Development of an On-line Transient Classification System

N. Perera, A.D. Rajapakse, D. Muthumuni, R.P. Jayasinghe

***Abstract*—This paper describes the development of a transient classification system to distinguish transients originated by the faults from those originated by the other disturbances such as load and capacitor switching. The proposed classifier is based on a probabilistic neural network (PNN) and uses wavelet coefficients of the transient currents as the features. The transient classification system was developed on the well known PSCAD/EMTDC electromagnetic transient (EMT) simulation program. Testing of the transient classification system on a simulated High Voltage (HV) transmission system showed over 95% overall classification accuracy. Integration of the classification system into an EMT simulation program is expected to facilitate simulation studies on novel transient based protection methodologies.**

***Keywords*: transient classification, transmission system, neural networks, wavelet transform.**

I. Introduction

A multitude of causes such as lack of new capacity due to under investment, allowing of open access, and difficulty in obtaining permission to build new transmission facilities have forced the power transmission systems to operate under increased stress levels. It is important to provide fast protection against faults to prevent system instabilities in power systems which are operating at low margins of stability. Transient based protection techniques can potentially provide faster response compared to traditional phasor based protection techniques. In addition, transient based protection has some additional attractive features: they are immune to power swings and CT saturation, and less affected by fault impedance [1], [2]. Availability of fast, powerful DSPs enables economical implementation of relays that work on transient based techniques.

However, transient based protection relays are prone to malfunction during non-fault events that generate transients [1]. For example, switching of large loads or capacitor banks can generate transients similar to high impedance faults. Thus, in order to make transient based protection viable, a method is required to differentiate fault transients from non-fault transients. The main objective of this research is to develop a transient classification system that can be used as the front end of a transient based protection relay. However, such a classification system can have other applications, for example in the field of power quality enhancement.

This research investigates the problem of classifying the transients in measured currents into one of the two groups: (a) fault transients – the transients emanating from a fault, and (b) non-fault transients – the transients originated from normal switching event. In literature, several transient classification systems can be found. They are primarily proposed for classifying power quality disturbances. These classifiers use diverse array of intelligent techniques. The main techniques applied in the reported research are Neural Networks (NNs) [3], Dynamic Time Warping (DTW) [4], rule-based systems [5], Decision Trees (DTs) [6, 7] and Hidden Markov Models (HMM) [8, 9].

NNs can approximate any well-behaved function with an arbitrary accuracy and can deal with hard classification problems with significantly overlapping patterns, high background noise and dynamically changing environments. Therefore NNs are particularly suitable for identification of dynamic events [3]. Probabilistic neural network (PNN) is a neural network that is popularly used in classification applications. The PNN has several advantages such as fast training process, inherently parallel structure, and guaranteed optimal classification performance if a sufficiently large training set is provided [10].

The paper presents the development of a transient classifier to solve the above mentioned classification problem using a PNN based technique and its implementation on PSCAD/EMTDC electromagnetic transient (EMT) simulation software. The feature vectors, which are the inputs to the classifiers, were generated by wavelet decomposition of the current signals containing the transients. The performance of the proposed scheme is evaluated using transients simulated on a 12-bus high voltage power system. The rest of this paper is organized as following: Section II gives a brief introduction to the PNN based classification method. The pre-processing of the input currents and the implementation of the PNN are given in Sections III and IV respectively. Simulations and results are presented in Section V. Finally the conclusions are given in Section VI.

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II. STRUCTURE OF THE TRANSIENT CLASSIFIER

Fig. 1 shows the structure of the proposed transient classifier for three phase systems. The system takes three phase currents as the inputs. These currents are pre-processed using wavelet decomposition to extract various features in the incoming current signals. The proposed classifier consists of three PNN classifiers – one for each phase. Each classifier is trained using disturbances recorded from the phase to which it is connected. The final classification is made by a post processing decision making module that considers the outputs of all three PNN classifiers. With this structure, it is also possible to determine whether the fault is three-phase, line-to-line or line-to-ground fault.

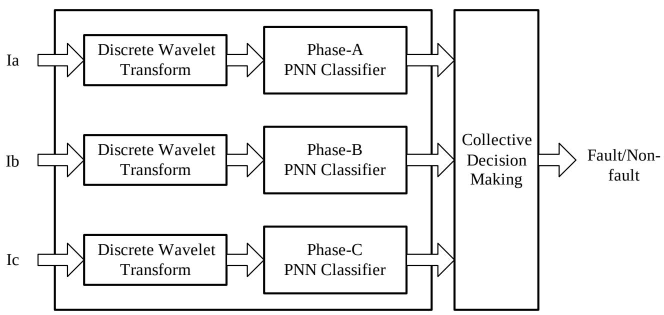

Fig. 1. Structure of the transient classifier

III. PRE-PROCESSING WITH WAVELET DECOMPOSITION

In classification problems, the success of classification is highly depended on the features used for classification. Relative strengths of different frequency components buried in a signal are good features for classification. Wavelet transform is well suited for decomposing a signal into different frequency bands and analyzing aperiodic signals such as transients [11]. More details of wavelet transform can be found in [12]. The authors have previously developed an online wavelet transformation tool that can be conveniently used in PSCAD/EMTDC simulation environment [13].

Figs. 2, 3 and 4 show examples of the wavelet decompositions of the current transients observed during a fault disturbance, a line switching disturbance and a capacitor bank switching disturbance respectively. The graphs show the currents in phase-A and their Wavelet decompositions determined up to six levels using Daubechies 4 (db4) mother wavelet. CA6 is the level six approximation wavelet coefficient which represents the low frequency portion of the signal. CD1-CD6 are the detailed wavelet coefficients that represent signal components at different high frequency bands, with the frequency range decreasing from CD1 to CD6. Some of the differences in these wavelet coefficients for fault transients and non-fault transients are clearly noticeable. In this paper, the signal energies contained in different frequency bands are used as features for classification. These energies, which are generally referred to as wavelet energies can be calculated using wavelet coefficients of the measured current signals.

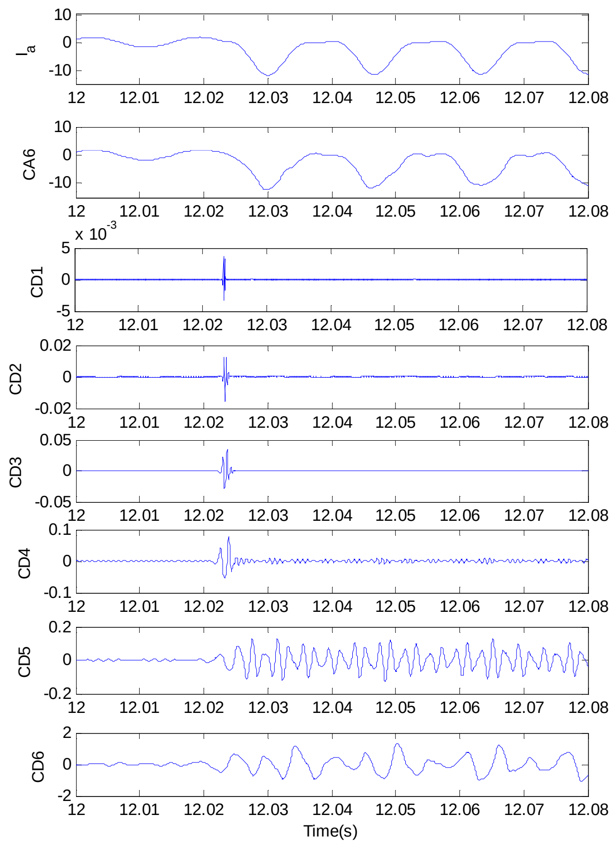

Fig.2. Fault disturbance and its Wavelet decompositions obtained using 'db4'

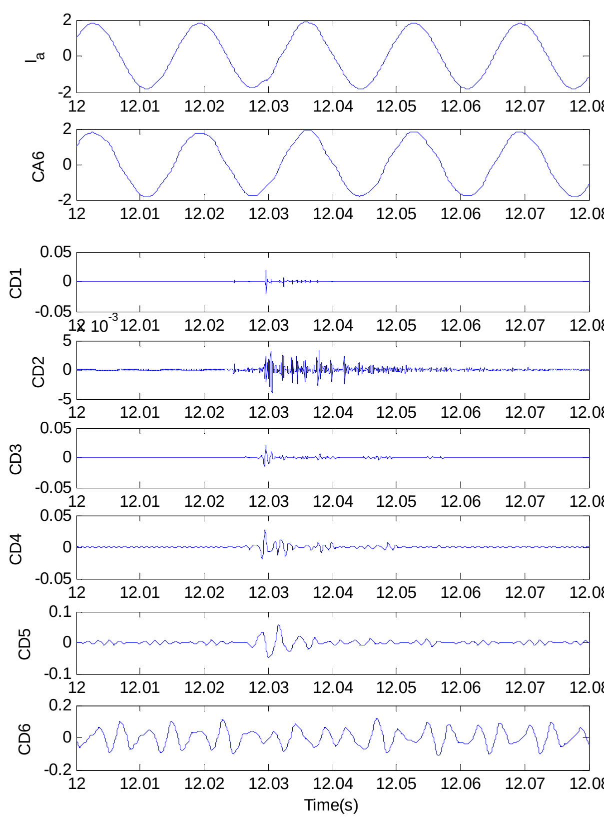

Fig. 3. Line switching disturbance and its Wavelet decompositions obtained using 'db4'

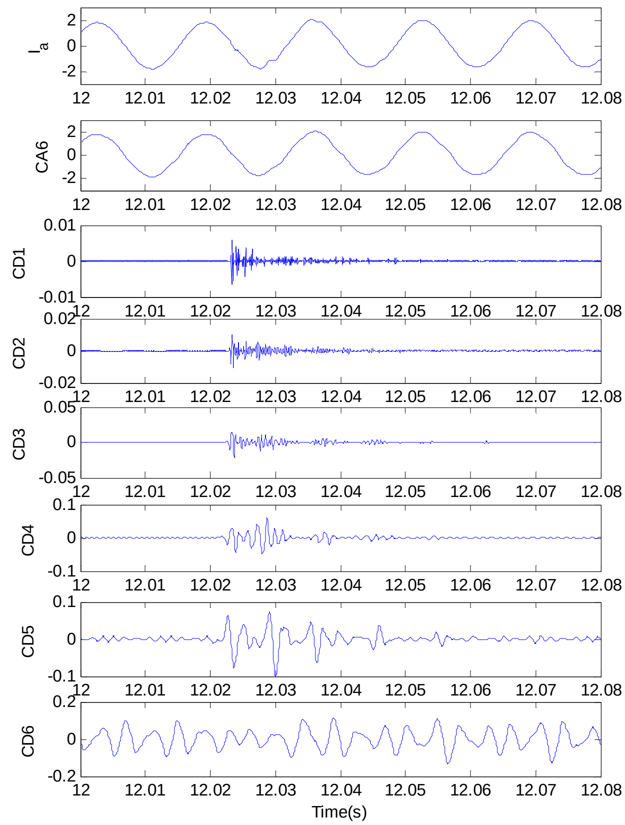

Fig.4. Capacitive load switching disturbance and its Wavelet decompositions obtained using 'db4'

The energy values of approximation wavelet coefficients ($EA6$) and the energy values of detailed wavelet coefficients ($ED1, ED2, \ldots ED6$) are calculated using (1) and (2).

$$EA6 = \sum_{j=1}^{N} \left| CA6_j \right|^2 \tag{1}$$

$$EDi = \sum_{j=1}^{N} \left| CDi_j \right|^2, i = 1 \ldots 6 \tag{2}$$

Here, N denotes the length of each wavelet coefficient in number of samples. These coefficients are the inputs to the PNN classifier described in the next section.

IV. Classifier

A. Probabilistic Neural Network

The PNN was introduced by Specht in 1990 [14]. It is fundamentally based on the well-known Bayesian classifier technique commonly used in many classical pattern-recognition systems. The nonparametric estimation technique known as Parzen windows is used to construct the class-dependent probability density functions for each classification category [15]. This is used to determine the probability of given vector pattern belonging to a given category. The PNN selects the most likely category for the given pattern vector by combining this with the relative frequency of each category. The Parzen estimate of the probability for input x belonging to category A is given by the probability density function

$$F_A(x) = \frac{1}{(2\pi)^{m/2} \sigma^m n} \sum_{j=1}^{n} \exp\left[\frac{(x - x_j)^T (x - x_j)}{2\sigma^2} \right] \tag{3}$$

where x is the m dimensional input pattern vector, j is the pattern number, x_j is the j^{th} training pattern for category A, n is the number of training patterns, m is the input space dimension, and σ is an adjustable "smoothing parameter." The parameter σ must be determined experimentally [16]. An input is assigned to the category for which it has the highest probability value. With PNN, no time consuming training is involved and online adaptation to new patterns can be easily implemented by way of modifying its training database with new patterns and their correct categories.

Fig. 5 shows the probabilistic neural network structure used to implement the decision rule for classifying the input disturbances into two classes. This network consists of four layers: input layer, pattern layer, summation layer and output layer. The input layer represents the input variables (x_1, x_2, x_3). The pattern layer is fully connected to the input layer, with one neuron for each pattern in the training set. The summation layer sums the outputs from the pattern-layer neurons. Each neuron in the summation layer corresponds to a particular category classification problem. A summation layer neuron sums up the outputs of pattern layer neurons which belong to the category it represents. The output-layer neuron produces a binary output value corresponding to the highest probability value [10].

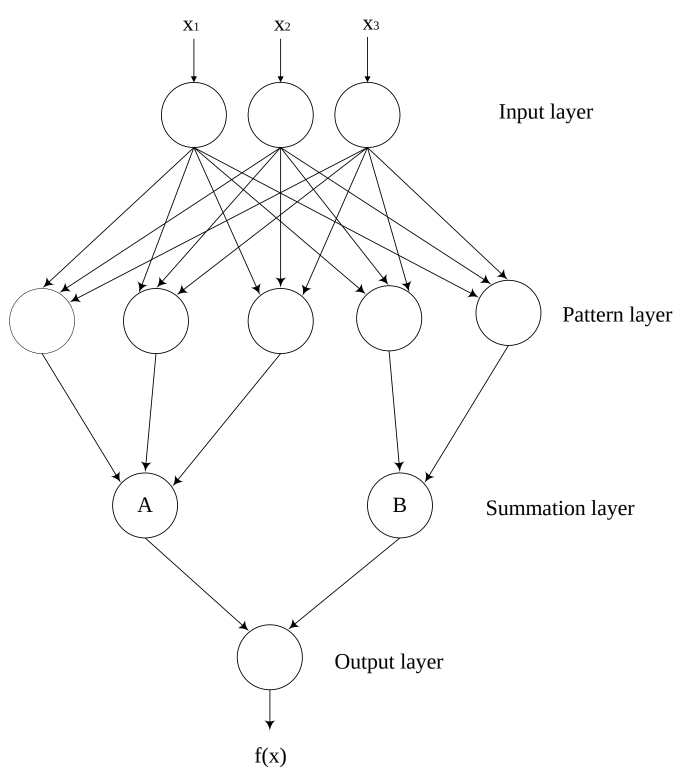

Fig. 5: Probabilistic Neural Network Structure [10]

B. Implementation of PNN

Simulation of the complete transient classification system in a power system transient simulation environment is convenient for repeated testing of the system under various conditions. Time domain simulation is also helpful to understand various issues such as time delays involved in pre-processing of signals. Therefore, a module for simulating a PNN was implemented in PSCAD/EMTDC simulation software. The main processing steps involve in implementation of the online PNN classifier in EMT simulation environment is shown in Fig. 6.

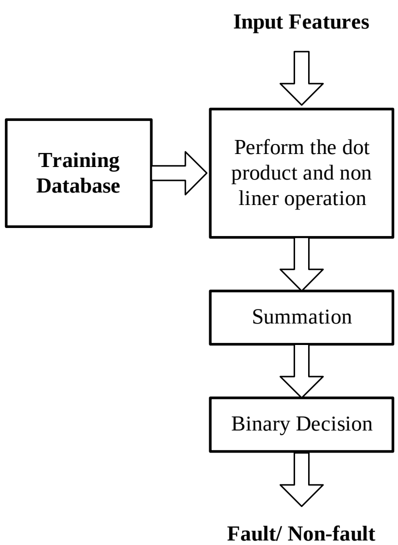

Fig 6: Processing steps involve in PNN

V. SIMULATION

In order to investigate the applicability of the proposed PNN based transient classification system simulations were carried out. Fig. 7 shows the high voltage power transmission system [17] used for the simulations. The transmission lines were modeled using frequency dependent phase domain transmission line models that take into account details such as skin effect. The bus-9 was used as the infinity bus and the generators *G2*, *G3* and *G4* were modeled as salient pole synchronous generators. The complete generator models included exciters, turbines and governors. The three-phase transformers were modeled including the effects of saturation. Simulations were carried out at a simulation time step of 5 μs in order to capture high frequency components of the signals. The transient classifier uses three phase current signals obtained through current transformers as inputs. The current transformers were also modeled in the simulation. Current signals obtained during different types of fault scenarios, capacitor switching, and load switching occurrences were sampled at 20 *kHz* sampling frequency and recorded. They were used to generate required feature vectors to train the classifier. The detail and approximation wavelet energies calculated up to three levels were used for the analysis. The implementation of the entire transient classifier system in PSCAD/EMTDC is shown in Fig. 8. The pre-processor shown in Fig. 8 were used to calculate the wavelet energies and combine the approximation coefficient and the three detailed wavelet coefficients into one vector to form the input for the PNN classifier.

A. Training Database

Hundred and forty fault events and 250 non-fault switching events were used as the training data set. The fault data set included different types of faults (ABC-G, ABC, AB, AG,

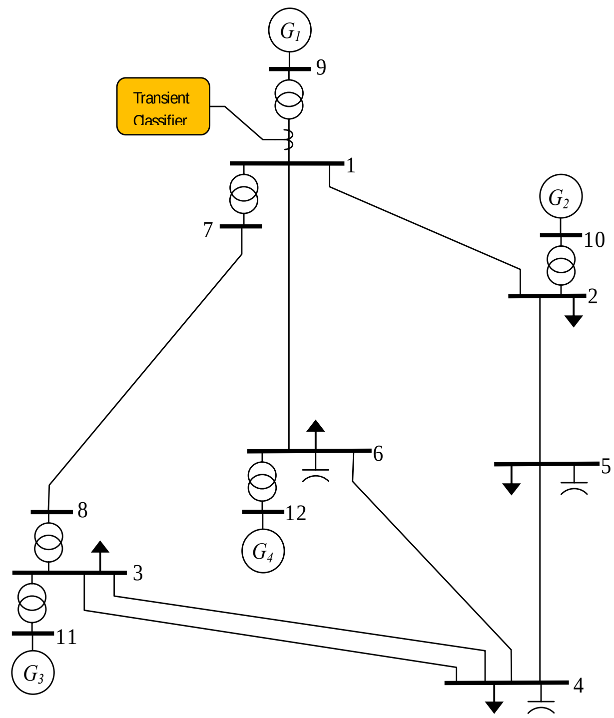

Fig. 7. 230/345 kV, 12-bus transmission system topology

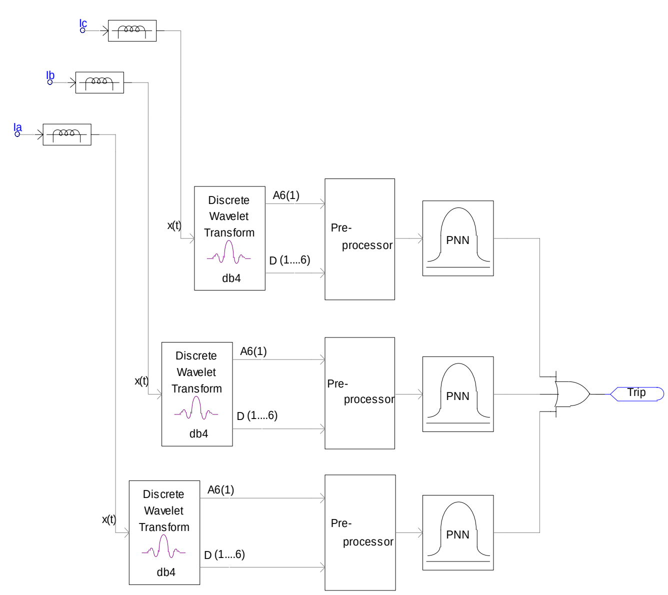

Fig. 8. Transient classifier system in PSCAD/EMTDC

BG, etc.), and were created with different fault impendence values and different fault inception angles. The non-fault events include transients occurred during load, line and capacitor bank switching, as well as steady state non-transient signals. Investigations were carried out using db4 mother wavelet which is considered well suited for power disturbance analysis [5].

B. *Classification Results*

In order to test the classifier simulations were carried out extensively with different types of disturbances simulated in the test transmission system. The classification results are summarized in Table-1.

According to the simulation results most of the fault and non-fault transients were correctly classified. Table-1 analyses the classification accuracy based on the type of disturbance. All misclassified faults were the high impedance faults which have fault impedances above 250 Ω. The lowest accuracy was observed in classification of the line-to-ground faults. A few of the line and capacitor switching events were also misclassified. However, the overall classification accuracy remained at 96%.

TABLE-1: ANALYSIS OF CLASSIFICATION RESULTS

Type of the transient		Number of events	Predicted Class: Fault	Predicted Class: Non-fault	% correct
Faults	A-G	25	23	2	92
	AB	25	24	1	96
	AB-G	25	24	1	96
	ABC	25	24	1	96
	ABC-G	25	25	0	100
	All Types	125	120	5	96
Non-faults	Load switching	25	0	25	100
	Line switching	25	1	24	96
	Capacitor switching	25	2	23	92
	All Types	75	3	72	96
All Transients		200			96

The proposed classifier uses current signals sampled at the frequencies ranging from zero to 20 kHz. The performance of the classifier was tested with noisy input signals. In order to investigate the effects of the noise, a number of cases were simulated with some noise injected into the system. No degradation of classification performance was observed. This is expected as classification is based on the abstract changes determined in the wavelet coefficients at different frequency bands during the disturbances. Thus the classifier will not be affected much unless the noise is very similar to the transients generated by faults.

Fig. 9 shows the time variations of various signals involved (current in phase A and its wavelet energies) in the classification of a fault simulated on the system on line 1-2 at 11.01 s. As shown in Fig. 9 the classifier was able detect the fault at 11.01475 s with a net response time of 0.00475 s.

In this paper, the required feature vectors (wavelet energies) were calculated using the reconstruction wavelet coefficients of the current signals. The same set of features can also be calculated using the intermediate wavelet coefficients [13]. By using this approach, the classification system response time can be made approximately half of the current system. Further this can reduce the amount of computations required in determination of wavelet energies.

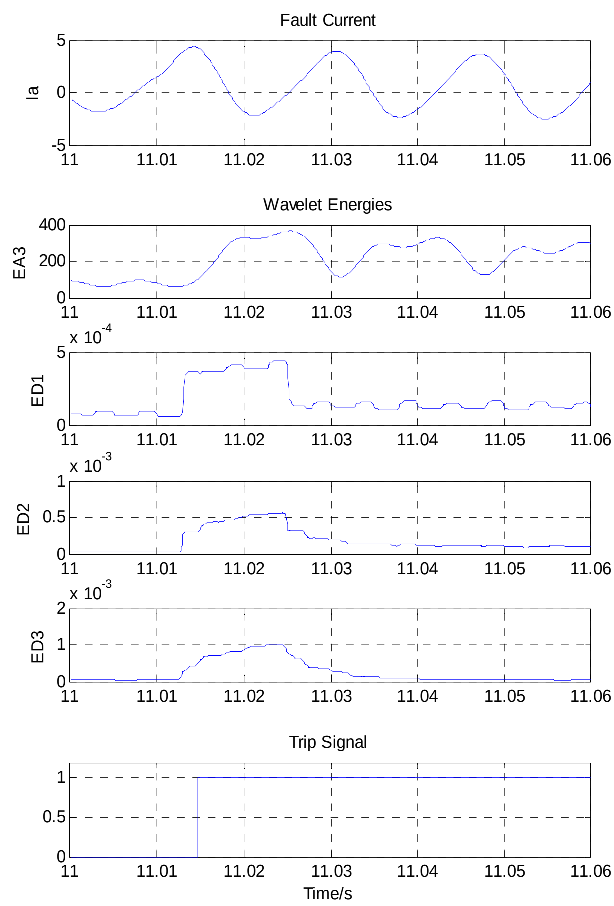

Fig. 9 An example of classification of a fault transient

C. *Applications and Improvements*

The developed transient classification will be used in a transients based protection scheme, to prevent the possible false trip signals generated due to non-fault transients. The structure of such a scheme is shown in Fig. 10. Further investigations are in progress to improve the accuracy and test the system using actual recoded waveforms. The main difficulty faced by the authors in this respect is the lack of sufficiently large number of recorded transients. It is possible to modify the algorithm to incorporate on-line learning of PNN, i.e. to improve the classification accuracy by using the new transients that the system observes during its operation. Furthermore, a hardware prototype of the classification system is being implemented in an FPGA.

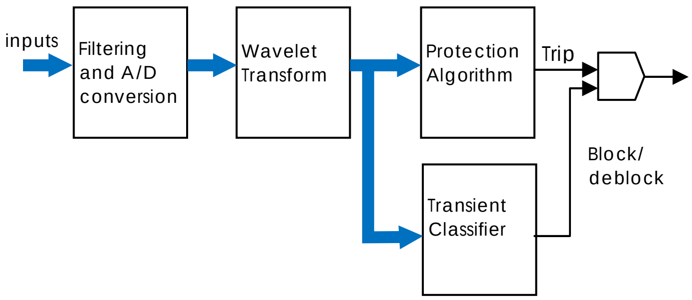

Fig. 10 Application of the transient classifier in protection

VI. CONCLUSIONS

The development of a PNN based transient classifier in an EMT environment is presented in this paper. The required feature vectors were generated using wavelet coefficients of the current signals observed during transients. Investigations carried out using a high voltage transmission system simulated in PSCAD/EMTDC showed very promising results. Implementation of the classification system in an EMT simulation program will be useful for the studies involving transient based protection relays where the proposed system would be used to discard non-fault transients.

VII. REFERENCES

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