APPLICATION OF ANN METHODS FOR INSTRUMENT TRANSFORMER CORRECTION IN TRANSMISSION LINE PROTECTION

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INTRODUCTION

Rapid and reliable operation of the power system protection and control is dependent on reasonably accurate measurements of electrical signals associated with controlled elements of the power system. On the base of phase voltages and currents the protective relays estimate the state of a circuit to make a decision: to trip the faulted circuit, or not-to-trip the sound one.

Current and voltage transformers influence the criterion values measurement particularly during disturbances in the system. Certain construction limitations of instrument transformers may in some cases cause maloperation or substantial delay in tripping of the protective relays. Current transformer saturation and discharging of the capacitive voltage transformer's internal energy during short circuits on an associated transmission line are the most important phenomena affecting accuracy of the voltage and current magnitude estimation.

The goal of this paper is to present ANN methods intended for dynamic compensation of Current Transformers (CTs) and Capacitive Voltage Transformers (CVTs) used for measurements in high voltage power systems. The nonlinear multilayer recursive Artificial Neural Networks (ANNs) have been used for modelling inverse transfer functions of the transformers. The faced problems as well as the results obtained for different network parameters are presented. The issue of correct application of these novel methods in real protective relays has been discussed.

Many studies on the correction of CTs and CVTs have been reported. In most cases presented approaches consist in searching of the inverse transfer function of a CVT as Saha et al (1) and Siguerdidjane et al (2) propose. Conventional as well as ANN methods for compensating CTs are presented by Braun et al (3) and Kang et al (4). However, the usage of broad ANNs or additional filtering of restored signals is required therein.

MODELLED SYSTEM DESCRIPTION

Since the design of ANN models requires an adequate amount of the representative data of the considered phenomenon, the operation of the 400kV power system shown in Figure 1 has been simulated by using the EMTP/ATP program.

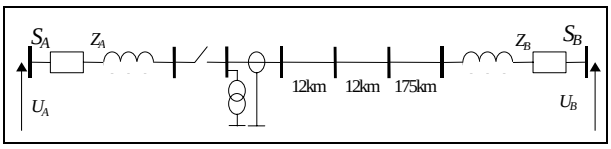

Figure 1: Structure of the modelled system

CT Model

Figure 2 shows the model of CTs used in simulations. The CTs have been modelled by means of the 98-type element that has been thoroughly tested and relevant results have been reported by Kezunovic et al (5). The magnetising characteristic curve of the investigated CT is shown in Figure 3.

CVT Model

Figure 4 presents the model of the EHV (400 / 22 / 0.11 kV, 50 Hz) CVT used in simulations. The model consists of:

- the capacitive voltage divider (C_1, C_2),
- the tuning reactor (L, R),
- the step-down transformer (L_{T1}, R_{T1}, L_m, R_{Fe}, L_{T2}, R_{T2}) with equivalent stray capacitance (C_{T1}) included at the primary winding,
- the antiferroresonance circuit and the CVT load: L_1, R_1, R_2, R_0, L_0

POWER SYSTEM OPERATION CONDITIONS

Taking into consideration factors affecting the level of distortions in the CT and CVT secondary signals, the following conditions were changed at each simulation: system impedance, type of short circuit, fault resistance, fault location, CT's load, fault angle, remanent flux. The obtained current and voltage waveforms have been used for preparing the training patterns. Since the reliable testing of an ANN should be carried out with the use of

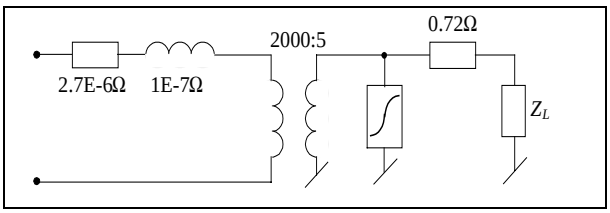

Figure 2: Diagram of the modelled CTs

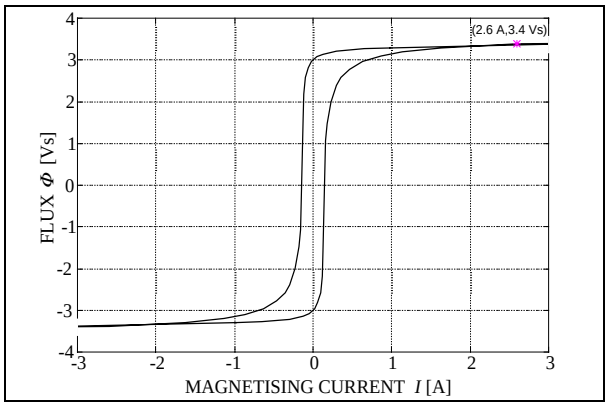

Figure 3: The magnetising characteristic of the CT core

data not presented during training, some additional simulations have been conducted with aforementioned parameters being changed randomly.

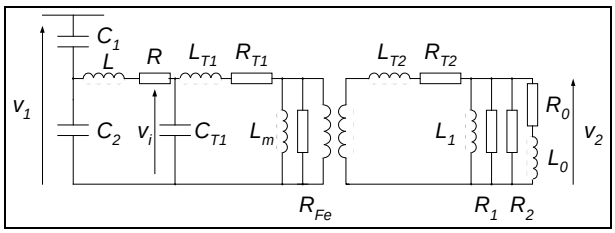

Figure 4: The model of a CVT

NEURAL APPROACH TO RESTORING SECONDARY SIGNALS OF INSTRUMENT TRANSFORMERS

The application of CT's and CVT's inverse transfer functions in the artificial neural network form is the main idea of the compensating of instrument transformers presented herein. This function set up in series with the transfer function of the CT (CVT) should assure identity of the primary and restored secondary signals. Since the CT's transfer function is a nonlinear one, the usage of the nonlinear artificial multilayer neural network with sigmoidal tangent activation functions assigned to neurons in hidden and output layers as presented in Figure 5 is required. Such a structure known as the Neural Network Output Error model (NNOE) is concisely described by the following nonlinear function with the regressor vector as an argument:

$$\hat{y}z^{-n_d} = F(x,\ldots,xz^{-n_w+1},\hat{y}z^{-n_d-1},\ldots,\hat{y}z^{-n_d-n_c+1}) \qquad (1)$$

where:

x - sample of the secondary signal,
$\hat{y}$ - sample of the restored signal,
n_w, n_c - the model order
n_d - a structural time delay

The secondary signal samples and compensated ANN's

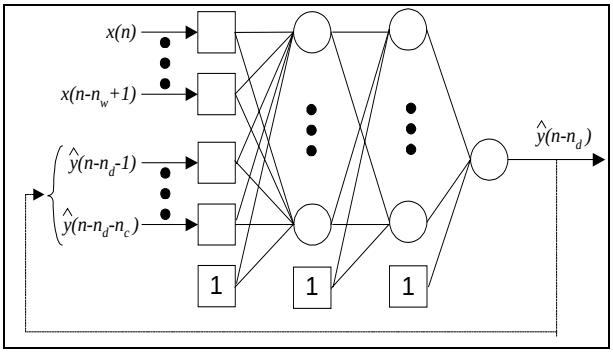

Figure 5: Architecture of the ANN compensator

output samples have been dynamically used for forming the input patterns to the net.

The Performance Indices

To assess the performance of the correctors two types of quality indices have been introduced. The first one measures the capability of the restoring the secondary signal:

$$err_S(n) = (\sum_{j=1}^{K} \frac{|y'(n,j) - \hat{y}(n,j)|}{Y'(j)} / K) \cdot 100\% \qquad (2)$$

where:

j - number of considered waveshapes from faulted phases,
K - total number of considered fault waveshapes,
n - number of a sample,
$y'(n,j)$ - n-th sample of the primary current referred to the secondary side of the j-th fault case
$Y'(j)$ - magnitude of the primary signal (estimated in the steady state of the j-th fault case),

The second one have been introduced to assess the usefulness of the restored signals for estimating the magnitude of the fundamental component of the primary signals:

$$err_A(n) = (\sum_{j=1}^{K} \frac{|Y'(n,j) - \hat{Y}(n,j)|}{Y'(n,j)} / K) \cdot 100\% \qquad (3)$$

where:

$Y'(n,j)$ - magnitude of the primary signal (estimated at n-th instant of the j-th fault case),

$\hat{Y}(n,j)$ - magnitude of the restored signal (estimated at n-th instant of the j-th fault case),

Full-cycle digital sine and cosine filters have been used for estimating the orthogonal components of considered voltage and current signals. They in turn have been used for estimating Y', $\hat{Y}$ magnitudes. It is evident that the lower the performance indices are, the better compensated signals coincide with target ones.

COMPENSATION OF THE CT

Utilising the modified Levenberg-Marquardt training method intended for real time recurrent neural networks, that is presented by Haykin in (6), many alternative compensators of the CT have been prepared. Parameters n_d, n_w, n_c and the size of an ANN were changed during investigations to determine the optimal their combination, that is such one which would guarantee the best performance of the obtained models. The investigations showed that there exists such a combination that makes it possible to achieve the satisfying levels of the performance indices. The thorough research has suggested that n_d, n_w, n_c should roughly take 1/10, 1/5, 2/5 of samples per a cycle of the fundamental component, respectively. It has turned out that the assumed sampling frequency does not affect these values. However, the increase of the sampling frequency in some cases may considerably speed up convergence of the training process. In particular, it is valid if time between the fault inception and the first saturation interval is often relatively short. Moreover, investigations revealed that to some extent the optimal value of n_d is dependent on the time-constant of the secondary circuit of the CT model. The greater the time-constant is, the longer delay should be introduced to get shorter time convergence of the training processes and to obtain ANNs of the better performances.

Compensation Results in Time Domain

Figure 6 and Figure 7 show the graphs of the performance indices in the time domain computed for the uncompensated and compensated secondary currents of CTs. The processed waveshapes have been chosen from training as well as testing data sets. Figure 6 refers to the compensation of the CT with the purely resistive load whereas Figure 7 to the CT with resistive-inductive load. The fault inception is referred at time 0 ms.

Figure 8 shows example results of the compensation and the amplitude estimation based on uncompensated and compensated currents. It is evident that the ANN corrects satisfactorily the shape of the secondary current. The amplitude estimation after the compensation is much more accurate than in the case of the estimation based on the distorted secondary current.

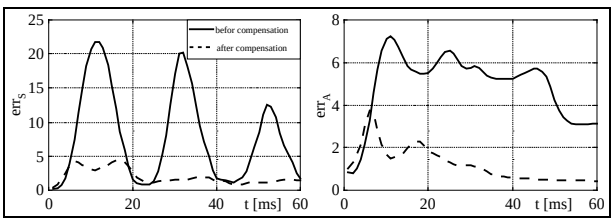

Figure 6: Graphs of performance indices in the time domain for the CT with the purely resistive load. Compensation carried out with the *8-8-1* ANN (f_s=1.6kHz, n_d=0; n_w=6; n_c=13)

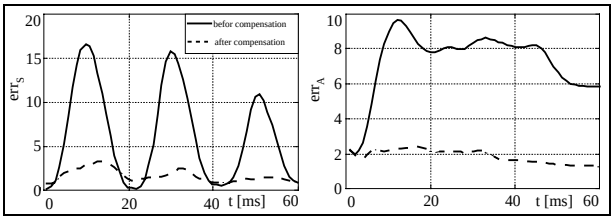

Figure 7: Graphs of performance indices in the time domain (the resistive-inductive load). Compensation carried out with the *8-8-1* ANN (f_s=1.6kHz, n_d=4; n_w=6; n_c=13)

COMPENSATION OF THE CVT

Let us assume that the function *F(*)* in equation (1) is to be realised as a single neuron or nonlinear multilayer ANN, where regressor (*) is to be composed of uncompensated and compensated secondary voltage samples. Similarly as in the case of the CT compensation n_d, n_w and n_c parameters have to be optimised. To meet this requirement series of training and testing procedures have been carried out for various network sizes and variable mentioned parameters.

The Single Neuron Model - results

Since a CVT, to some extent, can be treated as a linear element, it seems that its reverse transfer function could be modelled based on a single neuron artificial net. However, research revealed some superiority of the non-linear over linear approach. In addition, the performance of the achieved compensators has been verified over classical approach reported in (1). It is shown in Table 1 the model with n_w=4 and n_c=3 assures minimal number of neuron inputs and low values of indexes. Increase of n_w and n_c does not cause significant decrease of indexes. Moreover, comparison of results obtained with the use of single neuron architecture and the conventional approach indicates superiority of the former.

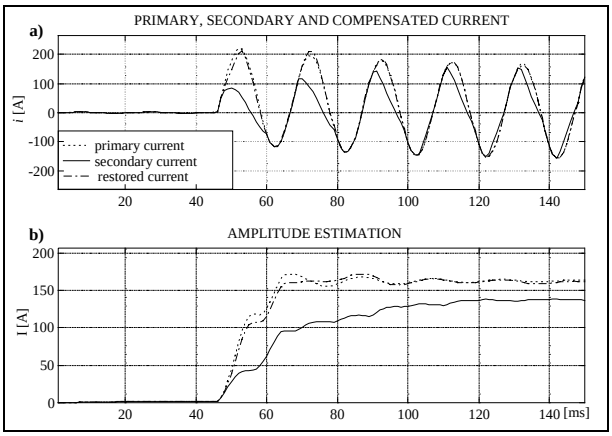

Figure 8: a) Plot of the phase *S* current generated from simulation of *R-S-T* fault at bus-bars (R_F=0). Compensation carried out by the ANN of *8-8-1* structure. b) amplitude estimation of primary, secondary and compensated currents

TABLE 1 -Compensation indexes as a function of n_w, n_c for single neuron compensators and the classical approach.

	n_W - n_C				classical approach	without compens
	3 - 3	4 - 3	4 - 4	5 - 4		
err_S	14.47	7.41	7.04	6.86	12.41	18.88
err_A	3.3	0.98	0.98	0.94	2.62	17.33

The Multilayer Non-Linear Model-results

To increase the model capacity multilayer ANNs have been investigated for the compensation purpose. Nets were trained with the use of the same training patterns as in the case of single neuron compensators. The architecture composed of 5 neurons in the hidden layer and one linear output unit has been chosen. The example of the secondary voltage restoration made with the non-linear network with n_w=n_c=8, n_d=0 and 5-1 logsig-lin structure is shown in Figure 9. The compensation indexes averaged over 2 cycles reached then values: err_S=1.66 and err_A=0.73. The indexes for various values of parameters n_w, n_c are presented in Table 2.

TABLE 2 -Results of the compensation made with 5-1 logsig-lin ANNs.

	n_w - n_c						
	3 - 2	3 - 3	4 - 4	5 - 4	5 - 5	6 - 6	7 - 7
err_S	5.73	7.21	2.38	3.22	3.46	2.97	1.35
err_A	2.58	3.61	1.25	1.07	1.33	0.96	0.83

The Problem of Stability

The simulations have shown that for some fault cases the linear and nonlinear compensators obtained from training processes may be unstable. Increase of the exponential component in the output signal for the linear compensator or total saturation of the output for a nonlinear one are symptoms of instability. Thus, we propose some ways to avoid such problems. In case of the linear net, it is possible to use the Jury-Marden criterion to compute stability conditions. Using this method the necessary tuning can be added. Our investigations have shown that the necessary change of weight values is insignificant and does not deteriorate compensation quality. However, nonlinear systems can not be adjusted in this way, especially when complex non-linear recursive ANNs are used. We suggest to deal with it satisfying some training conditions, such as: the minimal necessary number of neurons in the network and adequate number of training patterns (conditions for proper generalization).

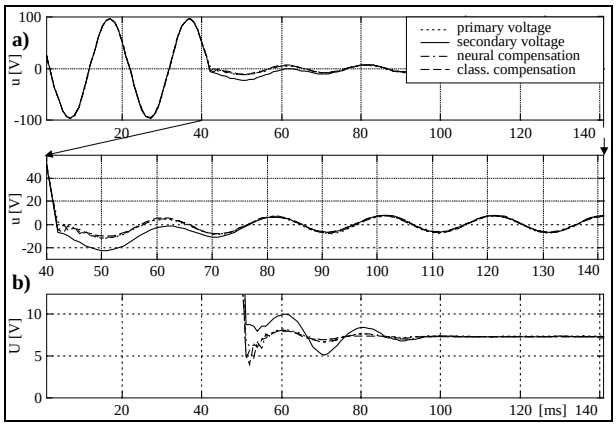

Figure 9: CVT under abrupt reduction of the primary voltage. (a) the primary, secondary and compensated secondary voltages, (b) the voltage amplitudes

CONCLUSION

The new approach to the CT and CVT compensation is proposed in this paper. The investigated ANN architectures assure significant improvement of the shape of the secondary signals. Since proposed compensators of the CTs are able to estimate the correct secondary current under different fault conditions, they can improve the sensitivity and maximise the stability of relays thus making the use of the CT with the reduced core cross section possible. Bearing in mind the stability of the linear single neuron compensator of the CVTs, it is proposed as an on-line algorithm in protective relays, whereas a non-linear one should be started just after fault recognition and stopped after approximately two cycles elapsed.

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