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Optimal Radial Basis Function Neural Network Power Transformer Differential Protection

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Abstract-- **This paper presents a new algorithm for protection of power transformer by using Optimal Radial Basis Function Neural Network (ORBFNN). ORBFNN based technique is applied by amalgamating the conventional differential protection scheme of power transformer and internal faults are precisely discriminated from inrush condition. The proposed method neither depend on any threshold nor the presence of harmonic contain in differential current. The RBFNN is designed by using Particle Swarm Optimization (PSO) technique. The proposed RBFNN model has faster learning and detecting capability than the conventional neural networks. A comparison in the performance of the proposed ORBFNN and more commonly reported Feed Forward Back Propagation Neural Network (FFBPNN), in literature, is made. The simulations of different faults, over-excitation, and switching conditions on three different power transformers are performed by using PSCAD/EMTDC software and presented algorithm is evaluated by using MATLAB. The test results show that the new algorithm is quick and accurate.**

Index Terms-- **RBFNN, Artificial neural network, Power transformer protection, FFBPNN, Differential relaying, PSO, Protective relaying.**

I. Introduction

Ptransformer is one of the important element among other components of power system. Electrical protective relaying of power transformer is usually based on a percentage differential relaying technique in which transient magnetizing inrush and fault must be distinguished because relays are prone to mal-operation in presence of inrush currents, which result from transients in transformer magnetic flux [1-2]. To over come from this problem, initially researchers were proposed three techniques i.e. (i) by introducing time delay in the differential relay (ii) To desensitize the relay for a given time, to override the inrush current (iii) adding a voltage signal to restrain or to supervise the differential relay. And latter on, to enhance the reliability of differential protection, researchers were utilized voltage signals, current signals and differential power [3] in three different methods that can be categorized as (a) Harmonic Restraint (HR), (b) Waveform Identification (WI) and (c) Other methods [4]. The HR is based on the fact that the second harmonic (sometimes the fifth) component of the magnetizing inrush current is considerably larger than in a typical fault current. The literature reveals that the first method, based on harmonic restraint, has been used extensively [5-8]. The HR based method sometime fails to prevent false tripping of relays because high second harmonic component are generated during internal faults and low second harmonic component generated during magnetizing inrush having modern core material of power transformer [9-12]. Therefore, the detection of second/fifth harmonic can not be taken as a sufficient index to discriminate between the magnetizing inrush and fault condition of power transformer. The second method consists of distinguishing magnetizing inrush and over-excitation condition from internal fault condition on the basis of waveform identification. This method was carried out by utilizing the differential current peaks, dead angle and the length of time intervals during which the differential current is near to zero [13-17]. In case of third method, multi-criteria aggregation technique based on fuzzy logic, differential power method, correlation analysis based techniques etc. were employed. However, for such approaches, there are no recommended criteria for setting the internal parameters of a relay. Another disadvantage of these methods includes the need to use voltage transformers and increased protective algorithm calculation cost.

The development of Artificial Neural Network (ANN) provides opportunity to improve and remove the drawback of conventional differential relaying to researchers. Since 1994 to 2007, mostly Feed Forward Back Propagation Neural Network (FFBPNN) approach is reported for discriminating different operating conditions of power transformer. In 1994, L.G. Preze et al. proposed an algorithm based on Multilayer Feed Forward Neural Network (MFFNN) to discriminate between magnetizing inrush and internal fault condition [12]. In 1995, P. Bastard et al. presented multilayer perceptions for power transformer differential relaying [18]. Similarly, up to 2007, many other researchers consider Multilayer Feed Forward Neural Network (MFFNN) for power transformer protection by considering different parameter like differential current, power, voltage and flux etc. [4, 19-23].

In recent time Radial Basis Function Neural Networks (RBFNNs), due to several important advantages over traditional multilayer perceptions, have become very popular [24-25]. These advantages include:

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- Locality of radial basis function and feature clustering algorithms and independent tuning of RBFNN parameters.
- Sufficiency of one layer of non-linear elements for establishing arbitrary input-output mapping.
- Solution of clustering problem can be performed independently from the weights in output layers.
- RBFNN output in scarcely trained areas of input space is not random, but depends on the density of the pairs in training data set.

These properties lead to potentially quicker learning in comparison to multilayer perceptions trained by back propagation [26].

This paper introduces a simple decision making method based on the Optimal Radial Basis Function Neural Network (ORBFNN) for discriminating internal faults from inrush currents. This algorithm has been developed by considering different behaviors of the differential currents under fault and inrush conditions. A comparison between the performance of ORBFNN and FFBPNN is presented in distinguishing between magnetizing inrush and internal fault condition of power transformer. Generally, training of RBFNN includes K-means clustering for calculation of centers, r-nearest neighbor heuristic for width or smoothing factor and subsequent training of output layer weights by least square techniques [27-29]. However, in this work optimal width or smoothing factor is obtained by using Particle Swarm Optimization (PSO) technique because smoothing factor is very important for RBFNN in pattern recognition and classification problems.

II. Radial Basis Function Neural Network

Radial Basis Function (RBF) is one of the member of feed forward neural network family with an input layer used as sensory unit (Sensing Unit) containing n neurons through which input vector $x \in R^n$ is fed to a single hidden layer containing q(t) RBF-type hidden neurons (at t iteration) and an output layer, containing L neurons. In RBFNN model, the activation function of hidden unit is determined by using the radial distance between the input vector and prototype vector. Generally, Euclidean norm is used to measure the radial distance. The network is designed to perform a nonlinear mapping from input space to the hidden space, followed by a linear mapping from the hidden space to the output space. The performances of RBFNN critically depend on the choice of the centers and width factor. The centers in RBFNN should be selected to minimize the total distance between the data and the centers so that the centers can properly represent the data. A simple and widely adopted square error cost function is used for network training. The square error E(t) at iteration t is computed in standard way:

$$E(t) = \frac{1}{2}\sum_{k=1}^{L}\left(d_k(t) - y_k(t)\right)^2 \qquad (1)$$

Where $d_k(t)$ is the desired output and $y_k(t)$ is the output of neuron k given by:

$$y_k(t) = \left(w_k\right)^T . \Phi(t) \qquad (2)$$

Where, $w_k = \left[w_{k1}, w_{k2}, \ldots\ldots, w_{kq(t)}\right]^T$ are the weights connecting the RBF hidden neurons with the output neurons and Φ(t) is the output of the hidden layer. Each hidden neurons represents a single RBF and computes a kernel function of x using any one of the function given in section IV. But in this paper Gaussian kernel function is considered as activation function, as suggested in [30]. The activation function is given as follows:

$$\Phi_j(t) = \exp\left(-\frac{1}{2}\sum_{i=1}^{n}\left(\frac{x_i(t) - c_{ji}}{\sigma_{ji}}\right)\right)^2 \qquad (3)$$

Where, $c_j = [c_{j1}, c_{j2}, \text{---------}\, c_{jn}]$ and $\sigma_j = [\sigma_{j1}, \sigma_{j2}, \text{-------}, \sigma_{jn}]$ are the center and width factor of the j[th] hidden neuron, respectively.

The schematic diagram of three layered radial basis function neural network is shown below in Fig.1.

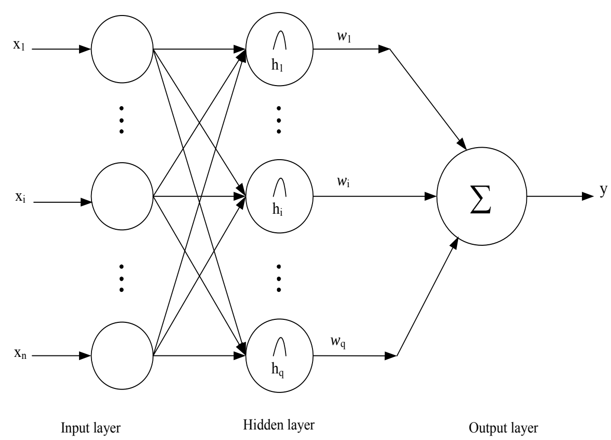

Fig. 1. Typical radial basis function neural network architecture

III. Particle Swarm Optimization Technique

PSO is a population based stochastic optimization technique developed by Eberhart and Kennedy in 1995 [31], inspired by social behavior of birds flocking or fish schooling. The main advantages of PSO algorithm are simple concept, easy implementation, robustness to control parameters and computational efficiency when compared with mathematical algorithm and other heuristic optimization techniques. PSO is designed and proved to be very effective in solving real valued global optimization problems [32]. Moreover, it does not require gradient information of the objective function under consideration, but only its values, and it uses only primitive mathematical operators.

In PSO, population is called swarm and individuals (i.e. the points) are called particles. Each particle moves with an adaptable velocity within search space and retains in a memory the best position it ever encountered. This best position is shared with other particles in the swarm after each iteration. Two variants of the PSO algorithm were developed [33]. One with a global neighborhood, and other with a local neighborhood. According to the global variant, each particle moves towards its best previous position and towards the best particle in the whole swarm, whereas according to the local variant, each particle moves towards its best previous position and towards the best particle in its restricted neighborhood [33]. In general, the global variant of PSO exhibits faster convergence rates, although, in some cases it may reduce the swarm's diversity very fast, thereby getting trapped in local minimizers. On other hand, the local variant, especially when the neighborhood size is small, exhibits superior exploration capabilities at the cost of slower convergence.

Assuming an n-dimensional search space, the position and velocity of individual i are represented as the vector $Z_i = (z_{i1}, z_{i2}, z_{i3} \ldots z_{in})$ and $V_i = (v_{i1}, v_{i2}, v_{i3} \ldots v_{in})$ respectively in PSO algorithm.

Let the best previous position $BP_i = (bp_{i1}, bp_{i2}, bp_{i3} \ldots bp_{in})$ and $GB_i = (gb_{i1}, gb_{i2}, gb_{i3} \ldots gb_{in})$, respectively be the best position of individual i and its neighbor's best position so far. The updated velocity of individual i is modified by using following equations:

$$V_i^{k+1} = wV_i^k + c1\,r1\left(BP_i^k - Z_i^k\right) + c2r2\left(GB_i^k - Z_i^k\right) \qquad (4)$$

$$Z_i^{k+1} = Z_i^k + V_i^{k+1} \qquad (5)$$

Where,

V_i^k = Velocity of individual i at instant k

w = Weight parameter

$c1, c2$ = Two positive constants called cognitive and social

$r1, r2$ = Random number between 0 and 1

Z_i^k = Position of individual i at iteration k

BP_i^k = Best position of individual i until iteration k

GB_i^k = Best position of the group until iteration k

Performance of each particle is measured according to a pre-defined fitness function which is problem dependant. The inertia weight w is employed to control the impact of previous history of velocities on the current velocity. A large inertia weight w facilitates global exploration (searching new areas) while a smaller inertia weight tends to facilitate local exploration to fine-tune the current search area. The inertia weight w can be set to the following (6) [34]:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \text{ x } iter \qquad (6)$$

Where,

$w_{\max} = 0.9$, $w_{\min} = 0.4$

$iter_{\max}$ = Maximum iteration number

$iter$ = Current iteration number

A pseudo-code of PSO to obtain optimal smoothing factor of RBFNN is given as following:

FOR each Particle
Initialize Particle
End
Do
FOR each Particle
Compute fitness function $f\left(\left(\sigma_i^{k+1}\right)\right)$ *by the leave-one-out misclassification proportion on training exemplar pattern set.*
If fitness value is better than the best fitness (BP) in history
Set current value as the new BP
END
Choose the Particle with the best fitness as the GB
FOR each Particle
Compute its velocity
Update its position (i.e. smoothing factor $f((\sigma_i))$
END
WHILE maximum iterations or stop criteria are not attained.

Leave-One-Out (LOO) error estimation is an important statistical tool for assessing generalization performance [35]. In the PSO method, a swarm of particle (i.e. smoothing parameter σ) is initialized randomly in $[0\ 1]^n$, n denotes the dimension of optimization problem. The LOO misclassification proportion on the training set is computed and this value is used as the fitness value i.e. $f(\sigma_i)$. In LOO method, RBFNN is trained using all but one of patterns from the training set. The executed pattern is subsequently used to assess the classification ability of the network. This process is repeated excluding a different pattern of the training set each time, until all patterns of this set are executed once. This adaptation process is terminated when maximum number of iteration is reached.

IV. Designing And Training of RBFNN

The basic topology of RBFNN consist of an input layer, one hidden layer and output layer as shown in Fig.(1). Hidden layer of RBFNN utilizes kernel functions, distributed in different neighborhoods of the input space, whose responses are essentially local in nature. Generally, the number of neurons in hidden layer is fixed heuristically. The sigmoid type of activation function used in multilayer feed forward networks to train with back-propagation, does not yield the approximating capabilities for RBF networks. The following activation functions Φ (v) are popular for RBFNN as reported in [30]:

i. Gaussian Function

$\Phi(v) = \exp(-v^2/2\sigma^2)$

ii. Thin SP line Function

$\Phi(v) = v \log v^{1/2}$

iii. Multiquadric Function

$\Phi(v) = (v2 + \sigma^2)^{1/2}$

iv. Inverse Multiquadric Function

$\Phi(v) = (v2 + \sigma^2)^{-1/2}$

Where,

$v = || x - c_j ||$

x = input vector and c_j is j^{th} center

σ = width factor or smoothing factor (real constant)

$||\ \ ||$ = Euclidean norm

In general, training of a neural network is a nonlinear optimization problem. FFBPNN and RBFNN both require iterative training before using it for classification between inrush and internal fault patterns of power transformer. But the RBFNN training procedure differs from the FFBPNN. FFBPNN is trained by supervised techniques: the set of weights are computed by solving a non-linear constrained equation set. On the contrary the training of RBFNN can be split into an unsupervised part and a supervised part. The unsupervised part is straight forward and relatively fast. Meanwhile its supervised part consists of solving a linear problem therefore it is also fast. Thus the training procedure of RBFNN is relatively less time and resources consuming. The training procedure of RBFNN can be clearly understood from the Fig. 2.

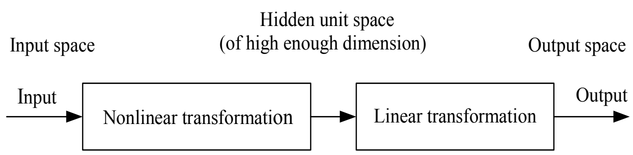

Fig. 2. Training procedure of radial basis function neural network

The design and training of an RBFNN consist of the following three steps:

i. Determining the centers

ii. Determining the widths

iii. Determining the weights

The first two parameters of RBFNN are determined by unsupervised learning methods and using training data only. The centers are determined by using K-means clustering techniques. The width or smoothing factor can be determined by two methods, i.e. given as fixed center method and Moody and Darken method. The fixed center method is given as:

$$\sigma = \frac{d_{\max}}{\sqrt{2M}} \tag{7}$$

Where, M is the number of centers and d_{max} is the maximum distance between chosen centers. Moody and Darken [36], proposed width factor σ_j by r- nearest neighbor heuristic:

$$\sigma_j = \frac{1}{r}\sqrt{\sum_{i=1}^{r} || c_i - c_j ||^2} \tag{8}$$

Where, c_i are nearest of centers c_j and a suggested value for r is 2 neighbor.

However, in this paper, RBFNN is deigned by considering K-means clustering and optimal width factor. The purpose of selecting K-mean is to get accurate centers. Clustering is used to improve the generalization process. The optimal smoothing factors are obtained by using PSO technique. The combination of these two techniques will improve the classification capability of RBFNN. The weights are calculated by a supervised, single-shot process using pseudo inverse matrices or Singular Value Decomposition (SVD) method.

V. Simulation And Training Cases

Five conditions are encountered during the operation of a transformer. These are:

- Normal condition
- Magnetizing inrush condition/ Sympathetic inrush condition
- Over-excitation condition
- Internal fault condition
- External fault condition

In the normal condition rated or less current flows through the transformer. In this condition normalized differential current is almost zero (only no load component of current). Whenever, there is large and sudden change in the input terminal voltage of transformer, either due to switching-in or due to recovery from external fault getting, a large current is drawn by the transformer from the supply. This results in core of transformer getting saturated. This phenomenon is known as magnetizing inrush, or in other words, inrush can be described by a condition of large differential current occurring when either the transformer is just switched on or the system recovers from an external fault. Magnetizing inrush can also occur in an already energized transformer when a nearby transformer is energized. A common situation of sympathetic inrush is encountered when a transformer is energized in parallel with another transformer already in service. The phenomenon which causes inrush current to flow in a previously energized transformer is known as the '*sympathetic inrush*'. As the paralleled transformer is being energized by closing the breaker, an inrush current is established in the primary of this transformer and this inrush current has DC component. The DC component of the inrush current can also saturate the already energized transformer, resulting in an apparent inrush current. This transient current, when added to the current of already energized transformer, results in an asymmetrical current that is very low in harmonics. This would be the current flowing in the supply circuit to both transformers. Sympathetic inrush current may not have sufficient amount of the second harmonic in it to prevent the relay from tripping. Sympathetic inrush current depends on same factors on which switching-in and recovery from fault magnetizing inrush current depends.

Among the various faults in transformer, phase-to-ground fault occurs most frequently. For protective device operation view point, phase-to-ground fault, may be further classified as following on the basis of fault current:

i. Heavy faults

ii. Medium level fault and

iii. Low level fault

In all the cases, the abnormality nature is almost same but the magnitude of currents resulting due to that are quite different. If the level of fault can be detected and accordingly protective action is taken than the major damage to the protected element can be prevented.

Three-phase transformers of 315 MVA, 400/220 kV, 200MVA, 220/110 kV and 160 MVA, 132/220 kV are modelled using PSCAD/EMTDC software [37]. The parameters used for the modeling of these transformers through PSCAD/EMTDC were obtained from M. P. State Electricity Board, Jabalpur, India. Since the magnitude and the wave-shape of inrush current depend on the switching-in angle, remanent flux in the core and the loading condition, the inrush condition is simulated with different switching-in angles and remanent flux varying from 0 % to 80 % of the peak flux linkages generated at rated voltage with no load and full load condition of transformer. The training signals are obtained by varying the switching-in angle from 0 to 360 degrees in step of 30 degrees, while testing signals are obtained by varying switching angle in step of 15 degrees. As transformers are not expected to be subjected to more than 15% over-voltage hence, the over-excitation condition is simulated by applying 115% of the rated voltage at full load. For internal faults, training and testing data is obtained by simulating phase-to-phase fault from 1% to 99% of power transformer winding turns. Phase-to-ground faults are also simulated at different locations such as 5%, 10%, 15%, and up to 50% from the neutral end of the winding as well as at transformer bushing. Some typical signals so acquired by simulating various operating conditions of transformer are shown in Figs. 3-6.

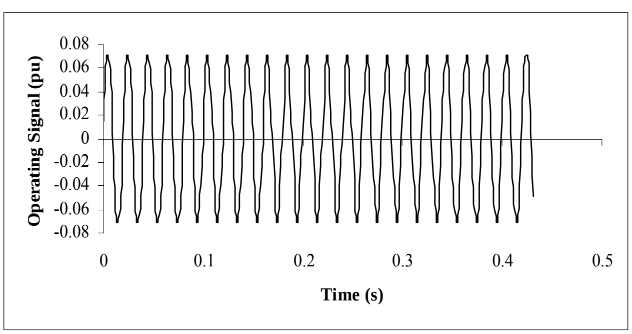

Fig. 3. Typical differential current waveform under normal operation

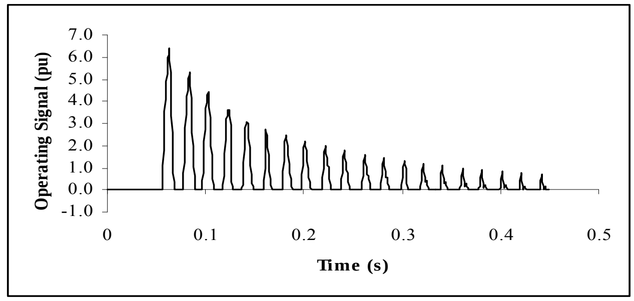

Fig. 4. Typical magnetizing inrush current waveform

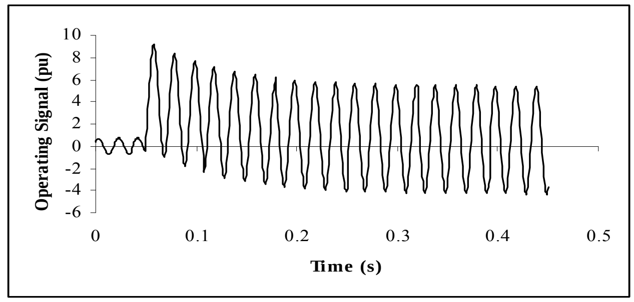

Fig. 5. Typical phase-to-ground fault current waveform

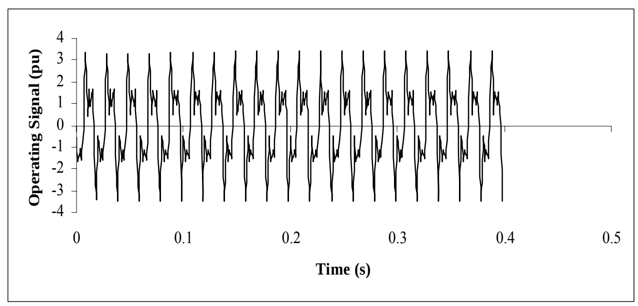

Fig. 6. Typical differential current waveform for over-excitation

Digital relays decide their operation on parameters of sampled measured quantity (differential current, in this case). The sampling rate and the data window size are chosen depending upon the algorithm being used. Since ORBFNN is based on waveform identification method, therefore, to recognize the wave-shape a window of one cycle duration is suitable and it is used in this work. The simulation is performed at the rate of 12 samples per cycle of 50 Hz A.C. supply in view of reported experience on different digital relay designs [38]. The developed protection algorithms were implemented in MATLAB.

VI. Implementation Of Optimal RBFNN

The differential current is taken as input of neural network. It is represented in discrete form, as a set of 12 uniformly distributed samples obtained over a data window of one cycle that is called a '*pattern*'. The sliding data window, consisting of one most recent and other of previous window, is fed to the neural network.

In proposed ORBFNN architecture, three layer structures are used. In first layer 12 neurons, in the hidden layer 11 neurons and in output layer one neuron is considered. The numbers of neuron of input layer are decided based on the dimension of the feature space i.e. 12 samples per cycle. Trial and error method is used to find out the optimal number of neurons in the hidden layer of the presented ORBFNN model. It can be seen, from Fig. 7, that as the number of neurons in hidden layer increase, the error decreases, but after certain number of neurons, the error increases again and the minimum error is obtained at 11 neurons in the hidden layer. Therefore, this number of neurons in the hidden layer is optimal for this application. At the output, as binary decision (to trip or not) is required, only single output is sufficient and therefore, the output layer consists of just one neuron.

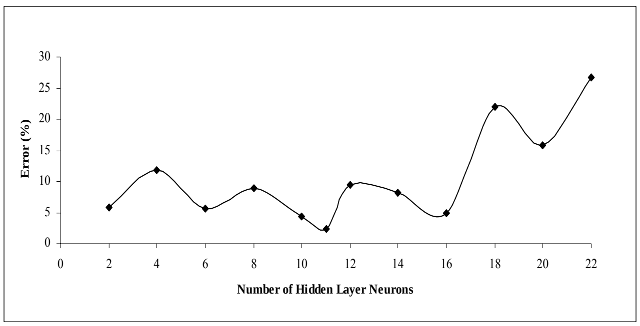

Fig. 7. The effect of hidden layer neurons on error

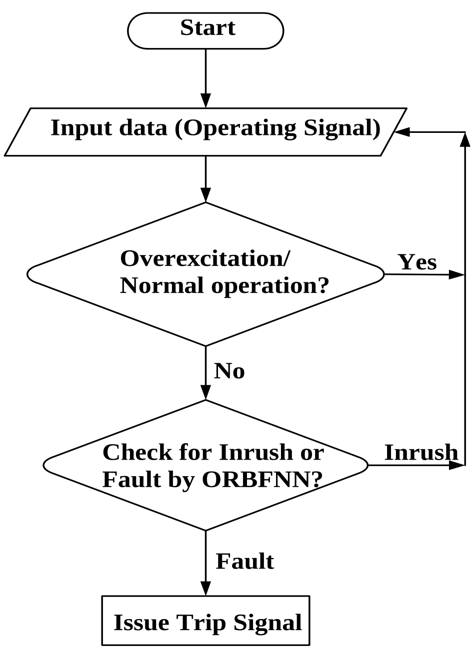

Fig. 8. Flow Chart Proposed Algorithm

In present work, optimal smoothing factor which is crucial for the classification accuracy of RBFNN is obtained by PSO. The local variant of PSO algorithm is used, as it exhibit better performance, compared to the global variant, due to its enhanced exploration capability. According to pseudocode given in section-III, PSO algorithm is initialized randomly with swarm of 20 particles. The typical range for the number of particles ranges from 20 to 40. The values of cognitive and social are taken as 2. The maximum number of iteration was set to 100 and inertia weight w is initially set at 0.9. In order to reduce this weight over the iterations, allowing the algorithm to exploit some specific areas, (6) is used. The particles are constrained in the range of 0 to 1, since smoothing factor lies in this range for the normalized data. The LOO strategy is applied for minimizing misclassification error on the training set, while misclassification error on the validation set is monitored after each iteration of the algorithm. The signal was sampled at the rate of 12 samples per cycle (over a data window of one cycle).

In training, inrush condition is indicated by zero (0) and fault condition is indicated by one (1). Out of 2356 sets of data 2178 sets are used for training of RBFNN with optimal smoothing factor which is already obtained by PSO and remaining 178 sets are used to test the trained network's generalization ability. The training and testing sets contain internal fault and magnetizing inrush/sympathetic inrush condition only as these two conditions are very difficult to discriminate as compare to other operating conditions like external fault condition, over-excitation and normal condition. From protection point of view, only these two conditions are necessary to identify as the relay has to give trip signal in case of internal fault condition only whereas in other conditions it should not operate. The discrimination between external fault and normal operating condition is made by comparing two consecutive peaks of operating signal. The over-excitation condition is determined by comparing voltage-to-frequency ratio with the rated voltage-to-frequency ratio. If these condition do not exist then magnetizing inrush and internal fault condition is checked by ORBFNN. The ORBFNN gives tripping signal if internal fault condition is found. The flow chart (Fig.8) clearly indicates these steps for discriminating different operating conditions of power transformer. For different conditions of the test set, fault current magnitude, remanent flux, load condition and switching-in angle were changed to investigate the effects of these factors on the performance of the ORBFNN model. The wave-shape of magnetizing inrush current changed with variation of switching-in instant of transformer which is varied between 0 to 360 degrees. Due to remanence flux, the magnitude of magnetizing inrush current may rise up to 2 to 8 times of magnetizing inrush current without remanence effect although the wave-shape remains same. It is found that the ORBFNN classifier based relay is stable even with such high magnitude of magnetizing inrush current caused by remanence flux whereas the conventional harmonic based relay may mal-operate due to such high magnitude magnetizing inrush current.

$$\text{Classification Error (in \%)} = \frac{\text{No.of False Positive} + \text{No.of False Negative}}{\text{Total Number of Test Cases}} \times 100$$

$$\text{Classification Accuracy (in \%)} = 100 - \text{Classification Error (in \%)} \quad (9)$$

Table I

IMPROVEMENT IN CLASSIFICATION ACCURACY (IN %) WITH ORBFNN AND FFBPNN

Training transformer ratings	Tested transformer ratings					
	315 MVA		200 MVA		160 MVA	
	FFBP NN	ORBF NN	FFBP NN	ORBF NN	FFBP NN	ORBF NN
315 MVA	99.31	100	95.50	97.29	98.87	99.32
200 MVA	96.62	97.97	99.43	100	97.18	98.64
160 MVA	98.80	99.32	96.62	98.64	99.43	100

Table II

NUMBER OF POST DISTURBANCE SAMPLES REQUIRED FOR DECISION BY FFBPNN AND ORBFNN BASED RELAYS

Cases	Number of samples required (Actual)		Maximum Number of samples required (Logical)	
	FFBPNN	ORBFNN	FFBPNN	ORBFNN
Magnetizing inrush (0^0)	11	07	12	12
Internal fault (Light phase-to-ground fault at 2%)	10	06	12	12

The FFBPNN model has 12 input neurons in the first layer, 11 neurons in hidden layer and one neuron at output layer. The hidden layer and output layer neurons uses bi-directional sigmoid activation function. Similar type of FFBPNN structure is selected so that comparative performance study can be made for the same cases as considered for ORBFNN.

After extensive experimentation on ORBFNN and FFBPNN architectures, the performance results are shown in Table-I and Table-II. The training procedure of ORBFNN is relatively less time and resources consuming in comparison of FFBPNN as explained in section IV. Moreover, in case of FFBPNN at least four parameters are to be tuned whereas in case of ORBFNN single parameter is to be tuned.

The classification accuracy is calculated by using (9). Out of 178 test patterns, 89 test sets were inrush patterns and remaining 89 test sets were internal fault patterns. The inrush test patterns consists of sympathetic inrush patterns and magnetizing inrush patterns at different switching-in angles, remanent flux, and loading conditions while internal fault test patterns are made up of phase-to-ground fault and phase-to-phase fault at different locations. Table-I shows the classification accuracy tested with three different ratings of power transformers. From Table-I, it is observed that when the transformer of same rating are trained and tested, then higher classification accuracy is obtained (approximately 100 %), but if it is tested with different rating of transformer then minimum 95.50 % accuracy is achieved. From Table 1, it is clear that the classification capability of ORBFNN is better than the FFBPNN. Table-II presents the number of post disturbance samples required for decision making by the proposed ORBFNN and FFBPNN based transformer differential protection algorithm. In light internal fault cases, FFBPNN requires 10 samples after the fault occurrence that means about 16.67 ms are required for the fault detection while ORBFNN takes 6 samples i.e. 10.00 ms. However, it is observed that the relay operation is independent from the harmonics present in the operating signal and therefore no filtering is required in this method. It is found that the ORBFNN classifier based relay is stable even with high magnitude of magnetizing inrush current caused by remanence flux. The proposed ORBFNN model is successfully tested using relaying signals obtained by modeling the power transformers on PSCAD/EMTDC^{TM} and simulating various operating conditions.

The proposed algorithm can be implemented in real time with FPGA (Field Programmable Gate Arrays) concurrent hardware. It is also immune from the different harmonics contained in the operating signals which makes it simpler and robust than conventional digital filtering algorithms.

VII. CONCLUSION

This article presents a novel approach for discriminating between transformer internal fault and magnetizing inrush condition based on Optimal Radial Basis Function Neural Network (ORBFNN). The proposed algorithm is amalgamation of conventional transformer differential protection scheme and waveform identification scheme. The ORBFNN is feasible and efficient in solving classification problems, and a differential relay can be considered as a classifier. The optimal smoothing factor that is very important for radial basis function neural network is obtained by Particle Swarm Optimization (PSO) technique. The performance of the proposed ORBFNN is compared with one of the conventional neural network i.e. Feed Forward Back Propagation Neural Network (FFBPNN). From the results, it is evident that the ORBFNN has better pattern classification and generalization ability than the FFBPNN. Moreover, the ORBFNN is faster than FFBPNN and does not depend on the thresholds like Harmonic Restraint (HR) method. In the proposed method, stability of differential relay is ensured during the magnetizing inrush, sympathetic inrush, over-excitation and external fault conditions. The presented ORBFNN algorithm is quite accurate especially in case of modern power transformers that use high-permeability, low-coercion core materials.

The real time implementation of differential relay using the proposed algorithm with ORBFNN as the core classifier would essentially require ORBFNN processors. To the best of auther's knowledge, no ORBFNN processors specifically developed for relaying have been reported so far. This may be an attractive topic of research for those indulge in design and development of processors.

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