Application of Discrete Wavelet Transform and Chebyshev Neural Network for Differential Protection of Indirect Symmetrical Phase Shift Transformer

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Abstract:
The Indirect Symmetrical Phase Shift Transformer (ISPST) stands out from a power transformer due to its combination of electrically connected and magnetically coupled circuits. Hence in this work, an intelligent differential protection algorithm, based on Discrete Wavelet Transform (DWT) and Chebyshev Neural Network (ChNN), is proposed as main classifier to discriminate internal fault and inrush. Half cycle thee phase post fault differential current is considered for the proposed algorithm. PSCAD/EMTDC software is utilized to simulate different operating conditions of ISPST, resulting in the simulation of a significant amount of internal faults and inrush cases. The algorithm under consideration has undergone extensive evaluation across numerous cases, resulting in an accuracy rate exceeding 99%. The results indicate that the classifier based on DWT - ChNN yields extremely promising results, even when dealing with a noisy signal, current transformer (CT) saturation, and varying ISPST ratings. Superiority of the proposed algorithm is also compared with Multilayer Perceptron (MLP), Radial Basis Function Neural Network (RBFNN) and Probabilistic Neural Network (PNN) based approaches under the same conditions and it is found that proposed classifier is the most efficient and rapid among all alternative classifiers for the differential protection scheme of an ISPST under the considered conditions.

Keywords: Chebyshev neural network (ChNN), Discrete wavelet transform, Indirect symmetrical phase shift transformer (ISPST), Internal fault, Magnetizing inrush.

1. Introduction

Differential protection is a distinctive solution for protection of Phase shift transformer (PST) against winding fault in series and excitation unit due to its fast response, selectivity and sensitivity. Different types of PSTs have been the subject of numerous reports in the literature, discussing various current-based differential protection methods [1–4]. Differential protection of an Indirect Symmetrical (ISPST) and Delta-hexagonal PSTs has been discussed in [2], however the method proves ineffective when it comes to turn-to-turn faults. The stability of the system can be compromised by un-faulted situations like inrush current and external faults caused by a non-standard phase shift of an ISPST, which can impact the effectiveness of differential protection. To avoid this condition, Harmonic restraint (HR) methods, based on the second harmonic component are used widely [2, 5]. Phase shift compensation algorithm is used to avoid non-standard phase shift [6]. Currently, the transformers operate at high flux density as a result of advanced core materials that produce minimal harmonic components, even when experiencing magnetizing inrush conditions, which impacts the functionality of HR schemes [6]. An additional potential transformer, in conjunction with a current transformer (CT), is necessary to ensure the protection of the PST based on the normal operating voltage-current relationship and tracking of the tap-changer position [6,7].

In recent years, the utilization of artificial neural network (ANN) in power system protection and pattern classification has witnessed a significant rise owing to its remarkable generalization capability. However, appropriate architecture of neural network with optimal parameter (number of hidden layer, number of hidden neuron, activation function) for any peculiar classification application is still a major problem for all types of ANNs [8,9]. Various optimization techniques such as Particle Swarm Optimization (PSO), Ant Colony Theory, and Genetic Algorithm (GA) have been employed to optimize these parameters. The transient characteristic causes a distinction between the frequency characteristic of the fault and inrush. Hence for investigating a signal with in a bandwidth, Wavelet Transform (WT) has been verified as an efficient tool. Therefore WT has wide application for protection in power system. In this work, Discrete Wavelet Transform (DWT) (an amended signal processing tool) is used for the frequency analysis of differential current signal. The application of DWT along with other AI classifier has been reported in the literature [10].

In addition to that, Functional Link ANN (FLANN) has turned up as a improved AI technique for discrimination problem. A Chebyshev polynomial based integrated neural network for static function approximation is reported in [11]. Chebyshev Neural Network (ChNN) is a unit-layer network that offers advantages in terms of design and learning complexities. Additionally, it outperforms other classifiers such as SVM and fuzzy logic based systems due to the absence of a performance controlling parameter [12].

Hence using the superiority of DWT - ChNN, a new differential protection algorithm for the classification of internal fault condition from inrush condition is presented in this paper. In the present algorithm, PAS compensation is considered in account to resolve the problem of non-standard PAS between source and load sides of an ISPST for the differential protection [3,4]. Discrete post fault half cycle samples of the differential current are required for the algorithm with sampling frequency of 4 kHz. Proposed algorithm is evaluated with 13738 test cases with wide variation of ISPST parameters. The proposed algorithm is also tested in presence of 15% gaussian noise in differential current samples. Performance comparison of the algorithm is made with Harmonics restraint (HR), Multilayer perceptron (MLP), Radial basis function neural network (RBFNN) and Probabilistic neural network (PNN) based classifiers. The proposed algorithm proves its superiority by providing overall classification accuracy greater than 99%.

2. Discrete Wavelet Transform

Over recent years, wavelet transform (WT) emerges as an excellent mathematical tool for the transient analysis of signals [13,14]. The provided function is transformed into a windowing function with varying time widths. This enables the ability to emphasize longer time durations for low frequency components and shorter time durations for high frequency components. As a result, the analysis of signals with oscillations and localized impulses is enhanced. Wavelet analysis is highly effective in examining transients and enhancing current characterization, thereby facilitating the accurate identification of fault current from inrush current [15].

On performance investigation, in this paper Daubechies function (db8) is selected as a mother wavelet function. Daubechies function is a better frequency extractor than Haar. This is due to its low pass and high pass filter which resemble more ideal filters than those of Haar wavelet. On the other hand, because of its orthogonality, it satisfies Parsaval's theorem, not like biorthogonal wavelets, such as Coifet and Meyer wavelets [16]. Table I shows a band of frequencies at different wavelet function coefficient for sampling frequency of 4 kHz.

Table 1: Wavelet function coefficients at different frequency levels

Frequency component Hz	Wavelet component
1000-2000	D1
500-1000	D2
250-500	D3
62.5-125	D4
0-62.5	A4

3. Chebyshev Neural Network

ChNN is a type of Functional Link ANN (FLANN) based on Chebyshev polynomials (ChPs). It is an architecture with a single layer, where the hidden layers of the MLP are disregarded by transforming the input patterns into a higher dimensional space. Each individual sample of the input pattern is expanded into multiple samples using the ChPs expansion. The ChPs consist of sets of orthogonal polynomials, which are obtained as the solution to the Chebyshev differential equation [17]. The ChPs stand out among the various orthogonal polynomials due to their superior convergence properties. When compared to regular polynomials, expansions in ChPs converge much faster for a wide range of functions. As a result, ChPs are widely regarded as fundamental functions for neural networks [11, 18].

The basic structure of the ChNN is shown in Fig. 1. As shown in the figure, l dimensional input pattern $[x_1\ x_2 ..... x_l]^T$ is enhanced in to a $(lm+1)$ dimensional expanded pattern $[1\ T_1(x_1)......T_m(x_l)]^T$ using m^{th} order ChPs. These *(lm+1)* dimensional expanded pattern are cycled through the single layer structure of ChNN. Initially, the entire weights matrix is set to some random values. The weighted sum of enhanced input is than passed through an activation function to get an output. Sigmoidal function is used as activation function in this classification problem. ChNN provides a computational advantage over the MLP due to absence of hidden layer [18]. ChNN is free from the controlling parameters because of that it requires less memory as compare to other ANNs [19]. Training of ChNN can be performed either with gradient descent or conjugate gradient or levenberg-marquardt (LM) method. It has been found that LM gives better result as shown in Fig. 2. Hence in the present work, LM back propagation learning algorithm with least square errors has been used for training of the ChNN.

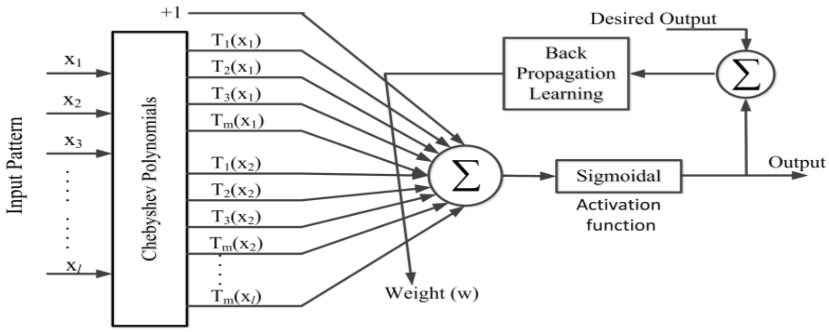

Fig. 1. Basic structure of Chebyshev Neural Network

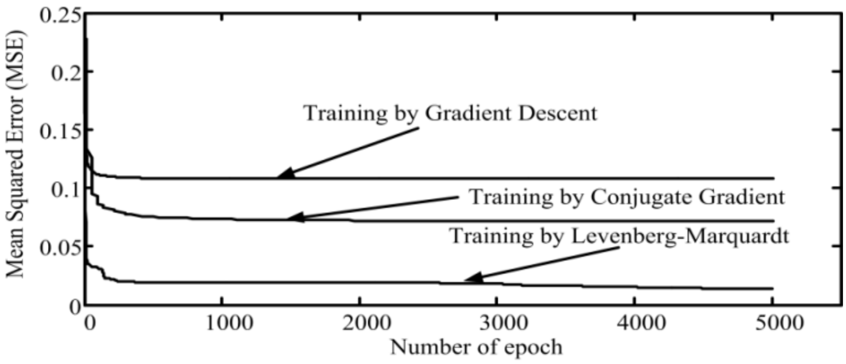

Fig. 2. Number of epoch vs MSE graph of different training method

4. Implementation of DWT - ChNN Based Algorithm

Fig. 3 shows the schematic flowchart of the DWT - ChNN based proposed differential protection algorithm. It is to be noted that half cycle post fault differential current samples at sampling frequency of 4 kHz (i.e., 32 samples/phase) have been considered to reduce the computational bourdon as well as time. These half cycle data are processed using DWT with 'db8' as mother wavelet. In the present work, four level of wavelet decomposition is found to be sufficient with DWT. Detail sub-bands '*cD4'* contains 16 resolution values which is considered as a featured vector for ChNN. '*cD4'* coefficient of phase '*a*' differential current for LG internal fault at different percentage of primary winding of series unit shown in Fig. 4. Similarly Fig. 5 shows the '*cD4'* coefficient of phase 'a' differential current for inrush condition at different switching angle.

In the further stage, the feature vector (i.e., '*cD4'*) of 16-dimension is expanded into 64-dimension feature vector using fourth order ChPs (1). It is revealed from Fig. 6 and 7 that feature vector has been enhanced with ChP expansion feature vector of phase 'a' for internal fault and magnetizing inrush current respectively. If the order of Chebyshev expansion is increased, the non-linear processing capability of ChNN would be stronger. However this would result in heavier computation burden. Therefore the order of Chebyshev expansion has been limited up to fourth order.

Once the expanded features vectors of for all the three-phases differential current is calculated, the expended feature vectors are formed as:

$$ChNN \;\; Input = [ChP_{cD4_a}, \;\; ChP_{cD4_b}, \;\; ChP_{cD4_c}]$$

where a, b and c represents phase

Hence total number of input for ChNN is 192 (3×64samples/pahse)

After configuring the ChNN using training cases data sets, the abnormality detection technique discriminates between normal and abnormal conditions (magnetizing inrush and internal fault). The abnormality detection technique is made by comparing two consecutive peaks of differential current [10]. The over-excitation condition is determined by comparing voltage-to-frequency ratio with the rated voltage-to-frequency ratio. Whenever the abnormal condition is detected, half cycle three phase differential current sampled at frequency of 4 kHz (system frequency of 60Hz) is considered as an input vector for the proposed algorithm. It discriminates the internal fault from magnetizing inrush in the form of ChNN output ('1' for an internal fault and '0' for inrush).

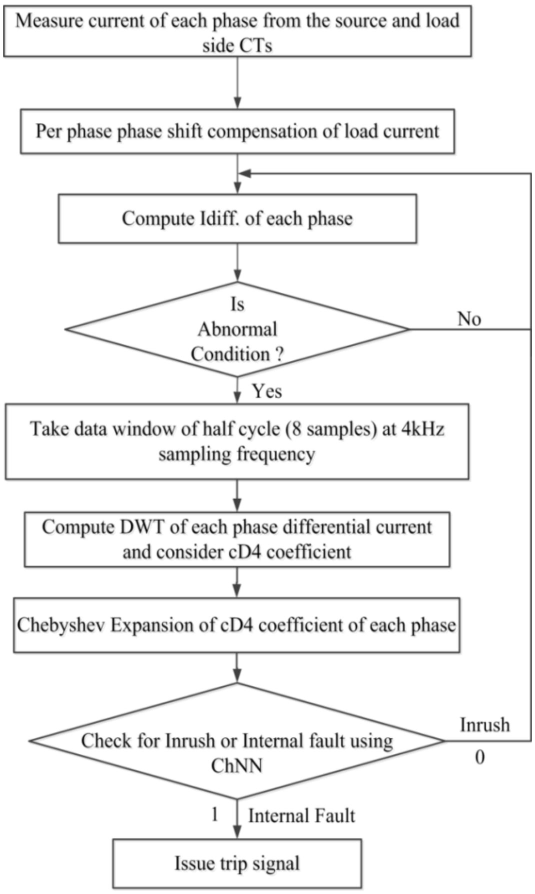

Fig. 3. Schematic flowchart of the proposed algorithm

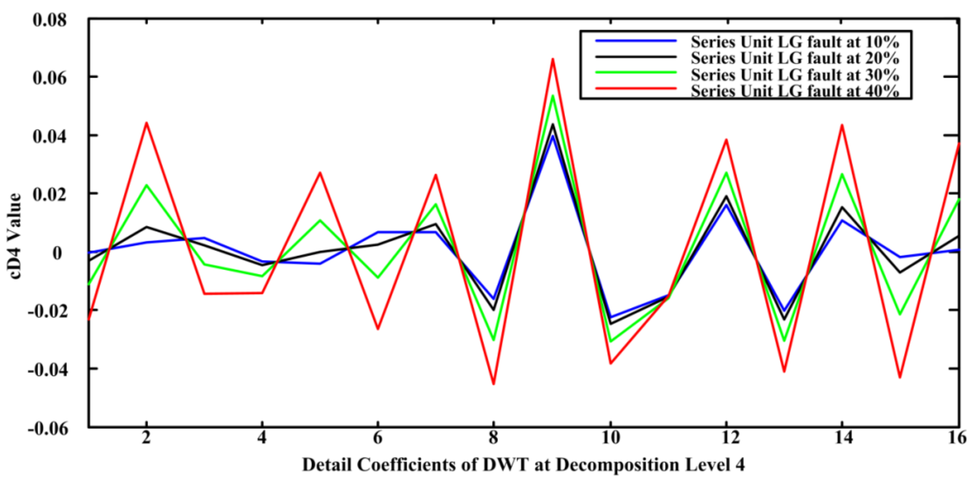

Fig. 4. Fourth level DWT decomposition, vector cD4 of phase 'a' for LG at primary of series unit

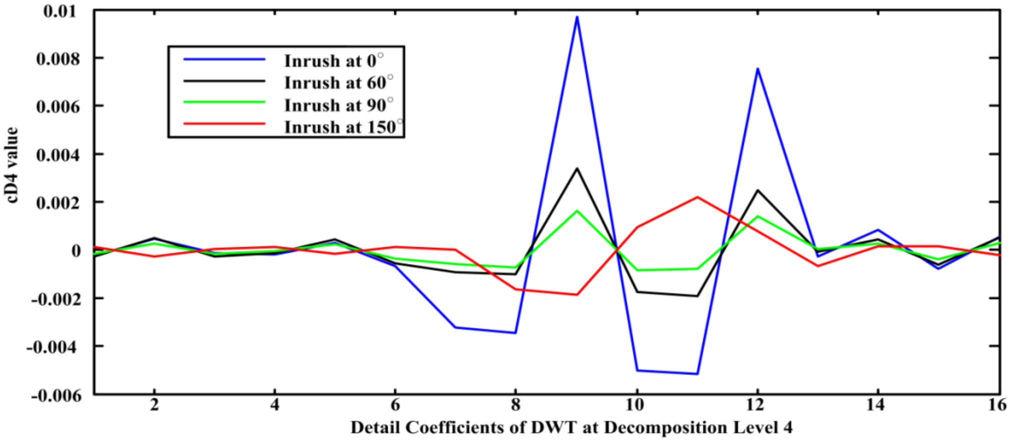

Fig. 5. Fourth level DWT decomposition, vector cD4 of phase ‘a’ for magnetizing inrush

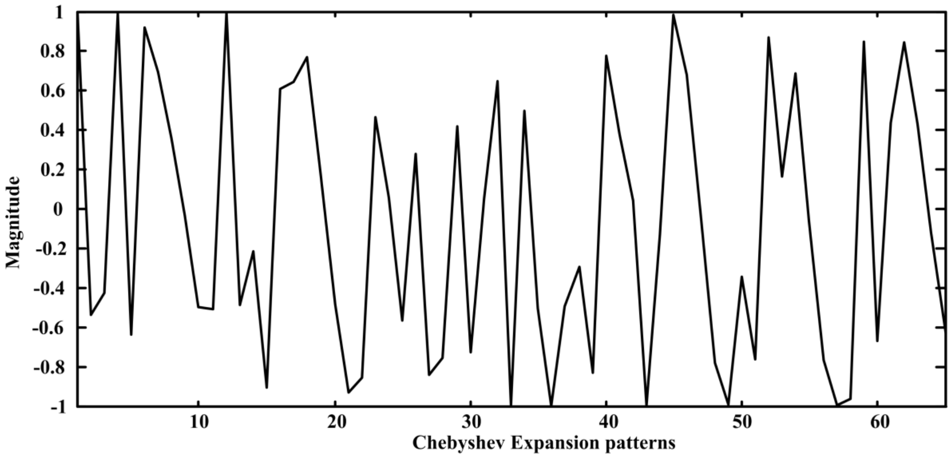

Fig. 6. Chebyshev expansion pattern of cD4 for internal fault

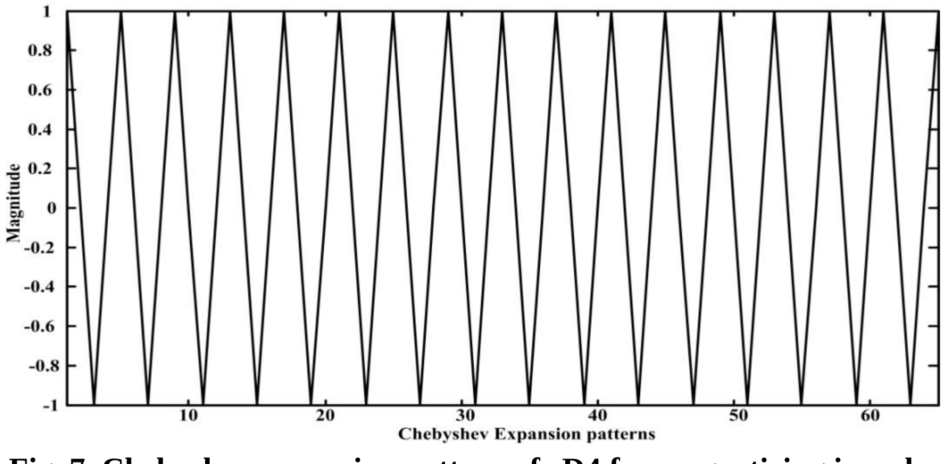

Fig. 7. Chebyshev expansion pattern of cD4 for magnetizing inrush.

In this classification algorithm true positive (TP) is used for internal fault (ChNN output=1), true negative (TN) for inrush (ChNN output=0), false positive (FP) for false classification of inrush and false negative (FN) for false classification of internal fault. Hence the classification accuracy (η) for the test cases is calculated by:

$$\eta\ (\%) = \frac{No.of\ true\ positive + No.of\ true\ negative}{Total\ no.of\ test\ cases\ (TP+TN+FP+FN)} \times 100\% \tag{3}$$

5. Simulation Studies

The effectiveness of the proposed algorithm has been investigated for a large number of internal fault and magnetizing inrush cases. A three phase 300MVA, 138kV/138kV, 1255A/1255A, 60Hz ISPST with max phase shift of ±30 degree in total 32 steps is considered for the illustration of the proposed algorithm [20]. Relevant CTs with the ratio of 2000/5A are connected in star on both side on the ISPST [21,22].

PSCAD/EMTDC has been used for simulation of various types of faults and magnetizing inrush conditions.The presence of residual flux is also included in the simulation of magnetizing inrush taken as 10%, 20%, 30% …80% of maximum flux at full-load. The case of sympathetic inrush is also taken in to account for the simulation to increase the accuracy of proposed algorithm.

Total 30528 cases are simulated by considering the condition of magnetizing inrush and fault at different percentage of winding and other ISPST parameter variation. The detailed information of all the cases is shown in Table 2. In this paper, out of 30528 (total cases), 16790 (55% of total) cases are used for the training and 13738 (45% of total) cases are used for the testing of DWT - ChNN based classifier.

Table 2: Detail of training and testing cases

Operating Conditions	No. of cases	Total no. of Cases
Internal fault	Fault in Excitation Unit-(Fault type: TT, LG, LL, LLG, LLLG **(5)**)×(load: no-load, on load **(2)**)×(Mode of operation: Advance mode, Retard mode **(2)**)×(Tap position: 0.1, 0.2, 0.4, 0.6, 0.8, 1.0 **(6)**)×(fault location: 1%, 2%, 5%, 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, **(11)**)×(Fault inception angle(FIA): 0° to 330 in step of 30° **(12)**)	15840
	Fault in Series Unit-(Fault type: TT, LG, LL, LLG, LLLG **(5)**)×(load: no-load, on load **(2)**)×(Mode of operation: Advance mode, Retard mode **(2)**)×(Tap position: 0, 0.2, 0.4, 0.6, 0.8, 1.0 **(6)**)×(fault location: 2%, 5%, 15%, 25%, 40%, 60%, 80%, **(7)**)×(Fault inception angle(FIA): 0° to 330 in step of 30° **(12)**)	10080
Magnetizing Inrush	(Load: no-load, 10%, 25%, 35%, 40%, 60%, 75%, 90%, 100% **(9)**)×(Mode of operation: Advance mode Retard mode **(2)**)×(Tap position: 0 to 1.0 in step of 0.2 **(6)**)×(Switching angle: 0° to 330 in step of 30° **(12)**)	1296
Residual Inrush	(Load: on-load, no-load **(2)**)×(Mode of operation: Advance mode Retard mode **(2)**)×(Tap position: 0 to 1.0 in step of 0.2 **(6)**)×(Residual flux: 10%, 20%, 30%, 40%, 60%, 80% **(6)**)×(Switching angle: 0° to 330 in step of 30° **(12)**)	1728
Sympathetic Inrush	(Load: 10%, 25%, 40%, 60%, 100% **(5)**)×(Mode of operation: Advance mode Retard mode **(2)**)×(Tap position: 0 to 1.0 in step of 0.2 **(6)**)×(Switching angle: 0° to 330 in step of 30° **(12)**)	720
Fault and Inrush simultaneously	(Load: on-load, no-load **(2)**)×(Mode of operation: Advance mode Retard mode **(2)**)×(Tap position: 0 to 1.0 in step of 0.2 **(6)**)×(Fault type: LG, LG, LLG **(3)**)×(Fault and Switching angle: 0° to 330 in step of 30° **(12)**)	864
Total no. of cases		30528

Training cases (55% of the above cases)	16790
Testing cases (45% of total cases)	13738

6. Results and Discussion

6.1. Effect of Order of Chebyshev Polynomials on Classification Accuracy

Order of ChPs also affects the classification accuracy of the proposed algorithm; hence, to study its effect the order of ChPs is varied from 1 to 10. Fig. 8 shows the percentage classification accuracy of the test cases with different order of ChPs and reveals that fourth order of ChPs gives maximum accuracy (greater than 99%) for the proposed algorithm. Hence fourth order ChPs is considered for algorithm.

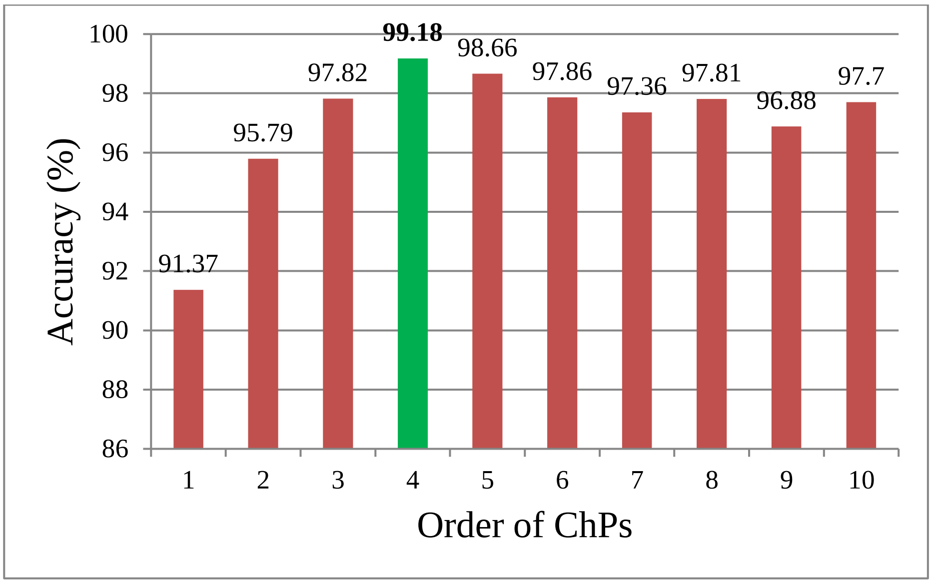

Fig. 8. Effect of order of ChPs on classification accuracy

6.2. Performance Evaluation of Proposed Algorithm

In the proposed algorithm, internal fault or inrush discrimination accuracy using half cycle data window length is shown in Table 3 which shows that the DWT - ChNN based proposed algorithm gives overall accuracy of 99.18%. From the detailed analysis of the different internal faults and inrush conditions, it is clear that fault in series unit is 100% classified and from excitation unit only TT and LG fault at minimum percentage due to minimum tap-position is failed. Lowest accuracy is found in case of the magnetizing inrush following an internal fault in any unit, which is very critical condition of abnormality.

Table 3: Classification accuracy for the 300 MVA ISPST

Operating Condition	Type of abnormality		No. of test cases	TP & TN	FP & FN	Accuracy (%)
Internal fault (11660)	Fault in Excitation Unit	TT	713*+713**	1378$^{\#}$	48†	96.63
		LG	713*+713**	1401$^{\#}$	25†	98.25
		LL	713*+713**	1417$^{\#}$	09†	99.36
		LLG	713*+713**	1426$^{\#}$	0†	100
		LLLG	713*+713**	1426$^{\#}$	0†	100
	Fault in Series	TT	453*+453**	906$^{\#}$	0†	100

	Unit	LG	453*+453**	906$^{\#}$	0†	100
		LL	453*+453**	906$^{\#}$	0†	100
		LLG	453*+453**	906$^{\#}$	0†	100
		LLLG	453*+453**	906$^{\#}$	0†	100
Inrush (1688)	Magnetizing Inrush		293*+293**	586$^{\#\#}$	0††	100
	Residual Inrush		389*+389**	770$^{\#\#}$	8††	98.97
	Sympathetic Inrush		162*+162**	314$^{\#\#}$	10††	96.91
Fault and Inrush (Simultaneously) (390)			195*+195**	378$^{\#}$	12†	96.92
Total Data (13738)			13738	13626	112	99.18
*Advance mode of operation, **Retard mode of operation, $^{\#}$True positive, $^{\#\#}$True negative, †False positive, ††False negative						

6.3. Performance Evaluation of Proposed Algorithm for Different Rating ISPST

The performance of the proposed algorithm is also evaluated for two different sized ISPSTs (1400MVA, 400kV/400kV, 2020A/2020A, ±25°, 60Hz and 480MVA, 230kV/230kV, 1205A/1205A, ±35.1°, 60Hz). Once again the data set is generated for both ISPSTs using PSCAD/EMTDC. This data set is tested on the same DWT - ChNN model which was trained by the data set of 300MVA ISPST. The accuracy of the proposed algorithm in classifying both ISPSTs for different cases is presented in Table 4. The classifier's overall accuracy has been determined to exceed 99%. Hence it is exciting to know that that the proposed algorithm remains unaffected by the rating and parameter of the ISPST.

Table 4: Classification accuracy for the different ratings of ISPST

1400MVA				
Operating Condition	No. of test cases	TP & TN	FP & FN	Accuracy (%)
Internal Fault	4608$^{\#}$	4576	32†	99.30
Inrush	576$^{\#\#}$	566	10††	98.26
Fault and Inrush (Simultaneously)	216$^{\#}$	207	09†	95.83
Total cases	5400	5349	51	99.06
480MVA				
Internal Fault	4608$^{\#}$	4587	21	99.54
Inrush	576$^{\#\#}$	570	6	98.96
Fault and Inrush (Simultaneously)	216$^{\#}$	205	11	94.91
Total cases	5400	5362	38	99.29
$^{\#}$True positive, $^{\#\#}$True negative, †False positive, ††False negative				

6.4. Performance Evolution Considering CT Saturation

The algorithm under consideration is also assessed for the impact of CT saturation during internal fault and the subsequent inrush following an internal fault. Source side CT is forced to saturate by considering remanent flux (up to 80%) and boosting the CT burden [23]. Table 5 shows the performance of proposed algorithm and found overall accuracy greater than 98% which shows that CT saturation negligibly influences the overall classification.

Table 5: Proposed algorithm considering CT saturation

Operating Conditions	No. of test cases	Proposed Scheme		
		TP	FP	%
Internal fault	2880	2829	51	98.23
Fault and Inrush (Simultaneously)	288	277	11	96.18
Total accuracy (3168)				98.04

7. Comparisons of MLP, RBFNN, PNN and ChNN

Neural network classifier such as MLP, RBFNN and PNN are most widely used for the classification problem [25]. These classifiers have been utilized to address the identical issue in order to compare them with the proposed DWT-ChNN based approach. The comparison has been made on the basis of architecture, number of required weight and classification accuracy. Furthermore, according to the literature, the discrimination time holds significant importance in relay operation and has also been taken into account for comparison. All neural network simulation studies have been carried out on MATLAB environment using an Intel(R) Core(TM) i7-2600 CPU 3.40 GHz with 16.0 GB RAM machine. No optimization technique is used in any neural network for the purpose of making the actual comparison among the various classifiers.

It is clear from Table 6 that ChNN gives better classification accuracy and takes less computation time due to less number of required weights as compare to others neural network.

Table 6: Comparison of various Neural Networks

Type of NN	Type of architecture	No. of weight required	No. of epoch	No. of case	No. of failure cases	%
ChNN	193-1	193	5000	13738	112	99.18
MLP	48-10-1	501	5000	13738	302	97.80
RBFNN	48-946-1	47301	1000	13738	625	95.45
PNN	48-16790-1	839501	1	13738	1051	92.35

8. Conclusions

This work presents a novel differential protection algorithm for safeguarding an ISPST, which is characterized by its precision, speed, and intelligence. The two-stage algorithm uses DWT for signal processing and ChNN is used for classification. In this algorithm, the discrimination is performed with half cycle data at sampling frequency 4 kHz after abnormality which makes it fast. The present work has taken into account all the variables that could potentially impact the accuracy of the proposed algorithm. The proposed algorithm gives overall accuracy greater than 99% and proves itself accurate even with the incorporation of signal noise, saturation of CTs and different rating of the ISPSTs. The algorithm's superiority is further demonstrated through a comparison with other available ANNs approaches.

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