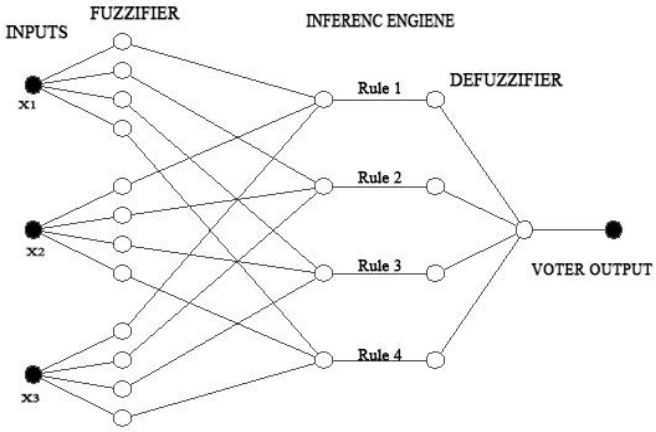
$$MSE = \frac{1}{n}\sum_{i=1}^{n}(t\arg et - output)^2 \tag{4}$$

In this formula, $i$is the number of each step and n is the number of all steps in the cycle of learning. Output is the model's output and Target is the system's target. In each cycle, output and target have different values.

This article has tries to use Anfis to offer a voter algorithm which is resistant against errors and comparison with other voters has a higher level of safety.

4. Methodology

This study is done on a redundancy system which has n items and outputs of a TMR system have been studied and compared with each other. For simulation of this system, this generating function is used: 100 sin (t) +100 in this function, an invariable distribution I used in the production of data. The model of test harness is used been used in most of the studies that are about this subject. Implementation and simulations of the new method have been done by Matlab software because this software is a high level programming language that focuses on the calculation techniques. This software is useful for mathematical operations, basic programming, and drawing chart and engineering graph.



Figur 3.Fuzzy inference system with subclustering model for voter in the studied area

ANFIS voter is presented with two models of initial structure:

First, ANFIS voter is generated with initial structures, and for ANFIS voters the following settings are used:

Two kind of methods for ANFIS in this paper is presented and they named by ANFIS voter A and ANFIS voter B.

ANFIS voter A: an initial structure with a subtractive clustering algorithm. Figure 3 shows basic structure of FIS through subtractive clustering in order to introduce models having rule 4 and output membership function 4 through following relation:

$$y_i = p_i(x_1) + q_i(x_2) + r_i(x_3) + k_i \tag{5}$$

y_i is a membership function relating to rule i and p_i, q_i, r_i *and* k_i linear parameters for rule i.

Voter output is calculated through following relation:

$$VoterOutput = \sum_{i=1}^{n} \frac{y_i - w_i}{w_i} \tag{6}$$

n is the number of rules and w_i is the influence level of i rule that is calculated through the following equitation(relation 7).

$$w_i = \mu_{1,i}(x_1) \times \mu_{2,i}(x_2) \times \mu_{3,i}(x_3) \tag{7}$$

$\mu_{j,i}$, is membership function of input *j* (*j=1*for x_1, *j=2* for x_2, *j=3* for x_3).

ANFIS voter B: an initial structure with a Fuzzy C-mean algorithm and 33 rules and 33output membership function. Generate Fuzzy Inference system structure form data using FCM clustering by extracting a set of rules that the models data behavior. When there is only one output, we can use it to generate an initial FIS for ANFIS training.

Then, Input Membership function parameters are optimized with a hybrid algorithm and the mean squares error (MSE) estimate for output Membership function parameters. Finally, this method is used to control over-fitting enhancing the generalization capability. Although the latter method has more rules than the first method and is time-consuming method but has better in dealing with large errors. Phase, is tried to reach the minimum value of MSE in model.

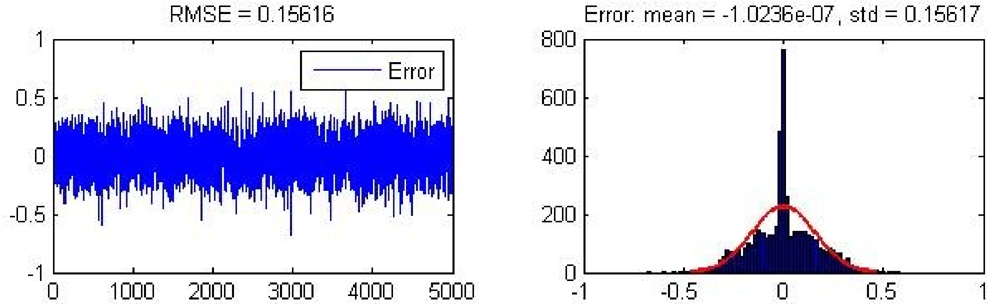


Figure 4. Train diagram for 5000 data and emax=1

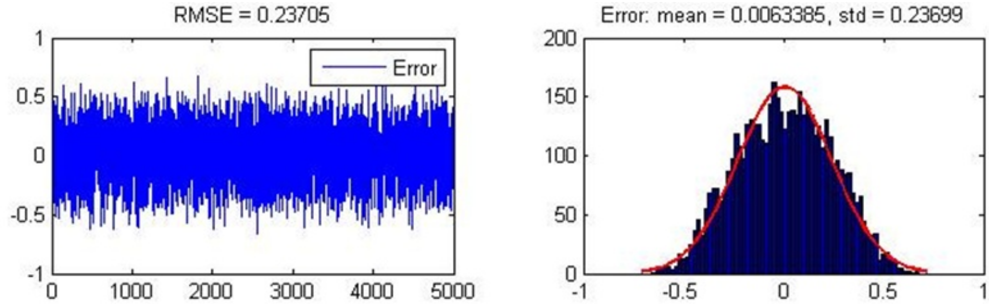


Figure 5. Test diagram for 5000 data and emax=1.

In figure 4, level of RMSE , MSE and output diagram and target in train phase in ratio to emax[1]=1 and 5000 data displayed. As it is shown that mean value RMSE is 0.15 that although it is not a very low value but for a threshold that is 0.5, RMSE value is calculated by relation (8), RMSE value show approximate of output and target.

$$RMSE = \sqrt{MSE} \qquad (8)$$

RMSE indicates "Root Mean Square Error" and the quantity in the square "MSE". "MSE" is calculated in relation (4).

In train phase, 3 conditions are considered for training ANFIS voter:

A condition when all of 3 voters work correctly.

A condition that one voter work correctly and 2 other voters have some error.

A condition that 2 voters work correctly and an error injects to one voter.

Next, can see output diagram and target in test phase in ratio to emax=1 and 5000 data (Figure. 5). At each stage of the learning phase output of the system and to compare the mean squared error, root mean square error and standard deviation calculated. Considering the amount of neuro-fuzzy system to update the network

[1]The largest error amplitude that applied at every cycle of the voting input.

parameters to produce output that is closer to the goal. In Figure 5, test phase is done on 5000 input data.

In each stage of educating output of model through comparing target and values of MSE, RMSE and STD are calculated. And through considering values of neuro-Fuzzy update network parameters in order to produce an output that is approximate to the target. Then, system is tested through 50% data.

Since the presented anfis voter, always have output. This increases the number of response or false outputs. So states that are likely to generate the incorrect output, it does not produce output or generate NaN output and this creates safe scenarios in voting system. For considering the safe conditions: first, the difference between inputs is calculated were then examined to determine the distance between two inputs (D_i) shouldn't be less than α and more than β; in other word $\alpha < D_i < \beta$ and α, β were obtained by Repeated tests on program. These are different for diverse error values.

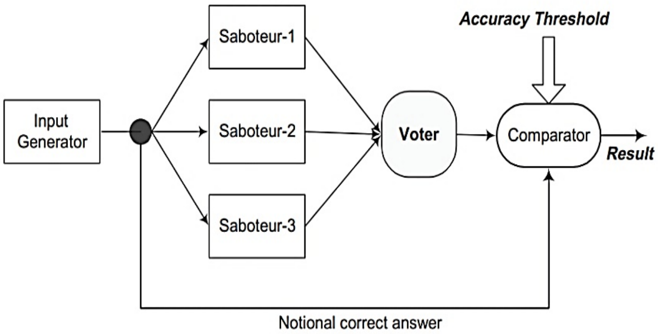


Figure 6. Experimental harness[5,6]

5. Experimental Method

On the purpose of testing voter, test harness is used. In figure 6, test harness is depicted for TMR system. This model is used in literature and it consists of one data generator, 3 saboteurs, one voter and one comparator. Data generator produces all needed data of different voting. A data generator produced all data of different voting cycles. A data that has been produced in each cycle will be sent to saboteur. In each cycle, 2 saboteurs are active randomly and inject fault to inputs. Then through using output algorithm, each saboteur is considered as a voter entry. Voter through using proposed algorithm will produce an output. On the purpose of testing accuracy of output that has been produced through voter, one comparator will be used in order to compare voter output and data product from data generator in the same cycle. If their difference is lower than thresholds, output of system is correct.

In this article is assumed threshold= 0.5 and voter, comparator, data generator, and repeater are fault-free.[5], [6]

For showing output results, is acted like before:

N: Number of all runs of a voter in a given test. N is10000 Test Data for each run [10].

Na: Number of agreed results among N output. Availability is defined as the ratio of agreed voter results to the number of voting actions: A=Na/N. A belong to [0 1] and ideally A=1[11], [12].

Nc: Number of agreed–correct results.

Nic: Number of incorrect agreed results. the safety criterion can be defined as S=1-Nic/N. S belong to [0 1] and ideally S=1 .[11]

Nb: Number of disagreed results among N outputs (number of benign outputs). N=Nc+Nic+Nb. [10]

System inputs are generated through function of 100 sin (t) + 100 and t=0.01

Always an error happens in 2 modules from 3 modules and produced through using random function and uniform distribution in return of [-emax +emax]. [5,6]

The obtained results are compared with majority and weighted average. We use these two algorithms for comparing an introduced algorithm that are used in most of practical systems.

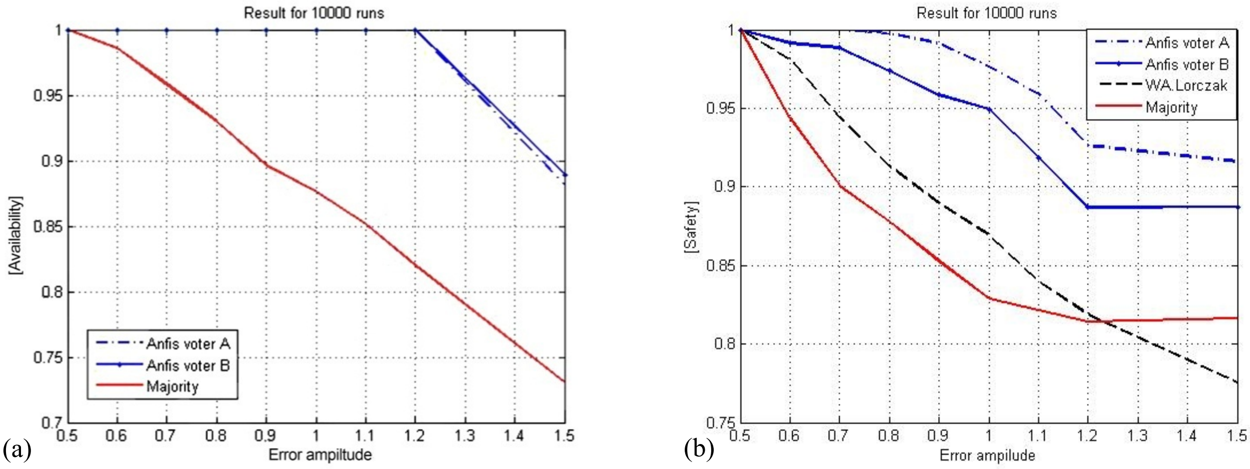


Figure 7. Voter performance with small errors: (a) availability and (b) safety

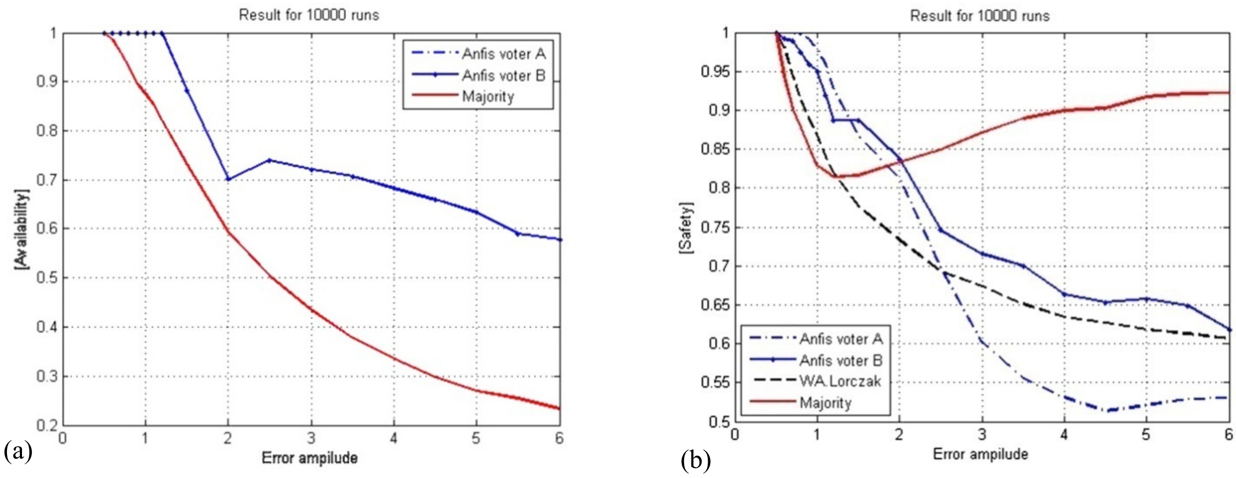


Figure 8. Voter performance with large errors: (a) availability and (b) safety

We mean magnitude of small errors as [-1,5 +1,5]and generally the reviewed error magnitude is [-6 +6] that in this range we reviewed total performance of algorithm and comparing with other algorithms.

ANFIS voter is under the effect of small and big errors, and safety and availability are computed.

The results have been compared with majority and weight average algorithms. Reasons of use majority algorithm to compare with presented algorithm, is one of the most voter algorithms and has better performance in the small errors range. The new algorithm is a weighted algorithm that using ANFIS to improve weight. So in comparison, the current work is evaluated by the weighted average algorithm.

Figure 7, shows availability and safety graphs of ANFIS voter-A, ANFIS voter-B, majority and weighted average for **small** errors amplitude. ANFIS voter-A has higher availability (3-17%) than majority and has higher safety (5-15%) than majority and weighted average. also ANFIS voter-B has same availability and has higher safety (4-12%) than majority and weighted average.

Table 1.Comparison of RMSE and standard deviation voting results.

emax	RMSE				standard deviation			
	majority	Weighted Average	ANFIS voter-A	ANFIS voter-B	majority	Weighted Average	ANFIS voter-A	ANFIS voter-B
1	0.3516	0.2945	0.2403	0.3050	0.2764	0.2321	0.1374	0.1913
2	0.5448	0.6000	0.3736	0.4534	0.4799	0.4760	0.2709	0.3667
3	0.6582	0.8882	0.6399	0.7856	0.6074	0.6074	0.4554	0.6185
4	0.7716	1.1736	0.8301	0.8736	0.7278	0.7278	0.6014	0.6953
5	0.8931	1.4889	0.9547	0.9890	0.8540	0.8540	0.7012	0.8229
6	1/008	1.7731	1.0855	1.0705	0.9719	0.9719	0.8221	0.8984

It should be mentioned that the availability of voter for weighted average is always equal to one; the weighted average can produce one output in each cycle of voting. Availability and safety is plotted for **large** errors amplitude in Figure 8. Both ANFIS voters have higher availability than (5-14%) majority voter. ANFIS voter-B gives higher safety than weighted average all the times and is up only to point emax=2 for majority. ANFIS voter-A has higher Safety to emax=2.1 than majority voter and is higher than weighted average to point emax=3.5.

Table 1, show values of RMSE and standard deviation related to different result of voting algorithms. As you can see, ANFIS voter has Mean error is less than the others. Regarding table1 and figure 7, it is observed that ANFIS based voter has better performance for small error amplitude rather than others.

6. Conclusion

This paper presented ANFIS voter that is established through Adaptive Neuro Fuzzy Inference System. Structure of neuro-fuzzy network is used a hybrid algorithm and two initial structures: subtractive clustering and FCM, for better performance of voter. Efficiency of ANFIS voter is tested through test harnessand injected on data inputs of error system. Then results of evaluating ANFIS voter are compared with other two algorithms and empirical results show that ANFIS voter give high availability than other voting algorithms and higher safety than majority and weighed average algorithms in small error regions. Because most voting algorithms are not able to generate accurate outputs in the presence of small errors so it can be a good candidate for high safety systems.

According to the explanations provided about the voting in a fault-tolerant systems and weighted algorithms; we can used other evolutionary algorithms to produce optimal weight in weighted algorithms. One of the evolutionary algorithms that have been used in recent years is genetic algorithms. Here can be used a combination of genetic algorithm and ANFIS to optimize weights.

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