Indirect Symmetrical PST Protection Based on Phase Angle Shift and Optimal Radial Basis Function Neural Network

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Abstract—This paper proposes a new algorithm for blocking the operation of Indirect Symmetrical Phase Shift Transformer (ISPST) differential relay when subjected to different operating conditions except internal fault condition. The proposed algorithm is amalgamation of Phase angle shift (PAS) threshold and Optimal Radial Basis Function Neural Network (ORBFNN). PAS between source and load side currents of fundamental frequency is used as threshold. PAS threshold identifies whether the abnormal condition is in ISPST or out of ISPST. ORBFNN is used for the discrimination of internal fault from magnetizing inrush condition. The ORBFNN is designed by using Particle Swarm Optimization (PSO) technique. The performance of proposed ORBFNN algorithm is compared with more commonly reported Feed Forward Back Propagation Neural Network (FFBPNN). The simulations of different operating conditions of an ISPST are performed by using PSCAD/EMTDC software.

Keywords— Differential protection; phase shift transformer; artificial neural network; particle swarm optimization;

I. INTRODUCTION

Phase Shift Transformer (PST) is an important electrical component used for the power flow control through specific line in a complex power transmission network. The basic function of the PST is to change the effective phase displacement between input and output voltage of a transmission line. Power flow control using PST is given by (1). There are different types of PST according to their construction as discussed in [1]. Indirect Symmetrical PST (ISPST) is widely used because of its features and simple construction as shown by line diagram in fig. 1. It helps in the utilization of power transmission lines which improve the system operating performance and efficiency.

\[ P = \frac{|V_S||V_L|}{X_T}\sin(\delta \pm \Delta \theta) \]  

where \( V_S \) and \( V_L \) are source and load side voltage, \( \delta \) is phase angle between \( V_S \) and \( V_L \), \( \Delta \theta \) is phase angle shift due to ISPST.

Considering the importance and cost of an ISPST, it requires fast and reliable protection. However, there are many protection schemes such as differential protection, overload protection, over excitation protection, through current backup protection etc. [2], but differential protection is the main protection scheme which is applied for internal faults in an ISPST. In differential protection, an ISPST is protected for both series and excitation unit [3, 4]. This needs 18 CTs, 9 for each protection, which makes the protection quite costly. Instead of this, ISPST protection can be done like power transformer by using phase angle shift compensation [5]. It takes time for calculation, which makes delay in tripping of relay. Furthermore, differential relay is prone to mal-operation in presence of magnetizing inrush current of an ISPST, which is caused by transient in ISPST magnetic flux [2]. As discussed about the power transformer, to enhance the reliability of differential protection, voltage signal, current signals and differential power is utilized in three methods such as Harmonic restraint (HR), waveform identification and other methods [6-7]. The HR principle is based on the second harmonic component of the magnetizing inrush which is considerably larger than in a typical internal fault current [8]. But the modern transformers are different in design and material, therefore run at high flux density, and hence generate low harmonics contents during the inrush currents, which affect HR scheme [9]. Similar to the power transformer protection, ISPSTs differential protection also brings challenge of non-standard phase shift between two ends [6, 10]. The introduction of Artificial Neural Network (ANN) in the protection has been removed the drawback of conventional differential relaying. There are different types of ANN such as Multilayer feed forward Neural Network (MFFNN), Feed Forward Back propagation Neural Network (FFBPNN) etc.
These have been used for discrimination of different operating condition (Normal, internal fault, magnetizing inrush etc.) by considering different parameter like power, voltage, differential current, flux etc. [11]. Radial basis Function Neural Network (RBFNN) has become a very popular algorithm due to several advantages over other traditional multilayer neural network [12]. These advantages include: independent tuning of RBFNN parameters, one layer of non-linear transformation is sufficient for input-output mapping and clustering problem is independent of output layer weight.

This paper proposes a simple decision making threshold based on the phase angle shift (PAS) which discriminate normal and external fault conditions from magnetizing inrush and internal fault conditions. An Optimal Radial Basis Function Neural Network (ORBFNN) is used for the discrimination of internal fault from magnetizing inrush condition. The ORBFNN has been developed based on slope of the differential current just before first peak after PAS decision under internal fault and magnetizing inrush condition. Generally, ORBFNN training includes r-nearest neighbor heuristic for width or smoothing factor, K-mean clustering for calculation of centers and training of output layer weights by least square technique [13]. However, in this paper calculation of centers and optimal width or smoothing factor is obtained by using Particle Swarm Optimization (PSO) technique because these factors are very important for ORBFNN to increase the accuracy in classification problem. A comparison between the performance of ORBFNN and FFBPNN is presented for the discrimination of internal fault from magnetizing inrush condition.

II. OPTIMAL RADIAL BASIS FUNCTION NEURAL NETWORK

RBFNN has become a very powerful tool to many technical problems because of its universal approximation capability and fast learning speed [12, 14]. The inputs to the hidden layer are the linear combinations of scalar weights and input vector \( x = [x_1, x_2, \ldots, x_n]^T \), where the scalar weights are usually assigned unity values and \( n \) is number of inputs. Thus the input vector becomes the input to each neuron in the hidden layer. The incoming input vectors are mapped by the radial basis function in each hidden node. The output layer produces a vector \( y = [y_1, y_2, \ldots, y_m] \) for \( m \) outputs by linear combination of the outputs of hidden nodes to produce the final output, which is given by (2):

\[
y = \sum_{i=1}^{k} w_i \phi(x)
\]

where \( w_i \) denotes the hidden-to-output weight corresponding to the \( i^{th} \) hidden node and \( k \) is the number of hidden nodes, \( \phi(x) \) is the hidden layer output of the \( i^{th} \) hidden node. Each hidden node represents a single RBF and computes a Gaussian kernel function of \( x \). Gaussian kernel function is considered as activation function, as suggested in [15]. The Gaussian activation function is represented as follows (3):

\[
\phi(x) = \exp \left( -\frac{1}{2} \sum_{j=1}^{n} \frac{(x_j - c_j)^2}{\sigma_j^2} \right)
\]

where \( c_j \) and \( \sigma_j \) denotes the center and width of the \( i^{th} \) hidden node respectively.

The structure of single input and single output, three layered radial basis function neural network is shown in fig. 2. Generally, the Gaussian RBFNN training is done in to two stages.

- Determine the optimal parameters of radial basis functions, i.e., Gaussian center and width or smoothing factor.
- Determine the output weight ‘w’ by supervised learning method.

The first stage is very crucial, since the performances of RBFNN critically depend on the choice of the centers and widths. In this work optimized values of centers and widths are calculated by PSO for each hidden neuron.

III. PARTICLE SWARM OPTIMIZATION TECHNIQUE

PSO technique is inspired by social behavior of birds, insects and fish. It is a population based stochastic optimization technique developed by J. Kennedy and R. Eberhart in 1995 [16]. The main advantages of PSO algorithm are simple concept, robust to control parameters, easy to implement and computationally efficient as compare to other optimization techniques. In PSO, population is called swarm and individuals are called particles. All particles move with an adaptable velocity within search space and recollect the best position it ever encounters in memory. The best position of particle is shared with other particles in the swarm after each iteration. In PSO algorithm, two variants were developed [17]. One is local variant and other is global variant. According to local variant, each particle moves towards its best previous position and toward the best particle in its restricted neighborhood, whereas according to global variant, each particle moves towards its best previous position and towards the best particle in the swarm [17]. In general, the global variant exhibits faster convergence rates compare to local variant. The particle expresses the ability of fast convergence.

\[\text{Fig. 2. Typical Single input, single output RBF network}\]
to local and/or global optimal position(s) over a small number of generations.

Consider an $n$-dimensional search space, there are three elements, current position $P_i = (p_{1i}, p_{2i}, \ldots, p_{ni})$, current velocity $V_i = (v_{1i}, v_{2i}, \ldots, v_{ni})$ and the past best position $Pb_i = (pb_{1i}, pb_{2i}, \ldots, pb_{ni})$ for particle $i$ in the search space to represent their features. Each particle in the swarm is iteratively updated according to the predefined attributes assuming that the fitness function $f$ is to be minimized so that new velocity of every particle is updated by (4):

$$V_{i}^{k+1} = w^k V_i^k + c_{1} r_1 (Pb_i^k - P_i^k) + c_2 r_2 (G_b^k - P_i^k)$$  \hspace{1cm} (4)

where $k$ is the number of iteration, $V_i^k$ is the velocity of the $i^{th}$ particle for iteration $k$, $w^k$ is the inertia weight of velocity, $c_1$ and $c_2$ denote the acceleration coefficient, $r_1$ and $r_2$ are two uniform random values in the range between (0, 1), $Gb_i^k$ is global best position until iteration $k$. The new best position of the $i^{th}$ particle is calculated by (5):

$$P_i^{k+1} = P_i^k + V_i^{k+1}$$  \hspace{1cm} (5)

The past best position of each particle is updated by:

$$Pb_i^{k+1} = \begin{cases} Pb_i^k, & \text{if } f(P_i^{k+1}) \geq f(Pb_i^k) \\ P_i^{k+1}, & \text{otherwise} \end{cases}$$ \hspace{1cm} (6)

Each particle performance is calculated according to a predefined fitness function $f$ which is problem dependent. The inertia weight $w$ is usually a monotonically decreasing function to control the impact of previous history of velocities on the current velocity. The inertia weight $w$ can be set to the following [18]:

$$w^k = w_{max} \times \frac{w_{max} - w_{min}}{iter_{max}} \times iter^k$$  \hspace{1cm} (7)

where $w_{max} = 0.9$, $w_{min} = 0.4$, $iter_{max}$ is maximum number of iteration and $iter^k$ is $k^{th}$ iteration number.

In this work, the fitness function $f$ to optimize the width and center of RBFNN is defined by the mean square errors (MSE) of its outputs for all training samples. The optimal width $\sigma$ and center $c$ for the training set $(X_i)_{i=1}^m$ is given by fitness function:

$$f(\sigma, c) = \arg \min \sum_{i=1}^{m} \left( t_i - \exp \left( - \frac{\|X_i - c\|^2}{2\sigma^2} \right) \right)^2$$ \hspace{1cm} (8)

where $t_i$ is the desired output for the input sample $X_i$.

IV. PROPOSED ALGORITHM

During ISPST operation it encounters anyone of the following condition:

- External Fault Condition
- Over-excitation Condition

Out of these operating conditions differential relay should operate only in internal fault condition. But due to non-standard phase shift between two ends of an ISPST, differential current is not equal to zero. It requires phase shift compensation, which increases the relay time of operation due to compensation calculation. The proposed algorithm is based on the PAS threshold between source and load side current for each phase. Normal operating condition in advance and retard phase shift mode of operation with maximum PAS and PAS threshold is shown in fig. 3. The non-standard phase shift will vary between these two boundaries of an ISPST. In case of magnetizing inrush PAS becomes approximately equal to $–90$ degree because it is primarily inductive at no-load as revealed in fig. 4. But in case of on-load magnetizing inrush, PAS becomes less than $–90$ degree, because of loading condition. In case of internal fault in series unit or excitation unit, either source current or load current would be reversed and hence PAS between them becomes greater than $–90$ degree as shown in figs. 5-6. But in few cases (such as turn to turn), the PAS becomes less than $–90$ degree due to non-reversal of current either source or load side and advance phase angle shift. In case of external fault condition, there is no reversal of current either source or load side and hence PAS between them is almost equal to zero as shown on fig. 7. Fig. 8 shows case of over-excitation with PAS threshold. Hence a PAS based threshold can discriminate other operating condition from magnetizing inrush and internal fault condition.

![Fig. 3. Phase angle shift of phase ‘a’ in normal operating condition](image1)

![Fig. 4. Phase angle shift of phase ‘a’ in case of magnetizing inrush at time $t=0.15$sec.](image2)
V. SIMULATION AND TRAINING CASES

The proposed algorithm has been evaluated for aforementioned operating conditions of an ISPST. Differential currents are obtained for each phase with star connected current transformers (CTs) on both sides of an ISPST using PSCAD/EMTDC. The line diagram is shown in fig. 11.

Three phase 300MVA, 138kV/138kV, 1255A/1255A, 60Hz ISPST with max phase shift of ±30 degree and maximum loading of 240MW and 180MVAR is considered to

![Fig. 5. Phase angle shift of phase ‘a’ in case of internal fault (A-G) in excitation unit at time t=0.15sec.](image)

![Fig. 6. Phase angle shift of phase ‘a’ in case of internal fault (A-G) in series unit at time t=0.15sec.](image)

![Fig. 7. Phase angle shift of phase ‘a’ in case of external fault (A-G) at time t=0.15sec.](image)

![Fig. 8. Phase angle shift of phase ‘a’ in over-excitation condition](image)

Discrimination of internal fault current from magnetizing inrush current is based on the following characteristics of the differential current as shown in fig. 9:

- A large slope characteristic of the waveform near to peak in case of magnetizing inrush condition.

This feature can easily discriminate internal fault condition from magnetizing inrush condition. An Optimized RBFNN is used for the discrimination between internal fault and magnetizing inrush condition using this feature. The flow chart for the proposed algorithm is shown in fig. 10.

![Fig. 9. Behavior of (a) Magnetizing Inrush and (b) Internal Fault](image)

![Fig. 10. Flowchart for proposed algorithm](image)
test the performance of the proposed algorithm [3]. Relevant CTs with the ratio 2000/5 are connected in star on both sides of an ISPST whose parameter is reported in [19]. Since the wave shape and magnitude of the magnetizing inrush current depends on the switching-in angle, loading condition and remanent flux in the core, the magnetizing inrush condition is simulated with varying switching-in angle, different loading condition and remanent flux varying from 0% to 80% of the peak flux generated at rated voltage in advance and retard mode of operation. The training and testing signals are obtained by varying switching-in angle in step of 30 degree from 0 to 360 degree. Along the various faults in ISPST series and excitation unit, phase to ground faults and turn-to-turn faults occurs more frequently. For protection device point of view, phase-to-ground fault can further be classified as heavy level fault, medium level fault and low level fault. In all the cases, abnormality nature is almost same but magnitude of differential current changes. So the training and testing data is obtained by simulating phase-to-ground fault from 1% to 50% of series and excitation unit winding turns with the help of transformer fault model presented in PSCAD. Phase-to-phase and three-phase-to-ground fault is also simulated with different fault inception angles for advance and retard mode of operation of an ISPST. External fault is also simulated for phase-to-ground, two-phase-to-ground and three-phase-to-ground fault. Some typical signals for various operating condition of an ISPST are shown in figs. 12-16.

The digital relay decides their operation on the basis of slope of differential current just before first peak after disturbance detected by PAS threshold. The data window size is chosen depending on the algorithm being used. Since ORBFNN is based on slope identification method, a calculated slope is given as an input to ORBFNN, therefore data window size is one.

![Fig. 12. Typical differential current waveform under normal operating condition of retard phase angle shift](image)

The proposed ORBFNN of three layer architecture is used. In first layer one neuron as an input, in the hidden layer four neurons and in output layer one neuron is taken. Trial and error method is used to find out the optimal number of neuron in the hidden layer. Fig. 17 shows the percentage mean square error (MSE) corresponding to number of neuron in the hidden layer. It is clear that minimum MSE is found corresponding to four number of neuron in the hidden layer. At the output layer, only binary decision (to trip or to not trip) is required, therefore only single neuron is sufficient in output layer.

In present work, optimal width and center is crucial for the classification accuracy of RBFNN. It is obtained by PSO. The parameters settings of the PSO algorithm are initialized
randomly with 20 swarm particles. Typically the number of swarm particles ranges between 20-40. The value of acceleration coefficients is chosen 2.2 for both \( c_1 \) and \( c_2 \). The maximum number of iteration is set to 1000. The inertia weight is monotonically decreasing function which is given by (7). In training, the output of internal fault is indicated by one and for magnetizing inrush it is indicated by zero. Out of 1869 sets of data, 1402 (75\% of total) sets are used to train the ORBFNN with optimized widths and centers which is obtained by PSO technique. Remaining 467 (25\% of total) sets are used for the testing to check the generalization ability of trained network.

The FFBPNN model is used for the comparative study. It has one input neuron in the first layer, four neurons in hidden layer and one neuron in output layer. The unipolar sigmoidal activation function is used in the hidden layer and output layer. Similar type of FFBPNN structure is selected to perform the comparative study with ORBFNN. The performance results of FFBPNN and ORBFNN is shown in Table-I. The classification accuracy is calculated by (9). From the Table-I, it is clear that ORBFNN gives better classification accuracy as compare to FFBPNN.

![Image](image.jpg)

**Fig.17. Effect of number of hidden layer neuron on MSE**

\[
\text{Classification Accuracy(\%)} = \left(1 - \frac{\text{Number of False}}{\text{Total number of sets}}\right) \times 100
\]  

(9)

<table>
<thead>
<tr>
<th>Neural Network Topology</th>
<th>Operating Condition</th>
<th>Number of Sets</th>
<th>Training Accuracy (%)</th>
<th>Testing Accuracy (%)</th>
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<td>Magnetizing Inrush</td>
<td>1123</td>
<td>94.5</td>
<td>93.5</td>
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<td>Internal Fault</td>
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<td>93.2</td>
<td>92.8</td>
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**REFERENCES**