Indonesian Journal of Electrical Engineering and Computer Science
Vol. 1, No. 2, February 2016, pp. 300 ~ 309
DOI: 10.11591/ijeecs.v1.i2.pp300-309

Loss of Excitation Faults Detection in Hydro-Generators Using an Adaptive Neuro Fuzzy Inference System

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Abstract

This paper presents a new approach for Loss of Excitation (LOE) faults detection in Hydro-generators using Adaptive Neuro Fuzzy Inference System. The proposed scheme was trained by data from simulation of a 345kV system under various faults conditions and tested for different loading conditions. Details of the design process and the results of performance using the proposed technique are discussed in the paper. Two different techniques are discussed in this article according to the type of inputs to the proposed ANFIS unit, the generator terminal impedance measurements (R and X) and the generator RMS Line to Line voltage and Phase current (V_{trms} and I_a). The two proposed techniques results are compared with each other and are compared with the traditional distance relay response in addition to other techniques. The results show that the proposed Artificial Intelligent based technique is efficient in the Loss of Excitation faults (LOE) detection process and the obtained results are very promising.

Keywords: *Adaptive Neuro Fuzzy Inference System, Loss of Excitation, Hydro-Generator, Dynamic Performance, Simulation*

1. Introduction

Loss of Excitation (LOE) is a very widespread fault in synchronous machines and can be caused by short circuit of the field winding, unexpected field breaker open or Loss of Excitation (LOE) relay mal-operation. According to the statistics in China, the generator failure due to Loss of Excitation (LOE) accounts for 69.5% of all generator failuresas described in [1, 2]. Loss of Excitation (LOE) may cause sharp damages to both generator and system. For the generator; when Loss of Excitation (LOE) happens, a slip occurs which may cause rotor over heating due to the slip frequency in rotor circuits. Also, as the machine operates as an induction machine after Loss of Excitation (LOE) conditions, large amount of reactive power supplied by stator current is required and the stator may suffer over heating because of this large current. On the other hand, for the system; its voltage declines after the generator lose its excitation, because the generator operates as an induction machine and absorbs reactive power from the system. For some weak system, the system voltage may collapse due to the Loss of Excitation (LOE) of an important generatoras explained in [3]. Also, when a generator loses its excitation, other generators in the system will increase their reactive power output. This may cause the overloading in some transmission lines or transformers and the over-current relay may consider this overloading as a fault and isolate the non-fault equipment [4-14]. These above reasons motivate this research work to solve for this problem.

In the middle of the 20thcentury, a single phase offset mho relay was developed for the high speed detection of Loss of Excitation (LOE) conditions in synchronous generators. This distance relay approach was developed to provide enhanced selectivity between Loss of Excitation (LOE) conditions and other normal or abnormal operating conditions and to provide the operating times necessary for optimum protection of both the generator and the system [15]. Over the years, the offset mho relay has been widely accepted for loss of excitation protection and experience with the relay has been accepted. The relay has demonstrated its capability of

Received September 20, 2015; Revised January 12, 2016; Accepted January 28, 2016

detecting different excitation system failures and to discriminate between such failures and other operating conditions. The relatively few cases of incorrect operation that have occurred can be refered to incorrect relay connections (major cause), and blown potential transformer fuses. Regardless of this accepted experience, there has been some user worry about the performance of distance type of relaying for loss of excitation protection. In particular, there has been concern over possible incorrect operation of the relay when operating the generator in the underexcited region, during stable transient swings and during major system disturbances that cause under frequency conditions. In view of this continuing concern over relay performance, a general study was launched to review the performance of the offset mho Loss of Excitation (LOE) relay different system conditions. Subsequently, many approaches and algorithms have been addressed to solve the generators Loss of Excitation (LOE) problem such as:

a) Fuzzy inference mechanism based technique [16].
b) ANN based technique [17].
c) Adaptive Loss of Excitation relay basedon time-derivatives of impedance[18].
d) Adaptive loss of excitation protection relay based on the steady-state stability limit [19].
e) Technique based on the derivative of the terminal voltage and the output reactive power of the generator [20].

Thus, the necessity for this article came into sight as the deficiency of Loss of Excitation (LOE) distance relays became clear. Moreover; these distance relays behavior to different Loss of Excitation (LOE) conditions is totally depending on the generator loading and the percentage loss of excitation and many loss of excitation (LOE) conditions are not detected by these relays. Therefore, the need for developing an Artificial Intelligent (AI) based relay to overcome these problems appeared.

This article presents two recent optimization algorithms based on Artificial Intelligence (AI) techniques. The two different techniques discussed in this article classified based on the type of inputs to the proposed ANFIS unit, the generator terminal impedance measurements (R and X) and the generator RMS Line to Line voltage and Phase current (V_{trms} and I_a). The two proposed techniques results are compared with each other and are compared with the conventional distance relay response in addition to other techniques. The results show that the proposed Artificial Intelligent (AI) based techniques are efficient in the Loss of Excitation faults (LOE) detection process. The obtained results are very promising. The rest of the paper is organized as follows: Section 2 presents the system under study, while Section 3 describes the Adaptive Neuro Fuzzy Inference System technique, on the other hand, Section 4 illuminates the simulation environment and finally, Section 5 presents the results and discussion.

2. System Under Study

The system used in the investigations of this paper is shown in Figure 1. It consists of two hydro-generators which are connected via transformers to an infinite-bus system through a 300 km, 345 kV transmission line. The system data are given in Appendix-A, as given in [21]. The PSCAD/EMTDC simulation package is used for in the simulation process [22].

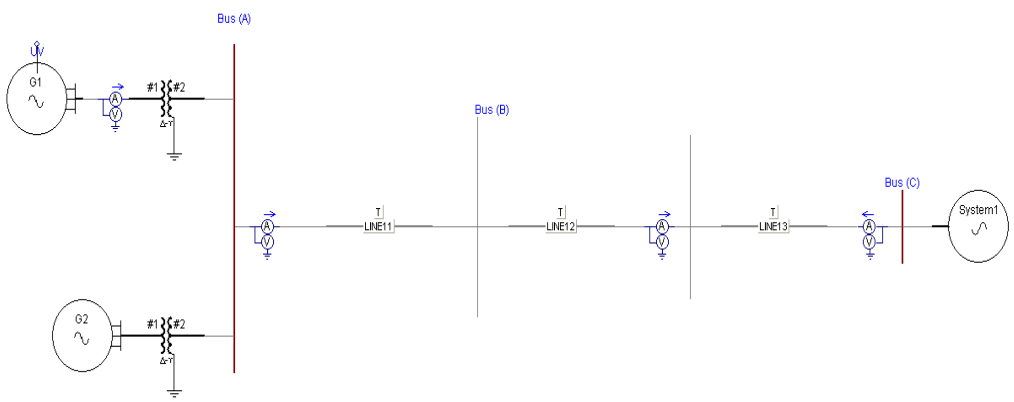

Figure 1. One-line Diagram of the Simulation Model in PSCAD

3. Adaptive Neuro Fuzzy Inference System (ANFIS)

A Fuzzy Logic System (FLS) can be viewed as a non-linear mapping from the input space to the output space. A FLS consists of five main components: Fuzzy Sets, fuzzifiers, fuzzy rules, an inference engine and defuzzifiers. However fuzzy inference system is limited in its application to only modeling ill defined systems.

These systems have rule structure which is essentially predetermined by the user's interpretation of the characteristic of the variables in the model. It has been considered only fixed membership functions that were chosen arbitrarily. However, in some modeling situations, it cannot be distinguished what the membership functions should look like simply from looking at data. Rather than choosing the parameters associated with a given membership function arbitrarily, these parameters could be chosen so as to tailor the membership functions to the input/output data in order to account for these types of variations in the data values. In such case the necessity of the ANFIS becomes obvious. Adaptive Neuro-Fuzzy networks are enhanced FLSs with learning, generalization, and adaptive capabilities. These networks encode the fuzzy if-then rules into a neural network-like structure and then use appropriate learning algorithms to minimize the output error based on the training/validation data sets [23-28].

Neuro-adaptive learning techniques provide a method for the fuzzy modeling procedure to learn information about a data set. It computes the membership function parameters that best allow the associated fuzzy inference to track the given input/output data.

A network-type structure similar to that of an Artificial Neural Network (ANN) can be used to interpret the input/output map. Therefore, it maps inputs through input membership functions and associated parameters, and then through output membership functions and associated parameters to outputs. These parameters change through the learning process.

The used ANFIS is assumed to have the following properties [27, 28]:

a) It is zeroth order sugeno-type system.
b) It has a single output, obtained using weighted average defuzzification. All output membership functions are constant.
c) It has no rule sharing. Different rules do not share the same output membership function; the number of output membership functions must be equal to the number of rules.
d) It has unity weight for each rule.

Figure 2 shows the architecture of the ANFIS, comprising by input, fuzzificaiton, inference and defuzzificaiton layers. The network can be visualized as consisting of inputs, with N neurons in the input layer and F input membership functions for each input, with F * N neurons in the fuzzificaiton layer. There are F^N rules with F^N neurons in the inference and defuzzificaiton layers. It is assumed one neuron in the output layer.

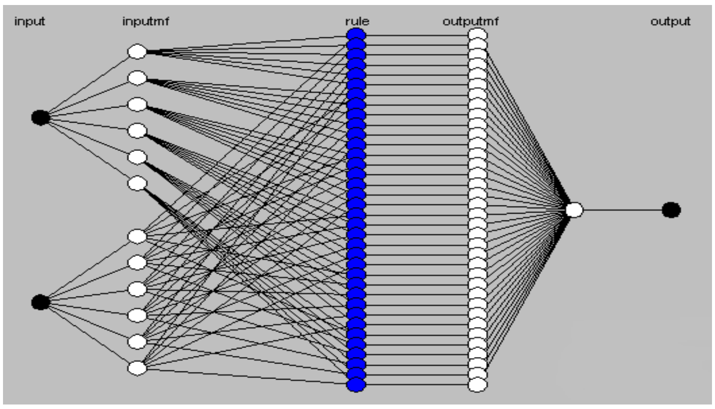

Figure 2. The Architecture of the ANFIS

The proposed ANFIS unit consists of two neurons in the input layer i.e. N=2, six Membership Functions (MF) for each input i.e. M=6 and constant membership function for the output layer, Appendix-B.

4. Simulation Environment

The simulation environment based on the MATLAB software package (The Math Works, Natick, Massachusetts, USA) is selected as the main engineering tool for performing modeling and simulation of power systems and relays. The PSCAD/EMTDC program is used for detailed modeling of a power network and simulation of interesting events. Scenario setting and a relaying algorithm will be implemented in the MATLAB program, while the data generation for training and testing of this algorithm will be executed by the PSCAD/EMTDC program.

The used training data to train the ANFIS are taken at Loss of Excitation (LOE) fault conditions and no-fault conditions.

The fault conditions are carried out at different Loss of Excitation (LOE) fault types:

a) Partial Loss of Excitation (LOE) faults.
b) Complete Loss of Excitation (LOE) faults.

These fault conditions are carried out at different generators loading conditions (18.5%, 25%, 35%, 40%, 50%, 55%, 60%, 65%, 70% and 80%) with inception fault time T_f= 5 sec and different Loss of Excitation (LOE) cases (20%, 25%, 50%, 60%, 70%, 75%, 80% and 100%).

Two different proposed methods are compared with each other in this article for the purpose of Loss of Excitation (LOE) faults detection, one method is based on the generator terminal impedance measurements (R and X) and the other is based on the generator RMS Line to Line voltage and Phase current (V_{trms} and I_a) measurements, the obtained results from both schemes are better than [29, 30].

Testing data are chosen randomly from the data that were included in the training process, while the validation data are chosen at different conditions data that not were included in the training process to ensure the proposed method proficiency.

The sequence of the proposed (R and X) technique is based on transformation of the generator terminal voltages and stator currents magnitudes and angles which are obtained by Fourier Transform to impedance measurements (R and X) which are involved in the training, testing and validating processes.

Figure 3 presents the flowchart for the Loss of Excitation (LOE) detection procedure of the proposed (R and X) protection scheme. On the other hand, Figure 4 depicts the flowchart for the Loss of Excitation (LOE) detection procedure of the other proposed (V_{trms} and I_a) protection scheme.

5. Results and Discussion

The system was simulated using PSCAD/EMTDC as well as Matlab and the results of simulation are explained in this paper.

5.1. The Proposed (R and X) Protection Scheme

The inputs to the ANFIS unit are the generator terminal impedance measurements (R and X) which are obtained from the generator terminal voltage and stator current values, and the testing data are chosen to have data from the training process while the validation data are chosen to have data not included in the training process.

Table 1 presents the testing data of the proposed (R and X) ANFIS scheme. The testing data are included inthe training process.Table (2) illustrates the validation data of the proposed (R and X) scheme. The validation data are not included in the training process and are chosen at different generator loading and Loss of Excitation (LOE) conditions.

Table 1 and 2 depict the promising accuracy of the proposed (R and X) ANFIS in detecting the generator Loss of Excitation (LOE) faults under different loading conditions and compare it with the conventional distance relay response. The testing time column shows the Loss of Excitation (LOE) detection time by the proposed ANFIS relay, which when compared to the traditional distance relay trip time shows the promising efficiency of the proposed (R and X) ANFIS scheme.

For example, the 1st row in Table 2 describes when the generator losses 50% of its excitation at T_f = 5 sec while it was loaded by 80% of its' full load, the conventional distance relay will detect the Loss of Excitation (LOE) fault at "14.5 sec", while the proposed (R and X) ANFIS scheme will detect this fault at "6 sec" which means that the fault will be detected after its inception time by "1 sec" through the calculated index "I_{R40}" which is greater than the threshold value "0.85".

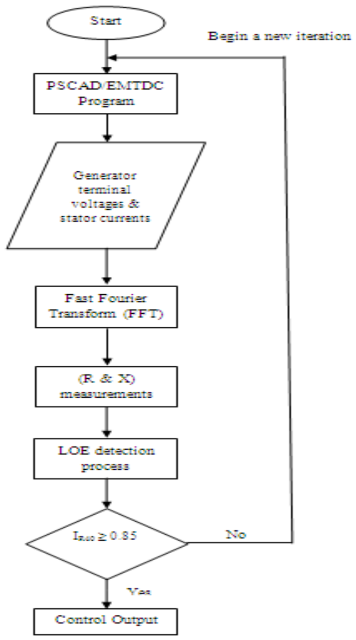

Figure 3. Flowchart for the Loss of Excitation (LOE) Detection Procedure based on (R and X)

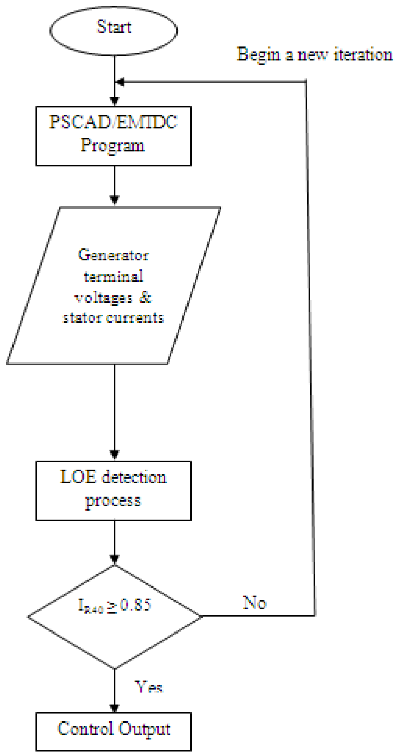

Figure 4. Flowchart for the Loss of Excitation (LOE) Detection Procedure based on (V_{trms} and I_a)

Also, the 4th row in Table 2 presents when the generator losses 75% of its excitation at T_f = 5 sec while it was loaded by 70% of its' full load, the conventional distance relay will detect the Loss of Excitation (LOE) fault at "13.2 sec", while the proposed (R and X) ANFIS scheme will detect it at "5.8 sec" through the calculated index "I_{R40}".

From the below Tables (1) and (2) calculated indices (I_{R40}) it is easy to conclude that the output of the proposed (R and X) ANFIS unit should be fairly chosen as:

a) $I_{R40} \geq 0.85$ for Loss of Excitation (LOE) conditions and
b) $I_{R40} \leq 0.2$ for no-fault conditions.

The proposed (R and X) ANFIS relay detects the different Loss of Excitation (LOE) conditions within about (300-1400 msec) after the fault inception under different generator loading conditions from (18.5% to 80%) which is more efficient than the conventional distance relay.

5.2. The Proposed (V_{trms} and I_a) Protection Scheme

On this scheme, the inputs to the ANFIS unit are considered to be the generator RMS Line to Line voltage and Phase current (V_{trms} and I_a).

Table 3 illustrates the testing data of the proposed (V_{trms} and I_a) ANFIS scheme, while Table 4 depicts the validation data of the proposed scheme. The validation data are not included in the training process and are chosen at different generator loading and Loss of Excitation (LOE) conditions.

Table 3 and 4 show how much the proposed (V_{trms} and I_a) ANFIS scheme is accurate in detecting the generator Loss of Excitation (LOE) during generator heavy loading conditions (more than 50% of its rated power) compared to the (R and X) ANFIS scheme.

For example, the 5th row in Table 3 shows when the generator losses 25% of its excitation at T_f = 5 sec while it was loaded by 50% of its' full load, the proposed (V_{trms} and I_a) ANFIS will detect the Loss of Excitation (LOE) fault at “9.7 sec”, which is more delayed than the proposed (R and X) ANFIS scheme which will detect the fault at “7.5sec” (as presented in Table (1)), on the other hand, the conventional distance relay will not detect the fault occurrence. The same is for the 13th row in Table 4, where the (V_{trms} and I_a) ANFIS will detect the Loss of Excitation (LOE) fault at “6.5 sec”, which is more than proposed (R and X) ANFIS scheme which will detect it at “5.3 sec” (as described in Table 2), while the conventional relay will not detect the fault occurrence.

On the other hand, when the generator is heavy loaded, as illustrated in the 1st , 4th and 16th rows on Table (4), it is clear that the (V_{trms} and I_a) ANFIS will detect the Loss of Excitation (LOE) faults faster than the other proposed (R and X) ANFIS scheme. For example, the 1st row in Table 4 describes when the generator losses 50% of its excitation at T_f = 5 sec while it was loaded by 80% of its' full load, the proposed (V_{trms} and I_a) ANFIS will detect the Loss of Excitation (LOE) fault at “5.6 sec”, which is faster than the proposed (R and X) ANFIS scheme which will detect the fault at “6 sec”, on the other hand, the traditional distance relay will detect the Loss of Excitation (LOE) fault at “14.5 sec”.

From the below Table 3 and 4 calculated indices (I_{R40}) it is easy to conclude that the output of the proposed (V_{trms} and I_a) ANFIS unit should be chosen as:

a) $I_{R40} \geq 0.85$ for Loss of Excitation (LOE) conditions and
b) $I_{R40} \leq 0.25$ for no-fault conditions.

The proposed (V_{trms} and I_a) ANFIS scheme detects the Loss of Excitation (LOE) faults within (500-900 msec) after the fault inception when the generator loading is more than 50% of its' rated power faster than the other proposed (R and X) ANFIS scheme which detects the LOE faults within (300-1400 msec) in wider loading range from (18.5% to 80%).

Thus, it is obvious that the generator terminal impedance measurements (R and X) and the generator RMS Line to Line voltage and Phase current (V_{trms} and I_a) as inputs for the ANFIS units give superior results more accurate than the conventional distance relays and other used techniques such as [29, 30], and are very close to the expected indices. These indices are the output values of the ANFIS unit. The expected value for Loss of Excitation (LOE) fault conditions is 1, and the expected value for no-fault conditions is 0. In addition, when using the threshold values as reference, the obtained results will lead to zero errors.

The tabulated results in Table (5) illustrate that the Response Time for the proposed Loss of Excitation (LOE) ANFIS relay based on (V_{trms} and I_a) measurements is less than that of Loss of Excitation (LOE) ANFIS relay based on (R and X) due to the ready measurements in the 1st scheme, while the 2nd scheme needs calculations for (R and X) values. This means that the difference in the Response Time is due to the required time in calculations of (R and X) values. However, the 2nd scheme covers wider generator loading conditions.

Table 1. Testing Data For The Proposed (R and X) ANFIS Scheme

% Generator Loading	% LOE	LOE Fault Inception Time (sec)	Conv. Distance Relay trip time (sec)	Testing time (sec)	R value	X value	Calculated Index "I_{R40}"	Expected Index	% Error
80%	75%	5	11.8	6	21.702484946	-.18872885161	0.874	1	**12.6**
80%	75%	5	11.8	8	14.431961029	-6.60340262718	1.001	1	**0.1**
80%	75%	5	11.8	7	17.985928518	-4.81989685374	1.003	1	**0.3**
80%	75%	5	11.8	6.5	19.959700891	-3.25863535618	1.009	1	**0.9**
50%	25%	5	-	7.5	33.220402476	-10.3889087234	0.865	1	**13.5**
50%	25%	5	-	8	31.748026335	-11.6538245134	0.987	1	**1.3**
50%	25%	5	-	2	38.980254685	-1.90026234583	0.166	0	**16.6**
50%	25%	5	-	3.5	39.094117515	-1.66298460533	0.103	0	**10.3**
70%	25%	5	35	6.1	25.007212336	-2.15599565675	0.853	1	**14.7**
70%	25%	5	35	7	23.364084426	-4.30483997607	0.995	1	**0.5**
70%	25%	5	35	8.5	20.559607506	-6.8828132688	1.002	1	**0.2**
70%	25%	5	35	3	26.072746656	-0.28033813466	0.105	0	**10.5**
70%	25%	5	35	4	26.071454780	-0.26951394394	0.1	0	**10**

Table 2. Validation Data For The Proposed (R and X) ANFIS Scheme

% Generator Loading	% LOE	LOE Fault Inception Time (sec)	Conv. Distance Relay trip time (sec)	Testing time (sec)	R value	X value	Calculated Index "I_{R40}"	Expected Index	% Error
80%	50%	5	14.5	6	21.759703656	-1.12944427988	0.856	1	**14.4**
80%	50%	5	14.5	7.5	17.802737965	-5.16357929149	1.002	1	**0.2**
80%	50%	5	14.5	4	22.976657326	1.06010676291	0.143	0	**14.3**
70%	75%	5	13.2	5.8	24.968773874	-2.24506421121	0.869	1	**13.1**
70%	75%	5	13.2	6	24.187353457	-3.1638805022	0.97	1	**3**
70%	75%	5	13.2	8	16.062579330	-8.48655870187	1.002	1	**0.2**
70%	75%	5	13.2	2.5	26.073994872	-0.29256800175	0.11	0	**11**
70%	75%	5	13.2	3.5	26.072537608	-0.27397205787	0.1	0	**10**
35%	75%	5	36	5.7	43.946262348	-16.8597356813	0.882	1	**11.8**
35%	75%	5	36	6	40.488254979	-18.7251925448	1.059	1	**5.9**
35%	75%	5	36	9	16.946908828	-20.803740385	0.996	1	**4**
35%	75%	5	36	4.5	47.169878256	-13.9930597882	0.08	0	**8**
25%	80%	5	-	5.3	58.230300018	-28.2163989537	0.934	1	**6.6**
25%	80%	5	-	6	46.22315421	-31.9958915062	1.038	1	**3.8**
25%	80%	5	-	8.5	16.310228765	-26.8067100233	0.993	1	**7**
25%	80%	5	-	4	59.250354743	-27.3367962253	0.094	0	**9.4**
80%	20%	5	24	6.4	21.787199161	-1.21745675159	0.865	1	**13.5**
80%	20%	5	24	7.5	20.024184886	-3.52645376589	1.006	1	**0.6**
80%	20%	5	24	15	11.944206638	-7.43431395269	0.9987	1	**0.13**
80%	20%	5	24	1.5	23.048544902	1.10041433155	0.118	0	**11.8**
80%	20%	5	24	3	23.055259668	1.24793741479	0.103	0	**10.3**

Table 3. Testing Data For The Proposed (VtrmsandIa) ANFIS Scheme

% Generator Loading	% LOE	LOE Inception Time (sec)	Conv. Distance Relay trip time (sec)	Testing time (sec)	V_{trms} (kV)	I_a (kA)	Calculated Index "I_{R40}"	Expected Index	% Error
80%	75%	5	11.8	6	22.1039403349	6.15473895178	0.913	1	**8.7**
80%	75%	5	11.8	8	19.9499867446	7.59776976215	0.9917	1	**0.83**
80%	75%	5	11.8	7	20.9389505073	6.79874267771	0.962	1	**3.8**
80%	75%	5	11.8	6.5	21.545492837	6.39715738451	0.936	1	**6.4**
50%	25%	5	-	9.7	22.8156947143	4.26372233932	0.86	1	**14**
50%	25%	5	-	2	24.1853845047	3.55665724573	0.22	0	**22**
50%	25%	5	-	3.5	24.1737469291	3.55510879725	0.23	0	**23**
70%	25%	5	35	6.1	22.5860386167	5.2676138315	0.913	1	**8.7**
70%	25%	5	35	7	22.1380556938	5.47053009617	0.929	1	**7.1**
70%	25%	5	35	8.5	21.5718305263	5.82951955847	0.952	1	**4.8**
70%	25%	5	35	3	23.1285410774	5.10601022447	0.13	0	**13**
70%	25%	5	35	4	23.1287487203	5.10353080899	0.129	0	**12.9**

Table 4. Validation Data For The Proposed (VtrmsandIa) ANFIS Scheme

% Generator Loading	% LOE	LOE Inception Time (sec)	Conv. Distance Relay trip time (sec)	Testing time (sec)	V_{trms} (kV)	I_a (kA)	Calculated Index "I_{R40}"	Expected Index	% Error
80%	50%	5	14.5	5.6	22.7325458622	5.87024619341	0.89	1	**11**
80%	50%	5	14.5	7.5	20.9698505845	6.73924137012	0.963	1	**3.7**
80%	50%	5	14.5	4	23.1301013869	5.78595531658	0.077	0	**7.7**
70%	75%	5	13.2	5.5	22.769924438	5.17262079063	0.877	1	**12.3**
70%	75%	5	13.2	6	22.2419457099	5.41025280814	0.925	1	**7.5**
70%	75%	5	13.2	8	20.3443215281	6.73790700902	1.019	1	**1.9**
70%	75%	5	13.2	2.5	23.1311322847	5.10582533742	0.123	0	**12.3**
70%	75%	5	13.2	3.5	23.1284259625	5.10345127336	0.131	0	**13.1**
35%	75%	5	36	5.7	22.7114108547	2.94652624889	0.85	1	**15**
35%	75%	5	36	6	22.5310482085	3.06901733206	0.902	1	**9.8**
35%	75%	5	36	9	21.0039384567	4.66437003799	1.019	1	**1.9**
35%	75%	5	36	4.5	23.1500185586	2.70620408002	0.2	0	**20**
25%	80%	5	-	6.5	22.0860724544	2.93699549769	0.863	1	**13.7**
25%	80%	5	-	8.5	21.1905383127	4.07455289665	1.019	1	**1.9**
25%	80%	5	-	4	23.165915076	2.04201972852	0.157	0	**15.7**
80%	20%	5	24	5.9	22.7645144459	5.91737574141	0.86	1	**14**
80%	20%	5	24	7.5	21.8267515929	6.30115523521	0.923	1	**7.7**
80%	20%	5	24	15	19.6016838869	8.11584341685	0.988	1	**1.2**
80%	20%	5	24	1.5	23.2802942717	5.79235491353	0.076	0	**7.6**
80%	20%	5	24	3	23.2447967124	5.79561559451	0.076	0	**7.6**

Table 5. Comparison between Different Loss of Excitation (LOE) Techniques

Technique	Generator Loading %	Response Time (sec)
LOE ANFIS relay based on (V_{trms} and I_a)	Higher than 50%	(500-900 msec)
LOE ANFIS relay based on (R and X)	From 18.5% to 80%	(300-1400 msec)
Conventional distance relay	From 18.5% to 80%	Minimum 7-8 sec.
Other technique based on "reactive power measurements"[29]	10% and 50%	Within 1120 msec
Other technique based on "R-X with directional element scheme" [30]	40% and 80%	6.931 and 4.175 sec.

6. Conclusion

This article presents a novel study of Hydro-generators Loss of Excitation (LOE) scheme using Adaptive Neuro Fuzzy Inference System (ANFIS). The necessity for this research work appeared due to the inaccurate response of the distance Loss of Excitation (LOE) relays which is completely depending on the generator percentage loading and the loss of excitation percentage. The Proposed Artificial Intelligent Approach demonstrates successful performance for Loss of Excitation (LOE) faults detection. Twovarious algorithms are used in this article, they are based on the type of the inputs to the proposed ANFIS unit for Loss of Excitation (LOE) fault detection, the generator terminal impedance measurements (R and X) and the generator RMS Line to Line voltage and Phase current (V_{trms} and I_a) measurements. The obtained results from both algorithms are compared with each other and compared with the conventional distance relay response in addition to other techniques. It was found that the generator terminal impedance measurements (R and X) and the generator RMS Line to Line voltage and Phase current (V_{trms} and I_a) play the essential rule in the Loss of Excitation (LOE) detection process. For fault detection task, all the validation data for the ANFIS schemes in the fault and no fault conditions give the expected outputs. The used data for testing and validation are of both kinds of data: used in training and not used in training respectively. Suggested indices for occurrence of the Loss of Excitation (LOE) conditions were introduced. The obtained results are very brilliant.

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