INTELLIGENT DISTURBANCE DIAGNOSIS IN POWER TRANSFORMERS BASED ON THE WAVELET TRANSFORM AND SUPPORT VECTOR MACHINE

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Abstract— This paper proposes a method based support vector machine and wavelet transform in order to discriminate different disturbances in power transformers appropriately, such as internal and external faults, and transformer energizations. The proposed method recreates the conventional differential function using a disturbance detector, by means of the energies of the wavelet coefficients, which enables the support vector machine (SVM)-based differential phase functions. Furthermore, the proposed method can work in conjunction with other system protections by sending warning signals, for example in external fault conditions of the transformer, so it makes the protection system more reliable and intelligent. Several events were simulated in the alternative transient program, such as external and internal faults, turn-to-turn and turn-to-ground fault with variations of fault resistance, fault inception angle, and fault type parameters, as well as transformer energizations. The method presented better success rate and a faster trip in the internal fault detection then the conventional different protection.

Keywords— Differential protection, power transformers, wavelet transform, support vector machines.

Resumo— Este artigo propõem um método baseado em máquina de vetor de suporte e transformada wavelet a fim de discriminar apropriadamente distúrbios em transformadores de potência tais como faltas internas, faltas externas e energização de transformadores. O método proposto recria a função diferencial convencional usando um detector de distúrbios, baseado nas energias dos coeficientes wavelet, o qual habilita as funções diferenciais de fase baseadas em máquinas de vetor de suporte. Além disso, o método proposto pode trabalhar em conjunto com outras proteções do sistema, enviando sinais de alarme, por exemplo, em casos de falta externa, tornando a proteção mais confiável e inteligente. Vários eventos foram simulados no software alternative transient program, tais como: falta externa, falta interna, Faltas entre espira-espira e espira-terra, variando-se o ângulo de incidência de falta e a resistência de falta. Faltas entre espira-espira e espira-terra foram variadas as percentagens dos enrolamentos. Além disso, foram simulados casos de energização de transformadores. O método apresentou melhor taxa de acerto e rápida atuação na detecção de faltas internas quando comparado com a proteção convencional.

Palavras-chave— Proteção diferencial, transformador de potência, transformada *wavelet*, máquinas de vetor de suporte.

1 Introduction

Power transformers are essential devices in a transmission and distribution system, since its operation is associated with the continuity of the electrical energy supply by interconnecting networks with different voltage levels. The increase of the number of nonlinear loads and the development of smart grids connected to the power systems might lead to nonsinusoidal operation and the occurrence of faults of the transformer (Masoum et al., 2017). Faults in power transformers are considered the more severe than faults in transmission networks (ABB, 1999). In addition, the cost of acquisition, installation, and repairs of power transformer are among the highest on the system. Therefore, condition monitoring of the power transformer is required to a quick and accurate diagnosis of disturbance as well predict fault condition (Masoum et al., 2017).

The differential function has been largely used in power transformer protection schemes. The idea of this function is to compare the currents that flow through the terminals of the protected transformer, so that in the occurrence of an internal fault, the equipment must be disconnected from the electrical system (Medeiros et al., 2016). However, a great disadvantage of this technique is associated to the false tripping during inrush currents in the transformer energization maneuver or external fault clearance situations, as well as the presence of the distorted currents due to the current transformer (CT) saturation. The commercial differential relays have used additional functions based on retrains and blocking harmonic components to improve the protection (Rahman and Jeyasurya, 1988), (Guillén et al., 2016), once that during energization there is the presence of second and fifth order harmonic components. The signal trip occurs when second or fifth harmonics the differential current exceeds a certain percentage of fundamental component (Medeiros et al., 2016). Therefore, these functions avoid the trip relay during inrush currents.

The problem is that these harmonics can appear in other operating conditions such as CT saturation, internal faults, and nonlinear loads bring on the relay misoperation (Guillén et al., 2016). In addition, the appropriate materials used in actual power core transformer producing low contend harmonic which may cause improper operation of the relay (Masoum et al., 2017), (Shah and Bhalja, 2013). Another problem is that the differential function no send trip signal for critical internal faults, that is an internal fault in the transformer windings involving few turns.

In order to face these limitations, new techniques and methods based on artificial intelligence and signal processing have been applied for discriminating internal faults from other power transformer disturbances accurately (Mao and Aggarwal, 2001), (Segatto and Coury, 2006), (Tripathy et al., 2010). Among these algorithms, the wavelet transform is an efficient tool for analysis of non-stationary signals at different levels of time-frequency, which makes it widely applicable in the detection of electrical power system disturbances (Costa et al., 2010), with applicability to the power transformer differential protection (Oliveira and Bretas, 2009), (Medeiros et al., 2016), (Medeiros and Costa, 2017). On the other hand, the characteristic of learning makes the artificial neural networks (ANN) able to solve many problems of pattern classification, such as fault classification in transmission lines (Silva et al., 2006), (Costa et al., 2006), (Swetapadma and Yadav, 2015), and power transformers (Tripathy et al., 2010), (Fernandes et al., 2016). For instance, (Mao and Aggarwal, 2001) was proposed the wavelet transform and a multilayer perceptron (MLP) neural network for classification of internal faults, external faults, and transformer energizations. An optimal probabilistic neural network (PNN) was proposed for the same purpose in (Tripathy et al., 2010). In (Segatto and Coury, 2006), an MLP algorithm was presented to discriminate internal faults from other events and a reconstruction of the saturated current signals was performed based on recurrent ANNs.

Techniques based on support vector machine (SVM) are comparable and often superior to those obtained by other learning algorithms, such as the ANNs (Haykin, 1998). For instance, MLP trained using the back-propagation algorithm, it supply a computationally efficient solution to the pattern-classification (Haykin, 1998), with simple architecture, nevertheless, the not optimal solution. In the order hand, the same problem can be to solved using SVM in a manner close to the optimal solution. Furthermore, the good accurate performance SVM do not need the domain knowledge built into the design of the machine. However, SVM demand on computation complexity (Haykin, 1998). It can be possible to achieve a classification performance comparable to that of SVM patter-classification problems using MLP. However, it needs to build problem-domain knowledge into the design of the MLP, and tune a multitude of design parameters (Haykin, 1998), which sometimes may not be feasible for difficult pattern-classification problems.

This paper proposes the application of SVM-based differential relay in order to discriminate different disturbances in power transformers appropriately, such as internal and external faults, and transformer energizations. The proposed method recreates the differential function using a disturbance detector, by means of the energies of the wavelet coefficients, which enables the SVM-based differential phase functions.

The method was assessed in a power system modeled in the alternative transient program (ATP) (Dommel, 1984). Several events were simulated, such as external and internal faults, internal fault clearance with variations of fault resistance, fault inception angle, and fault type parameters, as well as transformer energizations. The proposed method sent the trip signal in 100% of the internal fault cases, whereas it provided no trip to energization of transformers and external faults. The proposed differential protection scheme can work in conjunction with other system protections by sending warning signals, for example in external fault conditions of the transformer, in order to accomplish the protection more reliable and intelligent.

2 SVM-Base Differential Relay

The proposed relay consists of three SVM-based differential phase functions SVM 87TW A, SVM 87TW B, and SVM 87TW C, for phases A, B, and C, respectively. These functions use a combination of SVM and the Real-Time Stationary Wavelet Transform (RT-SWT) to recreate the conventional differential function. The protection zone of this relay is delimited by the current transformers (CT_1 and CT_2), which is represented in Fig. 1 by the hatched region. Fig. 2 depicts the block diagram of the proposed SVM-based differential relay. Further details of the algorithm are presented in the following subsections.

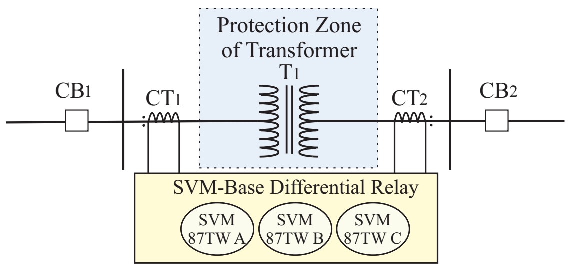

Figure 1: The basic block diagram of the SVM-based differential relay proposed.

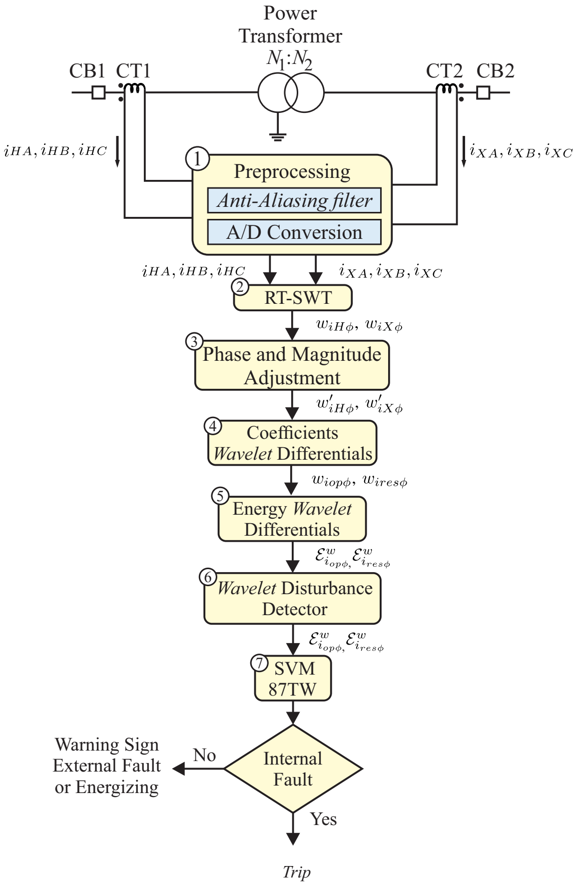

Figure 2: The SVM-based differential relay algorithm proposed.

2.1 Preprocessing (block 1)

At the beginning, the analog currents in the terminals of the primary $i_{H\phi} = \{i_{HA}, i_{HB}, i_{HC}\}$ and secondary $i_{X\phi} = \{i_{XA}, i_{XB}, i_{XC}\}$ of the power transformer are obtained through a current transformer CT_1 and CT_2, respectively. Theses analog currents are filtered by means of anti-aliasing filters with cutoff frequency of f_c attending the Nyquist criterion, followed by analog-to-digital conversions, where the currents are sampled at a sampling frequency f_s.

2.2 RT-SWT (block 2)

In each time step of the algorithm, the RT-SWT wavelet coefficients $w = \{w_{iH\phi}$ and $w_{iX\phi}\}$ of the currents are computed, which is defined as inner products of the wavelet filter h_ψ with the currents $i = \{i_{H\phi}$ and $i_{X\phi}\}$, per sampling k, as follows (Medeiros and Costa, 2017):

$$w(l,k) = \frac{1}{\sqrt{2}} \sum_{n=0}^{L-1} h_\psi(n) \mathring{i}(k - L + n + 1 + l), \quad (1)$$

where $k \geq \Delta k - 1$; $\Delta k \geq L$ is the length of sliding window; L is the length of h_ψ; $0 \leq l \leq L$;$\mathring{i}(k + m) = \mathring{i}(k - \Delta k + m)$ with $m \in \mathbb{N}^*$ (periodic signal in Δk samples); Δk is defined as f_s/f which f_s is the sampling rate.

In Eq. 1 the wavelet coefficients $w(0;k)$ with $l = 0$ are the wavelet coefficients of the conventional stationary wavelet transform (SWT), whereas $w(l \neq 0;k)$ are additional wavelet coefficients with border distortions which are for detecting overdamped transients of faults (Medeiros and Costa, 2017).

2.3 Phase and Magnitude Adjustments (block 3)

The differential protection needs that the primary and secondary currents measured by the differential relay are in phase. For instance, a transformer which has the windings connected in delta-wye, the winding currents will be 30° angular mismatch. If there is no adjustment for this phase, the relay will be understood as a fault condition and will therefore operate. Therefore, it is necessary to perform the phase and magnitude adjustment in order to calculate the differential currents.

In this paper the phase and magnitude adjustment is made in the wavelet coefficients, as follows (Medeiros and Costa, 2017):

$$\begin{bmatrix} w'_{HA} \\ w'_{HB} \\ w'_{HC} \end{bmatrix} = \frac{1}{TAP_H} M_H \begin{bmatrix} w_{HA} \\ w_{HB} \\ w_{HC} \end{bmatrix} \quad (2)$$

$$\begin{bmatrix} w'_{XA} \\ w'_{XB} \\ w'_{XC} \end{bmatrix} = \frac{1}{TAP_H} M_H \begin{bmatrix} w_{XA} \\ w_{XB} \\ w_{XC} \end{bmatrix} \quad (3)$$

where TAP_H and TAP_X are taps of the TC_1 and TC_2, respectively, used for magnitude adjustment. M_H and M_X are transformation array used for the angular mismatch adjustment.

2.4 Differential Wavelet Coefficients (block 4)

In the conventional transformer differential protection algorithms, the operating and restraining currents (I_{op} and I_{res}) are computed from CT secondary phasor currents. In the proposed method the differential operations are applied directly in the wavelet coefficients, as proposed by (Medeiros and Costa, 2017), which proved to be similar the conventional method. The differential wavelet coefficients $w_{diff} = \{w_{i_{op}}$ and $w_{i_{res}}\}$ are defined as follows (Medeiros and Costa, 2017):

$$w_{i_{op\phi}}(0,k) = \frac{1}{\sqrt{2}}(w'_{i_{H\phi}}(0,k) + w'_{i_{X\phi}}(0,k)), \quad (4)$$

$$w_{i_{op\phi}}(l \neq 0, k) = w'_{i_{H\phi}}(l,k) + w'_{iX\phi}(l,k), \quad (5)$$

$$w_{i_{res\phi}}(l,k) = w'_{iH\phi}(l,k) - w'_{iX\phi}(l,k), \quad (6)$$

where $0 \geq l < L$; $\Delta k \geq L$.

2.5 Differential Wavelet Energy (block 5)

The differential wavelet coefficient energy signal $\mathcal{E}^w_{diff} = \left\{\mathcal{E}^w_{i_{op\phi}} \text{ and } \mathcal{E}^w_{i_{res\phi}}\right\}$ are computed from the respective differential wavelet coefficients $w_{diff} = \{w_{i_{op}} \text{ and } w_{i_{res}}\}$, as follows (Medeiros and Costa, 2017):

$$\mathcal{E}^w_{diff}(k) = \mathcal{E}^{wa}_{diff}(k) + \mathcal{E}^{wb}_{diff}(k), \qquad (7)$$

where $k \geq \Delta k - 1$. $\mathcal{E}^{wa}_{diff}$ is due to the first $L-1$ boundary wavelet coefficients of the sliding window, defined as (Medeiros and Costa, 2017), (Costa, 2014):

$$\mathcal{E}^{wa}_{diff}(k) = \sum_{l=1}^{L-1} w^2(l,k), \qquad (8)$$

where $k \geq \Delta k - 1$. $\mathcal{E}^{wb}_{diff}$ is computed with no boundary wavelet coefficients of the sliding window with length $\Delta k - L$ (Medeiros and Costa, 2017), (Costa, 2014):

$$\mathcal{E}^{wb}_{diff}(k) = \sum_{n=k-\Delta k+L}^{k} w^2(0,n). \qquad (9)$$

2.6 The Wavelet Disturbance Detector (block 6)

The disturbance detection is based on a comparison between the energy signal and energy threshold $E^w_{diff} = \{E_{i_{op\phi}}, E_{i_{res\phi}}\}$ in order to detect the beginning of the disturbance. When any disturbance occurs, such as external faults, internal faults, and transformer energizations, it is expected an increase of the energy $\mathcal{E}_{i_{op\phi}}$ and $\mathcal{E}_{i_{res\phi}}$ due to the transients. Therefore, a disturbance is detected if (Medeiros et al., 2016):

$$\begin{cases} \mathcal{E}^w_{diff}(k-1) \leq E^w_{diff}, \\ \mathcal{E}^w_{diff}(k) > E^w_{diff}, \end{cases} \qquad (10)$$

where $k_d = k$ corresponds to the sampling in which the method detected the disturbance.

When a transient disturbance is detected though (10), accomplishes the comparison between $\mathcal{E}_{i_{op\phi}}$ and $\mathcal{E}_{i_{res\phi}}$ in order to detect the internal faults (Medeiros et al., 2016), whereas the internal fault detector in this paper is based on the SVM as addressed in the remainder of this section.

2.7 The phase function SVM 87TW (block 7)

Once the disturbance is detected, the algorithm enables the differential functions SVM 87TW in order to classify and discriminate internal fault, external fault and energization in power transformer appropriately. If the disturbance is associated to an internal fault, the SVM-based differential relay is able to send trip signal to the relay.

The SVM 87TW function protection is composed of SVM. It is not feasible to use as SVM input the window wavelet signal, since that would imply a very large number of input for the SVM and consequently difficult the convergence of the SVM (Mao and Aggarwal, 2001). Alternatively, the differential energy wavelet $\mathcal{E}^w_{diff}$ is stored in a sliding window with the last four samples $(k-3, k-2, k-1, k)$, with $k > kf + 3$, where k_f is the first fault sample. Therefore, with each new sample a displacement of one sample is performed, discarding the first sample and adding the new sample to the end of the sliding window. Fig 3 depicts a wavelet spectral energy vector with the sliding window with the first 4 fault samples.

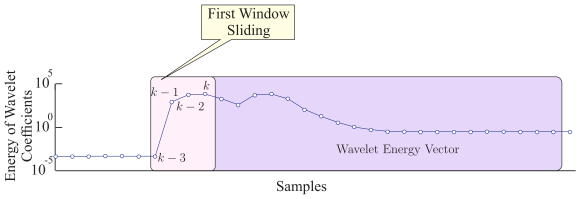

Figure 3: Vector of spectral energy wavelet.

The SVM used in the SVM 87TW function has as input the sliding window of 4 samples of the energies of the wavelet coefficients of the $\mathcal{E}_{i_{op\phi}}$ and $\mathcal{E}_{i_{res\phi}}$ currents, as shown in Fig. 4. Therefore, the SVM has 24 input patterns, 12 being the three operating currents and 12 the three phase restraint currents A, B and C, respectively.

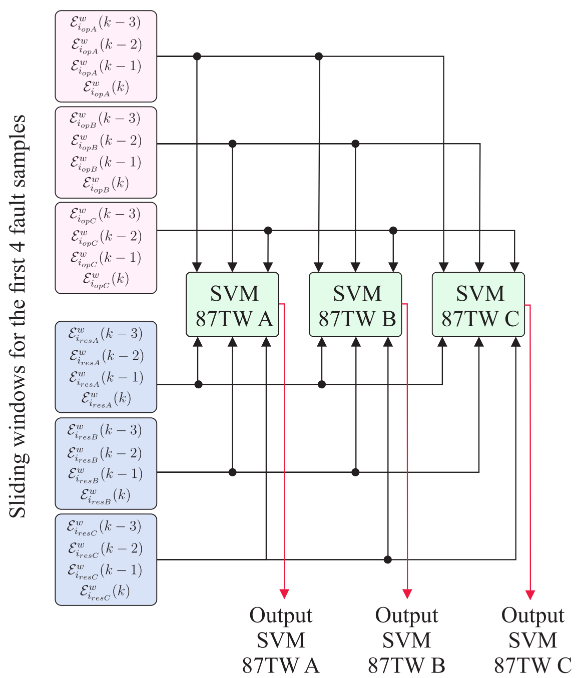

Figure 4: Inputs for SVM 87TW phase functions.

The target output of the SVM 87TW has value in accordance with Table 1. It is not necessary to use a target output to a normal condition, because the SVM 87TW functions are activated when occurs a transient disturbance.

Table 1: Target output of SVM 87TW.

Disturbance Type	Target Output
Transformer energization	1
External fault	2
Internal fault	3

3 Performance Evaluation

Fig. 5 depicts the power system used for evaluation of the SVM-based differential relay proposed for power transformer disturbance classification scheme, which was modeled by using the program ATP. CT models reported by the IEEE Power System Relaying Committee in [24]. C400 800-5 A and C800 1000-5 A CTs were used in the high-and low-voltage windings of the power transformer, respectively. Also, the CT in the neutral of the high-voltage winding was taken as C400 800-5 A. More details about the parameters of the power system are presented in (Medeiros et al., 2016).

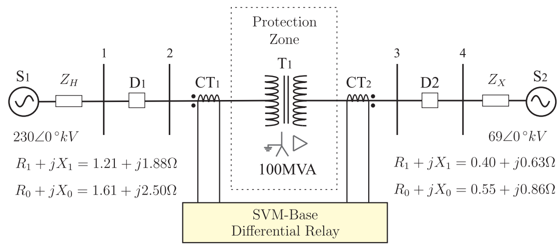

Figure 5: Single line diagram of the electrical system.

The databases with records of internal faults, external faults, and transformer energizations were generated in order to verify the performance of the SVM-based differential relay.

- **Internal fault**: faults into the power transformer differential protection zone, on the high and low voltage windings, between CTs and T1;
- **Critical internal fault**: turn-to-turn and turn-to-ground faults of the transformer windings;
- **External faults**: faults on the high voltage bus 2 and low voltage bus 3;
- **Transformer energization**: switching performed by the high voltage bus 2, with the secondary terminal opened.

Based on the electrical power system presented in Fig. 5, several oscillographic records with internal faults, external faults and energizing transformers were generated. Table 2 summarizes the characteristics of all the performed simulations, considering single-phase, two-phase and three-phase faults, varying the fault incidence angle (θ_i) and the fault resistance (θ_i) with steps equal to θ_i and ΔR_i, respectively. Turn-to-turn and turn-to-ground fault types were considered varing the winding percentages, as shown in Table 3.

Table 2: Database for performance evaluation of the SVM-based differential method.

Parameters	**Int. Fault**	**Ext. Fault**	**Energization**
Fault Inception Angle	$0^\circ \leq \theta_i \leq 180^\circ$ $\Delta\theta_i = 30^\circ$		$0^\circ \leq \theta_i \leq 180^\circ$ $\Delta\theta_i = 1^\circ$
Fault Resistance	$1 \leq R_i \leq 10\Omega$ $\Delta R_i = 1$		-
Fault Type	AG, BG, CG, AB, BC, AC, ABG, BCG, ACG, ABC		-
Number of Cases	1400	1400	180

Int.- Internal; Ext.- External.

Table 3: Database for performance evaluation of the SVM-based differential method turn-to-turned and turn-to-ground fault.

Parameters	**Internal Turn-to-GND Fault**	**Internal Turn-to-Turn Fault**
Winding Percent	$1\% \leq \theta_{esp} \leq 99\%$ $\Delta\theta_{esp} = 1\%$	$1\% \leq \theta_{esp} \leq 99\%$ $\Delta\theta_{esp} = 1\%$
Fault Type	AT	AT
Number of cases	196	196

GND: Ground.

The SVM-based differential relay preprocessing was designed for currents sampled at $f_s = 15.36$ kHz (256 samplings per cycle of 60 Hz), which is enough to evaluate transients generated by faults by using only the first level wavelet decomposition.

A white Gaussian signal with signal-to-noise ratio of 60 dB was added for each the databases illustrated in the Tables 2 and 3. This noise level is typical in transmission systems (Petrovic et al., 2012). For the treatment of the current signals it was used a second-order butterworth filter with cutoff frequency $f_c = 0.9f_s/2$.

The choice of the mother wavelet may change according to the application. When it comes to detection of short transients, the mother wavelet of the Doubechies family db (4), db (6) present better results, while for long transients, the db (8) and db (10) are better (COSTA, 2014). The works of Medeiros and Costa (2017) and Shah and Bhalja (2013b) used the db (4), in the first level of decomposition, to detect faults in power transformers, which obtained better results. In Medeiros and Costa (2017) one-cycle window is used to increase the sensitivity of the relay. Therefore, proposed method will uses the mother wavelet db (4) for the calculation of the wavelet coefficients with border distortions of the currents of the primary and transformer secondary.

The databases summarized in Tables 2 and 3 was randomly partitioned in two sets, 50% used for the training of the SVM 87TW functions protection and the 50% others for evaluated protection proposed SVM-based differential relay.

3.1 Performance of the Wavelet Disturbance Detector.

The detector proposed by (Medeiros and Costa, 2017) proved to be efficient in detecting the disturbances presented in Tables 2 and 3, obtaining a 100% accuracy in the detection of external faults, internal faults and transformer energization. The energy threshold E^w_{diff} was adopted equals 0,5.

3.2 Performance Assessment During the Training of the SVM 87TW Function.

The proposed SVM-based differential relay has three SVM 87TW phase differential protection functions, SVM 87TW A, SVM 87TW B and SVM 87TW C, respectively. As the principle of the performance of the phase functions is identical, then only a single SVM will be trained to be used in each of the three phase functions. It is expected that the SVM trained for function protection SVM 87TW A can be used for SVM protection functions SVM 87TW B and SVM 87TW C with the equal performance of the SVM 87TW A. For each record of the training the first 64 sliding windows of the last four 4 samples differential wavelet coefficients energy $\mathcal{E}^w_{i_{op\phi}}$ and $\mathcal{E}^w_{i_{res\phi}}$ were stored from the first sample fault. In this way, each training base record became 64 training partners. To reduce the training set, the training patterns were randomly chosen, which were subdivided into two sets, the training and test set, respectively, each with a percentage of 70 % and 30 % of the total training partners.

The confusion matrix for the test set of 1,350 patterns, from the trained SVM 87TW A function is illustrated in the Fig. 6 . The first three diagonal cells correspond to the percentage of correct classification of the three classes: energization (EN), internal fault (IF), external fault (EF). Each class contains 450 patterns. Only three patterns of energization are incorrectly classified as internal fault, which corresponds to 0.67% of all 450 evaluated patterns. Therefore, 99.33% are correctly classified. For the 450 internal fault patterns, 438 are predicted correctly by the SVM, however, 12 are incorrectly classified as energizing. Similarly, for the 450 internal fault patterns, 438 are predicted correctly by the network, and 12 are incorrectly classified as energizing. Thus, 99.32% of success rate was obtaiend. The trained neural network obtained an accuracy of 98.00% in the prediction of the test classes, being only 2.0% the error rate. Given these results, it is expected that the trained network get a good result like the SVM 87TW protection function.

Confusion Matrix

Output Class \ Target Class	EN	IF	EF	
EN	**447** 33,11%	**3** 0,67%	**0** 0,00%	**99,33%** 0,67%
IF	**12** 2,67%	**438** 32,44%	**0** 0,00%	**97,33%** 2,67%
EF	**12** 2,67%	**0** 0,00%	**438** 32,44%	**97,33%** 2,67%
	94,90% 5,10%	**99,32%** 0,68%	**100,00%** 0,00%	98,00% 2,00%

Target Class

Figure 6: Confusion matrix obtained from the SVM training for SVM 87TW A protection unit.

3.3 Performance Assessment Action for protection SVM-Based Differential relay

The proposed method was evaluated with respect the success rate and relay operating time considering half cases presented in the databases of the Tables 2 and 3, which were not used in the training of SVM. In the following subsections will be presented details of the performance of the SVM-based differential protection for internal faults, critical internal faults, external fault and transformer energization. In addition, the results obtained the proposed method was compared with the conventional method of differential protection proposed by (Tavares and Silva, 2014).

3.3.1 Internal Fault

The conventional method using the combination of the 87T and 87Q functions obtained a 98.27% a success rate with an average operating time of 16.77 ms for internal faults. The proposed method, only with the SVM 87TW phase functions, showed a 100% success rate for internal faults. In addition, the proposed method obtained an average time of 0.555 ms, therefore, its performance was superior to the conventional one.

Considering the obtained results, the SVM could be used without reduction of protection sensitivity and actuation time. Therefore, the training standards presented to the SVM, composed by the energies of the wavelet coefficients of the operation and constraint currents, contained sufficient characteristics so that the SVM could be able to correctly predict for cases, which implies in minimizing the training time of the SVM and size of the training set.

3.3.2 Critical Internal Faults: Turn-to-Turn and Turn-to-Ground Faults

The SVM 87TW phase functions protection obtained a success rate of 95.91% for turn-to-ground faults. Regarding the turn-to-turn faults, the proposed method obtained a success rate of 83.67%. Theses cases that the protection did not send a trip signal for the turn-to-ground cases involving 1% to 5% of the primary windings, which are connected in grounded star. They also did not send a trip signal for the turn-to-turn cases involving 47% to 53% of the windings of the secondary that are connected in delta. The average operating time of the SVM 87TW functions for internal turn-to-ground and turn-to-turn faults were 0.91 ms and 1.1 ms, respectively.

The conventional differential protection method obtained a success rate of 94.9%, with an average operating time of 17.7 ms. However, the conventional method only obtained this performance with the support of the negative sequence functions, since some of the critical cases were not detected by the differential phase functions protection with harmonic restriction. Therefore, the proposed method presents best performance to the conventional method using only the SVM 87TW phase functions and with an upper an average operating time relay.

3.3.3 External Fault and Energization

The proposed method did not send false trip signals in any of the cases of external fault and transformer energization. Similarly, the conventional differential protection method did not send false trip signals in the same cases evaluated. The proposed SVM-based differential relay has no problem in distinguishing internal energizing faults without using the harmonious content. In addition, it has provided additional information on the type of disturbance, for cases of transformer energization and internal fault, which can be used for power monitoring purposes and support the other protections of power system.

4 Conclusion

This paper presented a SVM-based differential relay for protecting power transformers based on both the support vector machines and the real-time stationary wavelet transform. The performance of the proposed method was superior to the conventional method, for the cases analyzed, showing that it is possible to recreating the differential protection using only the phase function, without the need of negative sequence function and harmonic content. In addition, the proposed method presented a faster operating time than the conventional method for internal faults. Furthermore, the proposed method has addition function, which send warning signals to the other system protections in abnormal conditions, such as external fault and energization.

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