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Artificial Intelligence Based Approach for Identification of Current Transformer Saturation from Faults in Power Transformers

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Abstract

Protection systems have vital role in network reliability in short circuit mode and proper operating for relays. Current transformer often in transient and saturation under short circuit mode causes mal-operation of relays which will have undesirable effects. Therefore, proper and quick identification of Current transformer saturation is so important. In this paper, an Artificial Neural Network (ANN) which is trained by two different swarm based algorithms; Gravitational Search Algorithm (GSA) and Particle Swarm Optimization (PSO) have been used to discriminate between Current transformer saturation and fault currents in power transformers. In fact, GSA operates based on gravity law and in opposite of other swarm based algorithms, particles have identity and PSO is based on behaviors of bird flocking. Proposed approach has two general stages. In first step, obtained data from simulation have been processed and applied to an ANN, and then in second step, using training data considered ANN has been trained by GSA & PSO. Finally, a proposed technique has been compared with one of the common training approach which is called Genetic algorithm (GA).

Keywords: Artificial Neural Network, Current transformer saturation, Genetic algorithm, Gravitational Search Algorithm, Internal Faults, Particle Swarm Optimization, Power Transformers.

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1. **Introduction**

Current transformer is important transfer equipment in electrical system. Its saturation may cause malfunction and no action of computer relays. In differential protection, when a fault occurs outside of protection region if Current transformers are saturated, input current summation to the relay, inadvertently cut the breakers. So far, different methods presented in literatures to detect this kind of current. For instance, in [1], a digital technique to protect bus bars has been presented. Proposed algorithm in that paper uses positive and negative sequence models of the power system, and also, in order to compute the current phasors from quantized samples of the waveforms provided by unsaturated and saturated Current transformers Fourier analysis technique has been used. Another algorithm which was based on the power system source impedance measurement has been introduced in [2], samples of a single Current transformer secondary current together with samples of the bus-bar voltage have been used for this algorithm. In this algorithm a first order differential equation, or RL model for the power system source impedance at the relay location is used in. to detect work state of Current transformer Changes on this impedance are used. After that in 2004 [3], the third difference of a secondary current has been utilized to detect Current transformer saturation. This current has points of inflection where saturation begins and ends. Authors believe that against the first difference of the current, the second and third differences of the current have larger values which are adequate to detect saturation. Also, in that paper, in order to soften the current an anti-aliasing low-pass filter has been used, but it leads to the third difference values reduction at those instants. Also, a symmetrical component analysis-based approach has been presented in [4] to detect Current transformer saturation in a numerical current differential feeder protection relay. The other approach presented in [5], that decaying factor in the decaying dc component has been used to define a detection index. To do this, the decaying dc component has been estimated using a phasor-based computation. When a Current transformer becomes saturated, this index will oscillate within a wide range. Therefore, a level-trigger concept can be developed to detect Current transformer saturation. Then, the current samples and phasors in the latest unsaturated period have been used to modify the saturated current samples. In addition, some especial algorithms are used in this field, for example; the wave shape of the secondary current has been considered in [6], this wave form will be severely distorted as the Current transformer is forced into deep saturation when the residual flux in the core adds to the flux change caused by faults. Therefore, in that paper, to detect Current transformer saturation some features contained in the waveform of that signal has been extracted using a morphological lifting scheme. Also to reconstruct healthy secondary currents a compensation algorithm has been stated in that paper. In [7], an algorithm is proposed for detection and compensation of CT saturation effects, based on: a least error squares (LES) filter which estimates the phasor parameters of the CT secondary current, a novel saturation detection method which uses the output of the LES filter for saturation detection, and a minimum estimation error tracking approach which enhances the precision of the phasor estimation. Now a day, specific algorithm which is used widely for dealing with this problem is Artificial Neural Network (ANN). It can help engineers to solve such problems very quickly and more accurate. Something which is important for using such algorithms is its training technique, different methods introduced to that that such as; Back Propagation And etcetera. But modern methods use optimization algorithms to train ANN for example; in [8], ANN-based classifier which is trained by Genetic Algorithm has been introduced to detect Current transformer saturation. Using MATLAB programming code the proposed GA optimization has been implemented. Artificial intelligence-based approaches are well known tools for classifying and detecting different situations in electrical Engineering problems. One of these approaches is Artificial Neural Network (ANN) that can be used in diagnosing transient conditions in power systems [9].

In this paper, two artificial based methods have been used to distinguish Current transformer saturation from fault currents. At first two different forms of swarm based algorithms; GSA and PSO have been used to train ANN. GSA works based on gravity law and in opposite of other swarm based algorithms and also is independent of initial particles' position, particles have identity and PSO is based on behaviors of bird flocking. Then, trained ANN has been used to discriminate Current transformer saturation from fault current. In order to prove that this training method is useful and leads to more accurate results, obtained results using two proposed algorithms and GA method which is one of the common methods for training ANN are compared. In the rest of the paper, in section two, concepts of Current transformer saturation have been presented. Then, in section three, four and five, Overview of GSA, PSO and GA methods have been explained, respectively. Also, in section sex, simulation and its results have been discussed and finally conclusion has been stated in section seven.

2. **Concepts of Current transformer Saturation**

In order to protect power systems it’s necessary to know the amount of current which is flowing in the line. Since this amount cannot be used in measurement and protection equipments and in the other hand isolation of these equipments is considered (viewed) as an important issue, thus somehow we should reduce this current and then use it for equipments mentioned before. This is done by Current transformers.

Consider the following circuit-based model for a power transformer in Figure.1.

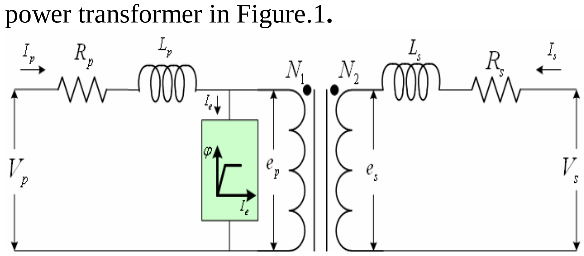

Fig.1. Circuitry model for a power transformer

For small amounts of primary currents and consequently secondary currents a voltage equal to Es is induced in the secondary which is very small. Flux generated by transformer is equal to (Es/4.44FN) and magnetizing current is small with the same ratio.

Consequently secondary current becomes N/ (primary current). If the primary current is increased, first secondary current increases by the same ratio and causes an increase in the amount of induced voltage in secondary. The increase in secondary voltage is done just by an increase in the amount of flux generated by the Current transformer. While flux is increasing transformer needs to draw high magnetizing current. Although after the knee point of B-H curve, increases of flux causes an inappropriate and sever growth in magnetizing current and this is due to non-linear nature of B-H curve of the Current transformer. It's worthy to note that magnetizing current is not completely sinusoidal but is wave that has a considerable peak value. While the primary currents are increasing a moment reaches that in which a very high magnetizing current is needed and almost all of the transmitted current is used for magnetizing. This means that a very small current is fed to the load and in this case it is said that Current transformer is fully saturated.

3. Overview of Gravitational Search Algorithm

Gravitational search algorithm is a memory-less optimization algorithm based on the gravity law. In the Newton's gravity law, each particle attracts other particles with a 'gravitational force'. The gravitational force between two particles is directly proportional to their masses and inversely to the square of the distance between them.

$$F = G\frac{M_1\, M_2}{R^2} \tag{1}$$

According to the experimental results, R has provided better results than R^2 in all experimental cases. That's why in the GSA, R has been used instead of R^2 [11].

In the GSA, agents are considered as objects and their performance are expressed by their masses which will be calculated by using a fitness function. The position of each agent corresponds to solution of the problem. By the gravitational force, all these agents attract each other. A heavy mass has a large effective intensity of attraction. Due to the forces that act on an agent from other agents, that agent can see atmosphere around itself. In this case gravitational force acts as an information-transferring tool. As a result, the agents tend to move toward the best agent. This mass will present an optimum solution in the search space.

A heavier mass means a more efficient agent. This means that better agents have higher attractions and move slower. It can be considered as an adaptive learning rate [11]-[12].

In a system with N agents (masses), the positions are defined as follow:

$$X_i = (x_i^1, \dots, x_i^d, \dots, x_i^n) \quad \text{For i=1, 2…, N} \tag{2}$$

At a specific iteration (t), the force acting on i^th mass from j^th mass is defined, as follow:

$$F_{ij}^d(t) = G(t)\frac{M_{pi}(t) * M_{aj}(t)}{R_{ij}(t)+\varepsilon}\ (x_j^d(t) - x_i^d(t)) \tag{3}$$

Where M_i and M_j are the masses related to i^th and j^th agent, respectively. Also ε is a small constant. And $R_{ij}(t)$ is the Euclidian distance between two agents. Also, first term of this equation is called Gravitation constant that depends on two controlling parameters; α and G0. In addition, t is the iteration of algorithm and T is the total iteration of GSA.

For better illustration, all forces acting from other masses on mass M1 has been shown in Figure.2.

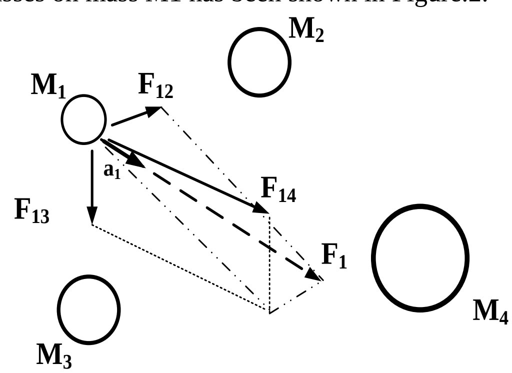

Fig.2. Illustration of GSA concept

Total force that acts on the i^th agent in a d^th dimension is calculated, as follow:

$$F_i^d(t) = \sum_{j=1\ j\neq i}^{N} rand_j\, F_{ij}^d(t) \tag{4}$$

In order to have a stochastic characteristic in the GSA, the total force in d^th dimension have been considered as random weighted summation of d^th components of the forces, where randj is a random number in the interval [0, 1].

There is a consideration for velocity and acceleration in the GSA. Each mass has a velocity and an acceleration which will be expressed as $v_i(t)$ and $a_i(t)$, respectively. The current velocity of each mass is equal to the sum of the fraction of its previous velocity and the velocity variation. Velocity variation or acceleration of each mass is equal to the force acted on the system divided by inertia mass.

$$a_i^d(t) = \frac{F_i^d(t)}{M_i(t)} \tag{5}$$

$$v_i^d(t+1) = rand * v_i^d(t) + a_i^d(t) \tag{6}$$

Where randi is a uniform random variable in the interval [0, 1]. This random term is the second random number in the GSA calculation and the presence of these terms will guarantee the randomized characteristic of the GSA. It should be noted that, $v_i(t)$

and $a_i(t)$, which are called GSA parameters, are velocity and acceleration in t^{th} iteration. Also, $v_i(t+1)$ represents the velocity in the iteration (t+1). After computing the acceleration and velocity of each mass, the new position of the masses could be considered, as follow:

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \tag{7}$$

New positions mean new masses. The gravitational and inertial masses are updated by the following equations:

$$m_i(t) = \frac{fit_i(t) - Worst(t)}{best(t) - Worst(t)} \tag{8}$$

$$M_i(t) = m_i\,(t))/\sum_{j=1}^{N} m_i\,(t) \tag{9}$$

Where $fit_i(t)$ represents the fitness value of the i^{th} agent at iteration t.

4. Overview of Particle Swarm Optimization

PSO simulates the behaviors of bird flocking. In PSO, each single solution is a ‘‘bird’’ in the search space. Here, it is called as ‘‘particle’’. For all of the particles fitness value has been calculated, which are evaluated by the fitness function to be optimized, and have velocities, which direct the flying of the particles. The particles are ‘‘flown’’ through the problem space by following the current optimum particles. PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In each iteration, each particle is updated by following two ‘‘best’’ values. The first one is the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called "pbest". Another ‘‘best’’ value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best which is called "gbest". After finding the two best values, the particle updates its velocity and positions based on following Equations [10]:

$$V_{new} = W \times V_{old} + C_1 \times r \times (P_{pb} - X_{cs}) + C_2 \times r \times (P_{gb} - X_{cs}) \tag{10}$$

$$X_{new} = X_{old} + V_{new} \tag{11}$$

Where W is the inertia weight, Vnew is the particle velocity, X_{cs} is the current particle (solution) of each particle, P_{pb} and P_{gb} are pbest and gbest, r is a random number between [0,1] and c_1, c_2 are learning factors.

Particle’s velocities on each dimension are clamped to a maximum velocity Vmax. If the sum of accelerations would cause the velocity on that dimension to exceed V_{max}, which is a parameter specified by the user then the velocity on that dimension is limited to V_{max}. In Figure.3, typical movement of one particle in solution space has been shown for better illustration of the PSO concept.

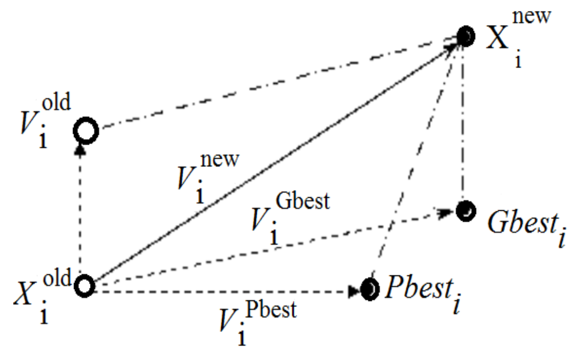

Fig.3. Typical movement of one particle in solution search space

5. Overview of Genetic Algorithm

Genetic Algorithms (GAs) are adaptive heuristic search algorithm premised on the evolutionary ideas of natural selection and genetic. The basic concept of GAs is designed to simulate processes in natural system necessary for evolution, specifically those that follow the principles first laid down by Charles Darwin of survival of the fittest. As such they represent an intelligent exploitation of a random search within a defined search space to solve a problem. In a genetic algorithm, a population of strings (called chromosomes or the genotype of the genome), which encode candidate solutions (called individuals, creatures, or phenotypes) to an optimization problem, is evolved toward better solutions. Traditionally, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible. The evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated, multiple individuals are stochastically selected from the current population (based on their fitness), and modified (recombined and possibly randomly mutated) to form a new population. The new population is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population. If the algorithm has terminated due to a maximum number of generations, a satisfactory solution may or may not have been reached.

6. Simulation Results and Discussion

6.1. Preparing the Current transformer saturation and Fault currents data

In order to simulation Current transformer Saturation and Fault situation and also feature extraction of their waveforms MATLAB/SIMULINK software has been used. In this paper, discrete sampled data of 2 to 25 MVA transformers based on [10] has been used. But, in order to show Current transformer Saturation an example for Current Transformer 25 VA has been simulated and can be seen in Figure.4, by simulating this model, current and flux are obtained that current and flux have been illustrated in Figure.5

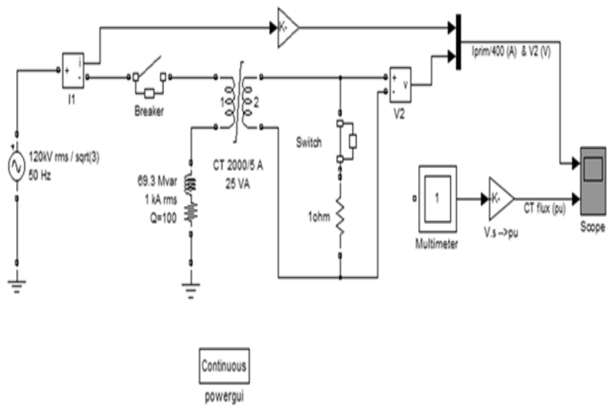

Fig.4. Simulation of Current transformer Saturation for 25 VA Current transformer

Data of simulated transformers in [10] have been applied to ANN as input data, also two classes have been considered as output for Current transformer Saturation and fault currents. In output "1 0" is Current transformer Saturation condition and "0 1" represents fault mode.

v

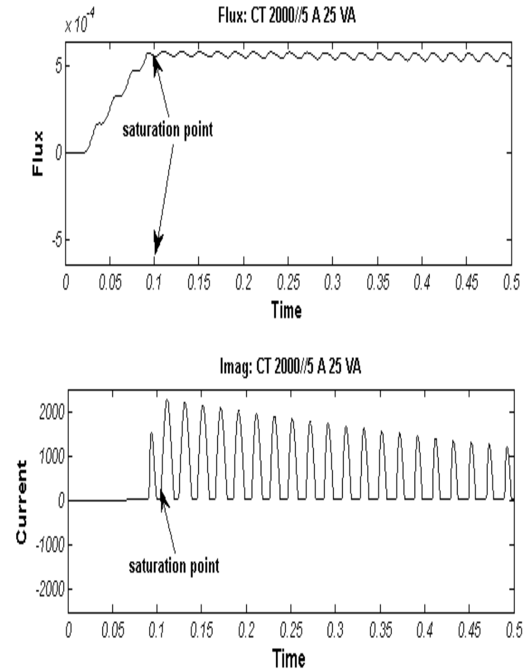

Fig.5. Typical differential flux and current waveform for CT Saturation.

As we know, it is impossible to apply analog signal to ANN, hence, discrete sample data have been extracted from Current transformer Saturation and fault current waveforms, and in order to have valid data, data in [10] has been used, but because of severe variation in that data, they cannot be used without any pre-processing. Therefore, these data have been normalized and after that, these data have been used for training ANN, as it can be seen in Figure.6 and Figure.7.

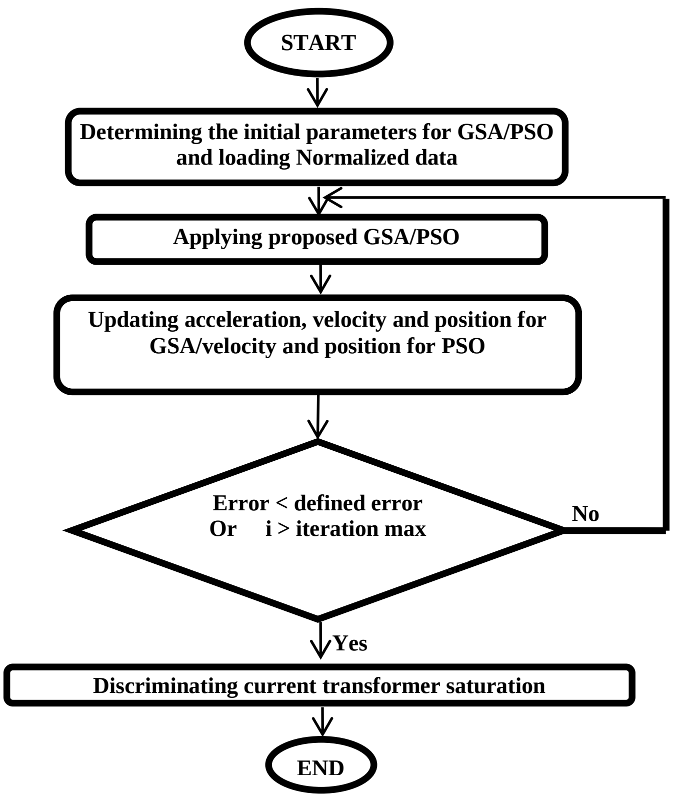

Fig.6. Flowchart of training ANN with GSA/PSO

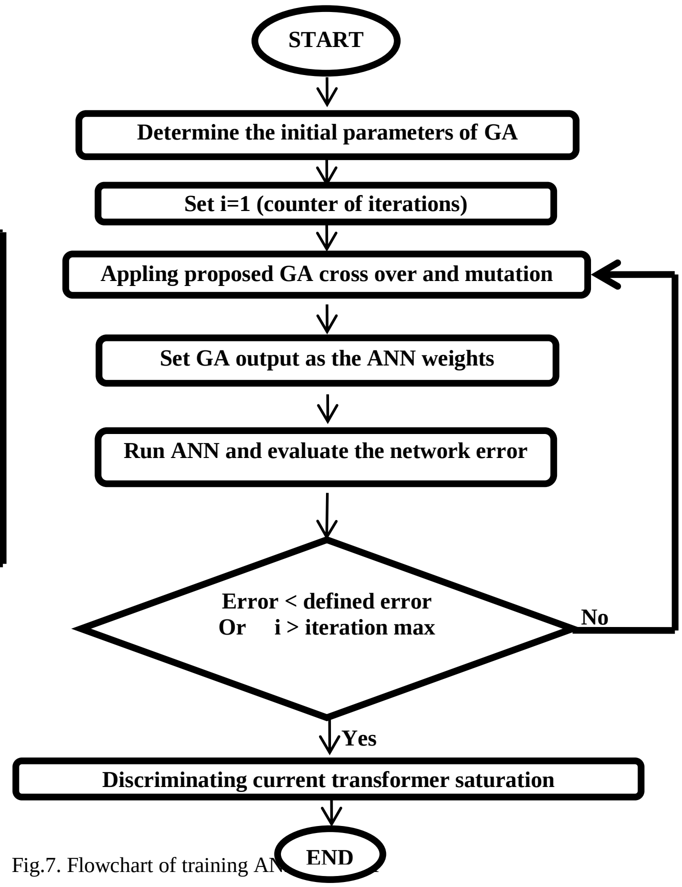

Fig.7. Flowchart of training AN

6.2. Results and discussion

After extracting three mentioned conditions, data of 4 transformers out of 5 have been randomly chosen as train data and other were test data. Also, for this work controlling parameters are; $\alpha = 15$ and $G_0 = 200$, and number of masses is equal to "10". In other hand, ANN has one input layer with 16 neurons, two hidden layers with 16 and 32 neurons and one output layer with two neurons based on three output classes. Also, GA and PSO have been used to train ANN. In this work parameters of PSO are: c_1= 2 and c_2= 2 and the number of particles are equal to "10" and parameters of GA are: numbers of chromosomes are equal to "10", mutation rate are equal to "0.05" and fraction of population kept (selection) are equal to "0.4".

At first ANN has been trained with train data, then test data have been used to test trained ANN, in Table.1, Table.2 and Table.3 , result data or in other word, actual output of ANN for train and test data using GSA, PSO and GA have been listed, respectively. In order to evaluate quality of training, Mean Square Error (MSE) has been used. In statistics, MSE of an estimator is one of the proper utilities to quantify the difference between a measured and the true value of the quantity being measured. MSE is a risk function, corresponding to the expected value of the squared error loss or quadratic loss. MSE measures the average of the square of the "error". Therefore, MSE function can be seen in equation (12).

$$MSE = \frac{\sum_{M,N}(target\ output - actual\ output)^2}{M*N} \qquad (12)$$

As a result, by using GSA, PSO and GA, MSE values become 1.4655e-23, 2.3528e-025 and 2.7401e-007, respectively. GSA, PSO and GA values' curve have been shown in Figure.8, Figure.9 and Figure.10, respectively. It is mentionable that in Figure.9, gray points are personal best for iteration and black line, is the global best. These figures show that using GSA's MSE curve converges at iteration 50. Also after 20 times run, it has been observed that mean value of MSE by GSA is about 3.5834e-016. From results, it can be understood that proposed algorithm can deal with discrimination between Current transformer

Saturation and fault currents very well and can do this work with negligible error.

Table.1
Test Results for Train Data and Test Data Using Implementation of GSA

Train data	Condition	Target output		Actual output		Error	
16MVA, 110/33kV	CT Saturation	1.0000	0.0000	0.9996	0.0010	0.0004	0.0010
	Fault Current	0.0000	1.0000	0.0011	0.9990	0.0011	0.0010
25MVA, 110/33kV	CT Saturation	1.0000	0.0000	0.9998	0.0007	0.0002	0.0007
	Fault Current	0.0000	1.0000	0.0008	0.0015	0.0008	0.0015
5MVA, 110/33kV	CT Saturation	1.0000	0.0000	0.9993	0.0011	0.0007	0.0011
	Fault Current	0.0000	1.0000	0.0009	0.9990	0.0009	0.0010
3MVA, 110/33kV	CT Saturation	1.0000	0.0000	0.9999	0.0014	0.0001	0.0014
	Fault Current	0.0000	1.0000	0.0010	0.9994	0.0010	0.0006
Test data	Condition	Target output		Actual output		Error	
2MVA, 110/33kV	CT Saturation	1.0000	0.0000	0.9999	0.0006	0.0001	0.0006
	Fault Current	0.0000	1.0000	0.0003	0.9999	0.0003	0.0001

Table.2
Test Results for Train Data and Test Data Using Implementation of PSO

Train data	Condition	Target output		Actual output		Error	
16MVA, 110/33kV	CT Saturation	1.0000	0.0000	0.9993	0.0024	0.0007	0.0024
	Fault Current	0.0000	1.0000	0.0013	0.9991	0.0013	0.0009
25MVA, 110/33kV	CT Saturation	1.0000	0.0000	0.9983	0.0013	0.0017	0.0013
	Fault Current	0.0000	1.0000	0.0018	0.9990	0.0018	0.0010
5MVA, 110/33kV	CT Saturation	1.0000	0.0000	0.9983	0.0014	0.0017	0.0014
	Fault Current	0.0000	1.0000	0.0012	0.9991	0.0012	0.0009
3MVA, 110/33kV	CT Saturation	1.0000	0.0000	0.9985	0.0014	0.0015	0.0014
	Fault Current	0.0000	1.0000	0.0010	0.9991	0.0010	0.0009
Test data	Condition	Target output		Actual output		Error	
2MVA, 110/33kV	CT Saturation	1.0000	0.0000	0.9992	0.0021	0.0008	0.0021
	Fault Current	0.0000	1.0000	0.0008	0.9991	0.0008	0.0009

Table.3
Test Results for Train Data and Test Data Using Implementation of GA

Train data	Condition	Target output		Actual output		Error	
16MVA, 110/33kV	CT Saturation	1.0000	0.0000	1.0000	0.0001	0.0000	0.0001
	Fault Current	0.0000	1.0000	0.0279	0.9986	0.0279	0.0014
25MVA, 110/33kV	CT Saturation	1.0000	0.0000	0.9990	0.0001	0.0010	0.0001
	Fault Current	0.0000	1.0000	0.0009	0.9990	0.0009	0.0010
5MVA, 110/33kV	CT Saturation	1.0000	0.0000	0.9996	0.0022	0.0004	0.0022
	Fault Current	0.0000	1.0000	0.0275	0.9986	0.0275	0.0014
3MVA, 110/33kV	CT Saturation	1.0000	0.0000	0.9996	0.0021	0.0004	0.0021
	Fault Current	0.0000	1.0000	0.0265	0.9984	0.0265	0.0016
Test data	**Condition**	**Target output**		**Actual output**		**Error**	
2MVA, 110/33kV	CT Saturation	1.0000	0.0000	0.9990	0.0003	0.0010	0.0003
	Fault Current	0.0000	1.0000	0.0099	0.9991	0.0099	0.0009

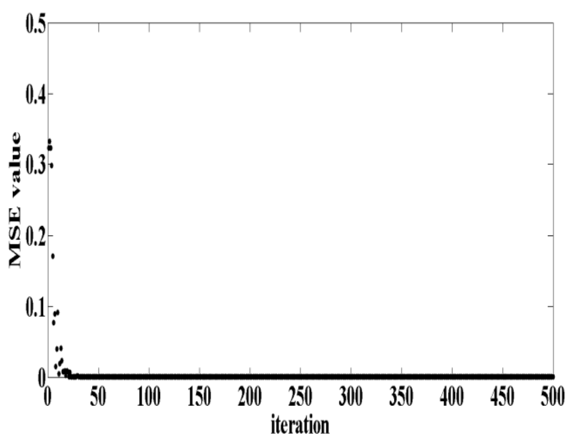

Fig.8. The MSE Variation Curve for GSA

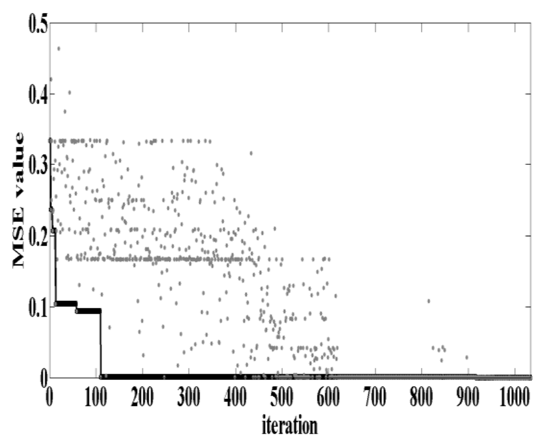

Fig.9. The MSE Variation Curve for PSO

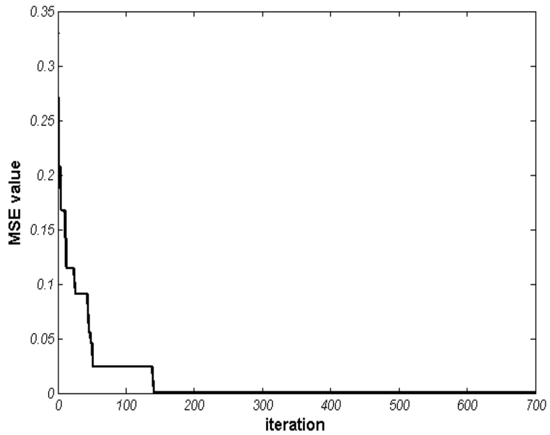

Fig.10. The MSE Variation Curve for GA

6.3. Comparison between different results using GA, PSO and GSA

In order to show quality of proposed algorithm in compared to Genetic algorithm (GA) and Particle swarm optimization (PSO) [10], normalized data of Current transformer Saturation and fault current of a 16MVA, 66/33kV transformer have been used. Results and performance comparisons of GA, PSO and GSA training have been illustrated in Table.4 and Figure.11.

Table.4
Comparison of obtained results using GA, PSO and GSA

Operating conditions	ANN architecture	Output during training and testing of ANN architectures					
		GA		PSO		GSA	
		Target	Actual	Target	Actual	Target	Actual
CT Saturation	16-32-2	1 0	0.9980 0.0021	1 0	0.9988 0.0018	1 0	0.9998 0.0002
Fault Current	16-32-2	0 1	0.0019 0.9989	0 1	0.0015 0.9990	0 1	0.0002 0.9998

Performance comparisons of GA, PSO and GSA

Parameters	GA	PSO	GSA
Convergence (iterations)	140	920	Less Than 50
Time taken for simulation (S)	1(s)	3(s)	18(ms)
Accuracy (%)	94	95	98

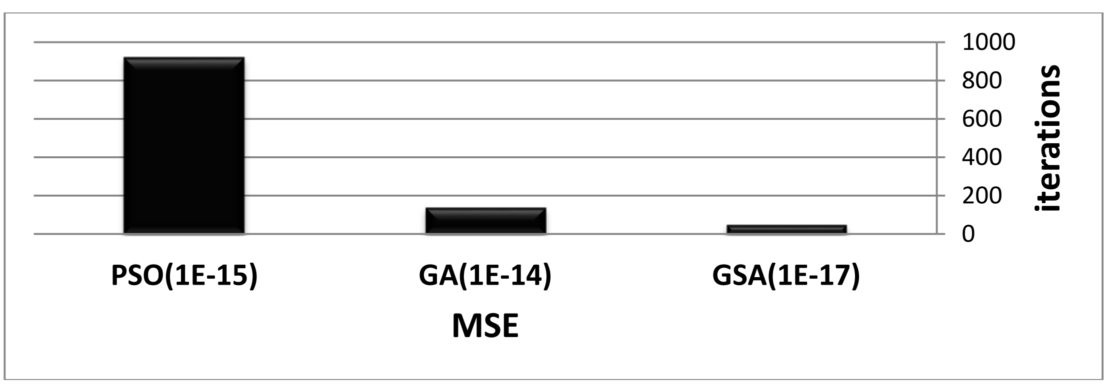

Fig.11. The comparison of the ANN training results using GSA, PSO and GA algorithms

Therefore, results show that in these three approaches GSA converges faster and also gives best MSE value in comparison with PSO-based and GA-based algorithms. In general, it can be said that, proposed training method especially GSA-based one, has more accurate and quick response in compared to other traditional training methods, particularly without any computational burden.

7. Conclusions

Current transformer is important transfer equipment in electrical system. Its saturation may cause malfunction and no action of computer relays. Therefore, proper and quick identification of this unexpected current is so important. By reviewing the results, it can be understood that ANN can be a good tool for classifying these kinds of malfunctions. Meanwhile, it can be understood that the proposed algorithm is very suitable and proper for training ANN and it can help engineers to design excellent classifier. According to the results, choose best controlling parameters for GSA and also optimum number of masses, besides using optimum number of layers and neurons are so important for reaching best results.

In this paper, ANN has been used to distinguish Current transformer Saturation from fault condition, but novelty is that a new approach has been proposed for training ANN. A new swarm-based algorithm which is called GSA has been proposed for training stage. In order to quality and ability of introduced method, this approach has been compared with one of the usual methods GA and the other swarm-based algorithm which is called PSO. The results show that using proposed algorithm training and testing time will be reduced, also more accurate and precise results can be obtained. The simulation results demonstrate that the proposed technique gives a very high accuracy in the classification of the transients about 95 percent.

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