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Reconstruction of CT Secondary Waveform Using ANN and Exponential Smoothing

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***Abstract* - Instrumentation transformers act as eyes and ears of a power system. Many measurement and protection related activities depend on current transformers (CTs) as primary sensing unit. Hence, it is of utmost important that the output of a CT should be absolutely trust-worthy. However, CTs show a tendency of getting saturated. This leads to an erroneous secondary waveform, which can lead to malfunctioning of systems which are dependent on CT. This paper proposes a technique to enhance ANN based reconstruction of erroneous secondary current waveform. The proposed technique uses artificial neural network to forecast ideal waveform. The network uses two inputs: 1. Erroneous secondary waveform. 2. Exponentially smoothed secondary waveform, which acts as an assisting input. The smoothing factor is determined using genetic algorithm. Extensive simulations indicate that the proposed technique efficiently generates reconstructed CT secondary waveform.**

***Index Terms* - Current Transformer Saturation, Artificial Neural Network, Exponential Smoothing, Genetic Algorithm**

I. INTRODUCTION

Current Transformers (CTs) play a pivotal role in power system measurement, control and protection. The successful operation of a protective relay entirely depends upon the ability of the CT to faithfully transform the fault current waveforms. The major problem with CT is its tendency to saturate during fault, i.e., the very time when it is expected to operate reliably [1]. Saturation of CT may lead to delay or even prevent tripping of relay. This may also result in loss of coordination with other relays [2]. CT can also saturate in case of increase in burden. The saturation can be prevented to some extent in design phase itself by increasing size of core, using core material with high permeability, etc. However, these solutions increase cost, weight and installation difficulties. [2]. Hence the present day trend is to use smaller low cost CTs and carry out digital restoration/reconstruction of secondary waveform.

Since 1996, many researchers have proposed various reconstruction schemes for this problem which are thoroughly discussed in [2]. Methods based on calculation of magnetization current are listed in [3-8]. However, these methods require a prior knowledge of remnant flux, magnetization curve and other CT parameters. Moreover, the computational time involved in these methods is much higher [2]. Methods proposed in [9] and [10] are based on regression techniques. The major drawback of these regression techniques is that their accuracy can be affected by the presence of harmonics [2]. It has been observed that Artificial Neural Network (ANN) based schemes are best suited for this problem due to their speed of response and accuracy. ANN based techniques do not require initial knowledge of remnant flux and CT parameters. Response time and accuracy of ANN based techniques are much better than regression based techniques [2].

ANN based methods are quite popular when it comes to CT saturation problem. However ANN based techniques have their own drawbacks. The accuracy of ANN based techniques considerably depends on the training data. ANNs require large amount training data for better accuracy. This may lead to the case of “overtraining”. An over-trained ANN can give poor results in case of data that was not provided during training. Better accuracy can also be achieved by using a network of complex topology, i.e. increasing the number of neurons or hidden layers or both. This makes the mapping process more complex and may increase computations. Also, in an attempt to achieve better accuracy during training, the network may lead to memorization or loss of generalization. A well trained ANN should not only map training data correctly but also produce correct results for those inputs which were not explicitly included in training data [11]. An expression has been proved in [12] for obtaining number of hidden nodes which are enough for learning a given number of training samples for feed-forward networks. Considering the variety of data required for CT saturation problem, the expression proved in [12] is bound to yield large number of neurons required. For best results, the ANN used should have a simple topology and should require minimal training data for accurate results. The proposed method deals with these problems efficiently. The proposed method tries to extract vital pieces of information that are hidden in the distorted secondary waveform using exponential smoothing. Extraction of these vital pieces of information can help in reducing the complexity of ANN without compromising with accuracy and using minimal amount of training data.

Exponential Smoothing is a well-known technique commonly used in financial forecasting. The method captures important trends/patterns from a noisy or random data. Exponential smoothing is a procedure which continuously revises a forecast considering more recent experiences [13]. Exponential smoothing tries to smooth out the data. Such a smoothed out waveform can be used as an assisting or supporting input to the ANN along with distorted secondary input. This can make it easier for an ANN to learn and map distorted data thereby giving better accuracy. The presence of such a supporting input will reduce the required size of the ANN. Exponential smoothing is a simple method and is very easy to implement. However, there is no formal rule for selecting smoothing factor and hence Genetic Algorithm (GA) is used.

A similar method is proposed in [14] for forecasting traffic flow. However the method uses only one input, i.e. the input pre-processed using exponential smoothing and the size of network is genetically optimized. The technique proposed in this paper uses both pre-processed (using exponential smoothing) and raw distorted CT secondary as inputs. Also, GA is used to determine the smoothing parameter. Exhaustive literature survey has revealed that none of the researchers have yet reported this method in the domain of CT saturation.

II. PROPOSED TECHNIQUE

The prerequisite to the proposed technique is detection of saturation. Various methods of saturation detection are proposed in [15-19]. The proposed technique will be applied once saturation is detected.

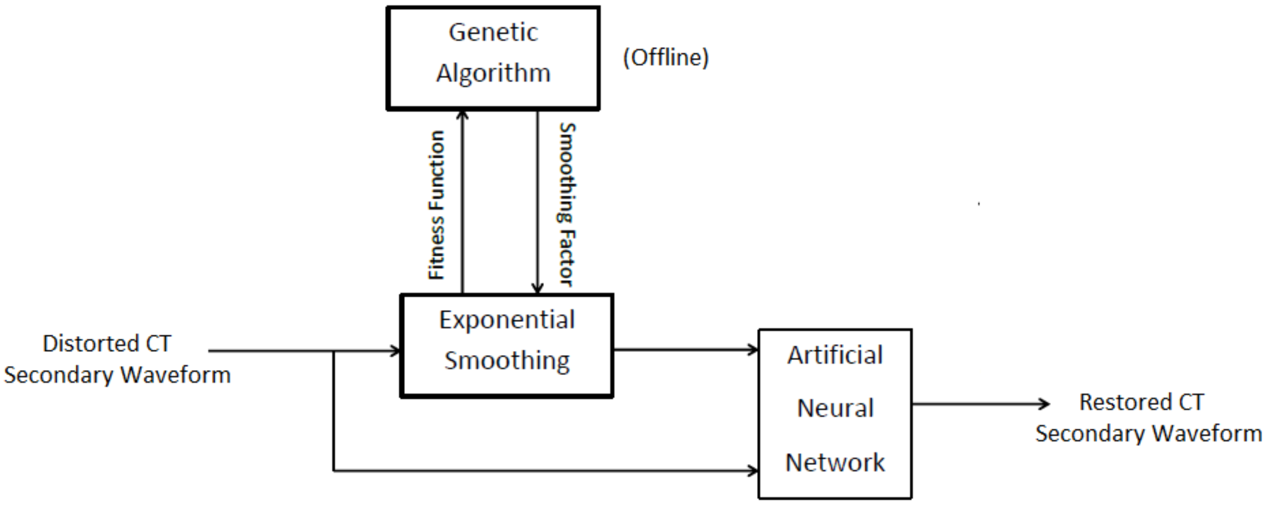

Figure 1: Block diagram of proposed technique

The block diagram of proposed technique is shown in figure 1. Exponential smoothing is performed as:

$$S_0 = X_0 \tag{1}$$

$$S_{T+1} = \alpha * X_T + (1-\alpha) * S_T \tag{2}$$

In above equations, S_T is the forecasted value of X_T (actual value) at time instance "T". Equation (1) is initialization step.

The first step during training period is to determine the best suited value of "α" or the smoothing factor. It shall be determined using Genetic Algorithm. Simplified flowchart of GA is shown in figure 2. The GA randomly generates population (values) of α. These values are encoded in a suitable way (e.g. binary, hexadecimal etc.). Some mathematical operations (genetic modifications) are performed on these encoded parameters and next generation of population (new values) is generated. The members of newly generated population are evaluated for their fitness by a fitness function. In this case, mean of absolute error is the fitness function. The error is calculated between target (ideal or normalized secondary waveform) and forecasted data generated by equations (1) and (2). The GA keeps on generating better generations and keeps on evaluating individuals for fitness till the stopping condition is met. In this way it comes up with the fittest value of α.

The second step is to obtain smoothed or forecasted input ("S" in equations 1 and 2) using exponential smoothing. It can be obtained using equations (1) and (2). The α in this case is the one obtained using GA in previous step.

The third step is to train the artificial neural network. The ANN shall take two distinct inputs: the actual input (distorted secondary waveform) and the smoothed input (obtained in previous step using exponential smoothing). The smoothed data will act as supporting or assisting data along with actual input data ("X" in equations 1 and 2).

During testing or implementation the same value of α will be used which was obtained using GA. It should be noted that GA is not used during testing and implementation as value of α is already obtained during training stage.

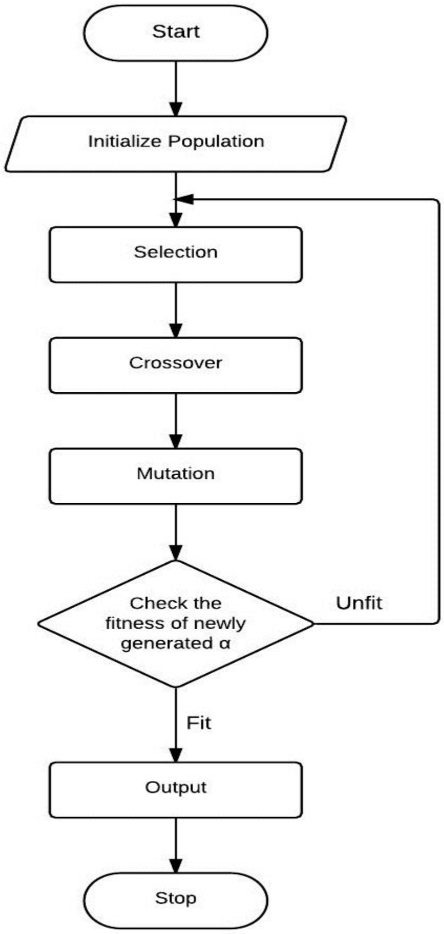

Figure 2: Simplified flowchart of GA

III. TESTING AND RESULTS

Complete implementation and testing was done using MATLAB. The ANN and GA were implemented using standard MATLAB toolboxes. The GA toolbox was kept on default settings. The current transformer model was implemented using MATLAB Simulink. The CT model, under investigation, was a 2000/5 A, 25VA CT with the primary winding which consisting of a single turn passing through the CT toroid core connected in series with the shunt inductor (load) rated 69.3 Mvar, 69.3 kV (120kV/sqrt(3)), 1 kA rms. This CT model is readily available in MATLAB and can be accessed using "power_ctsat" command. This model is convenient to use and can be used for studying various CT parameters [1].

The training data included set of 7 different training patterns. The primary was subjected to fault currents of values ranging from 24 kA to 36 kA. Different values of inception angle were used from 0 to 90 degrees. The burden was varied from 0.8 to 4 ohms. The ANN used consisted of 2 input nodes, 1 output node and 7 nodes in hidden layer (single hidden layer). Back-propagation algorithm was used for learning and Levenberg-Marquardt algorithm was used for training with tan-sigmoid as activation function. The smoothing factor or α was determined during each set of training pattern using GA. The final value of α used was average value of α obtaing in each training pattern.

For testing purpose, the inception angle of 48 degrees (not explicitly included in training data) was used and primary was subjected to fault current as shown in figure 3. The primary, in this case, was subjected to current with maximum peak of 30 kA, i.e. 15 per unit (not explicitly included in training data).

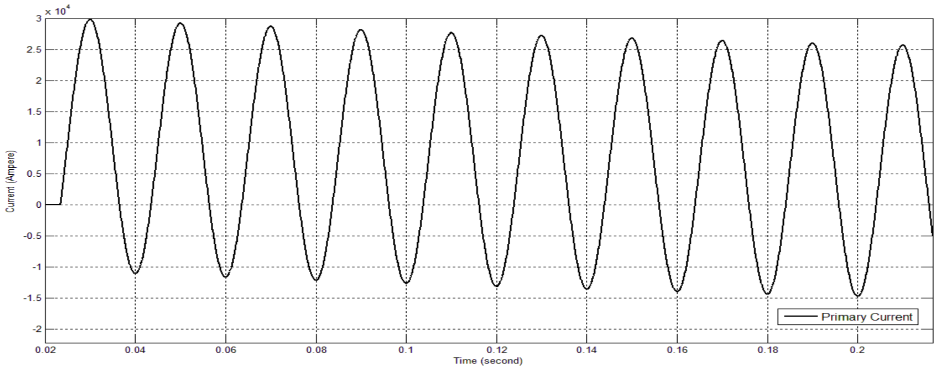

Figure 3: Primary Current

The secondary distorted waveform is shown in figure 4.

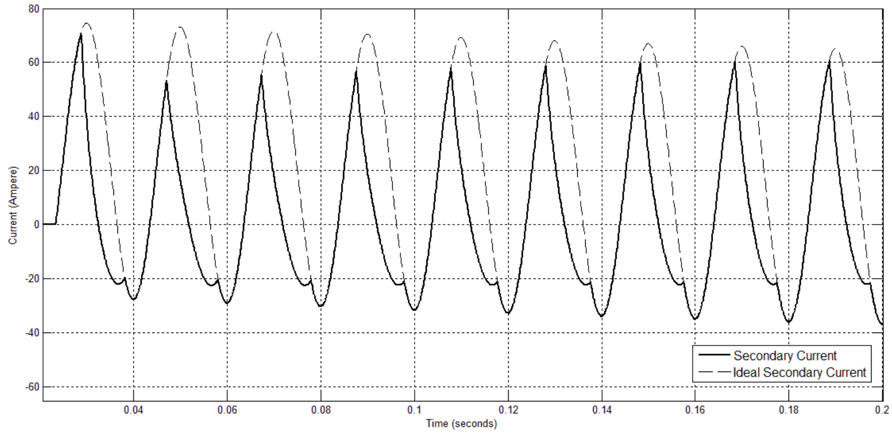

Figure 4: Distorted Secondary Waveform

The smoothed secondary waveform obtained using exponential smoothing along with actual secondary waveform is shown in figure 5.

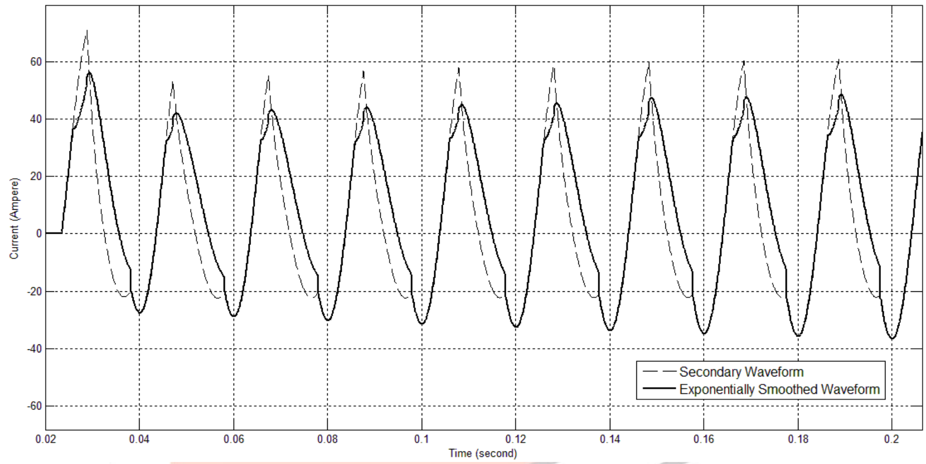

Figure 5: Smoothed Secondary Waveform

The smoothed secondary waveform and actual distorted secondary were presented as distinct inputs to the previously trained ANN. The output of ANN and its comparison with ideal output is shown in figure 6.

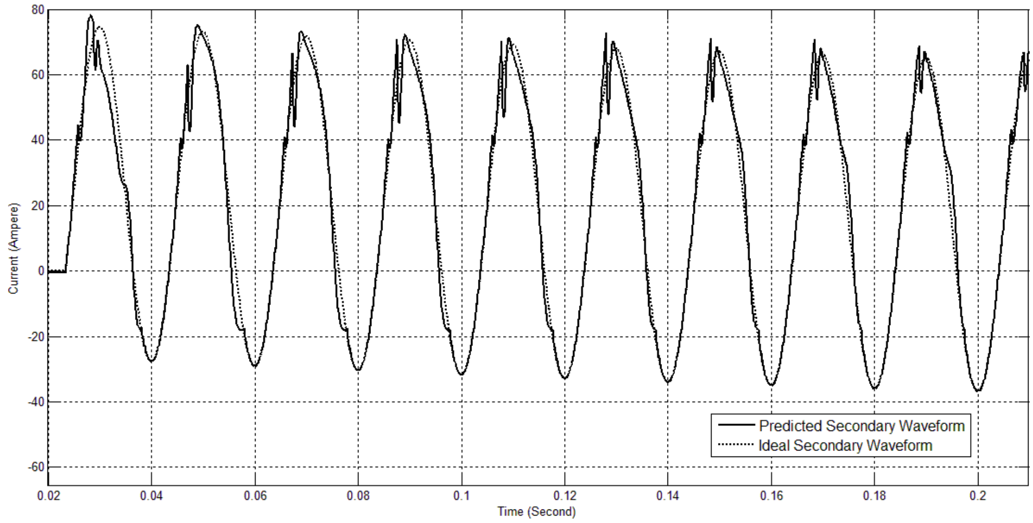

Figure 6: Output of ANN

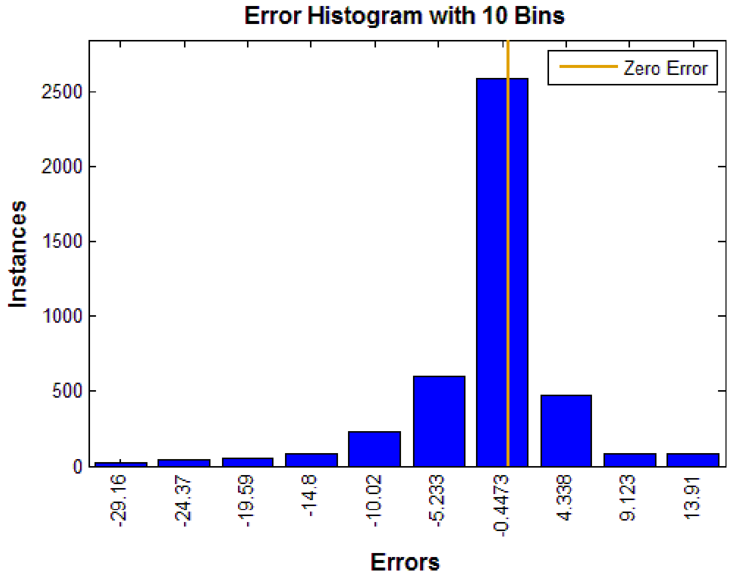

Figure 7: Error Histogram

IV. CONCLUSION

It can be clearly seen for figure 6 and 7 that a great deal of accuracy has been achieved with considerably smaller ANN (as compared to [20-22]) and with relatively minimal training data. The main purpose of this algorithm is to enhance the ANN based methods which are used in reconstruction of CT secondary. Exponential smoothing is mainly responsible for enhancement due to its ability to capture important trends. The accuracy of the ANN output as stated previously, depends upon the training patterns presented to it. The nature of distorted CT secondary waveform makes it difficult for ANN to map it. The processed or smoothed data helps the ANN to map better with relatively simple topology. It makes the ANN to generalize data rather than memorize it. The same technique can be used to enhance ANN based detection of saturation.

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