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Current transformer saturation compensation based on a partial nonlinear model

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ABSTRACT

This paper proposes a partial nonlinear model to accurately represent the nonlinear saturation characteristic of a current transformer (CT). Based on the model, the saturated section of the secondary current as well as the unsaturated section can be used in a regression process to estimate model parameters. The saturated section normally lies near the inception of a fault, therefore accurate parameters can be obtained faster compared with the methods using only unsaturated sections. The pre-fault remanent flux and DC-offset, which could significantly influence CT saturation, are both considered in the model, thus they do not affect the accuracy of the parameter estimation. The computational load of the regression calculation is significantly reduced by using separable nonlinear least squares (SNLLS) method. This provides the feasibility to implement the method for real-time protective relaying. The performance of the method has been evaluated on the data obtained from both PSCAD/EMTDC simulation and live recording with a test CT. The method has also been implemented in a Field Programmable Gate Array (FPGA).

1. Introduction

Iron-core current transformers (CTs) are widely used for current measurements in power systems due to their reliability and acceptable cost. Their major disadvantage is concerned with the saturation of the iron-cores, which causes the distortion of secondary currents appearing at the inputs of protection relays [1]. This may, in consequence, lead protection relays to malfunction. Two ways are normally used to alleviate this impact: (1) using large iron-core CTs to reduces the probability of the occurrence of CT saturation; (2) employing compensation algorithms to eliminate the influence of CT saturation. Obviously the latter is more economical.

In recent years, the techniques of compensating the secondary current distortion caused by CT saturation have been intensively studied. In [2], the magnetizing current of a saturated CT is estimated by applying the calculated instantaneous flux of the CT to the magnetization curve of the CT. This technique relies on the assumption that the remanent flux in the CT is zero prior to the fault, which has the drawback that the assumption cannot be guaranteed in every fault condition. In [3,4], the remanent flux problem is avoided by detecting the exact start points of the distorted secondary currents using difference functions and a morphological lifting scheme (MLS) respectively. The instantaneous flux at these points is equal to the flux at the knee point in the magnetization curve of the CT. However, due to the disturbances caused by anti-aliasing filters and noise, the start points detected by these methods may have large deviations from their true values. Some methods use a complex inverse function to get the compensated current with the saturated current as input [5,6]. Usually, an artificial neural network (ANN) is used as the complex inverse function. Theoretically, ANN can provide satisfactory compensation. However, it has to be trained with comprehensive data, which cover all the possible saturation scenarios of the CTs. Without these data and sufficient training, the accuracy of the ANN approach would not be ensured. Another group of methods apply a linear regression [7] and a discrete dynamic filter [8] on the unsaturated sections of the secondary current to reconstruct the compensated current. They utilize wavelet and a threshold criteria respectively, to extract unsaturated sections from a distorted secondary current. Using these methods, sufficient length of unsaturated sections is required to obtain accurate results. If the methods are used to deal with a severely saturated current, which has only a very short unsaturated section in each fundamental cycle, more than one cycle of the current is needed to get enough unsaturated sections.

In [9] the authors has proposed a novel method which can compensate CT saturation current accurately and rapidly. In this paper, the method has been further developed, thoroughly verified and implemented in a Field Programmable Gate Array (FPGA) based embedded system. Based on a partial nonlinear model, both unsaturated and saturated sections of a distorted secondary current are used by the method to conduct a nonlinear regression, therefore only a short section of current waveform is required to achieve an

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accurate estimation. Then a healthy secondary current waveform is reconstructed from the estimated parameters. The remanent flux is considered in the nonlinear part of the model, therefore it does not affect the accuracy of the estimated parameters. Tests show accurate parameters can be obtained within 0.5–0.8 of a cycle after fault occurrence. Moreover the phasor of the fault current could also be directly calculated from the parameters without waveform reconstruction. Normally, a multi-dimension nonlinear regression is difficult to be realized in a real-time embedded system, such as protection relays, due to its heavy computational load. However, this nonlinear regression can be transformed to a combination of a single dimension nonlinear regression and a multi-dimension linear regression by using separable nonlinear least squares (SNLLS) method. Thus, a great computational load reduction is achieved. The method has been implemented in an FPGA and tested in a real-time protection relay test bench. The test results indicate the potential of this method for future relaying applications.

2. Nonlinear regression model of secondary current

Fig. 1 presents a simplified equivalent circuit of a CT, where $i_p(t)$ is the primary current referred to the secondary side, $i_m(t)$ is the magnetizing current, $i_s(t)$ is the secondary current, Z_m is the excitation impedance, R_s and L_s are the total secondary resistance and inductance respectively. The relationship among the currents can be expressed as

$$i_p(t) = i_s(t) + i_m(t), \tag{1}$$

where $i_s(t)$ is measured through a CT. As functions of time, $i_p(t)$ and $i_m(t)$ are only rely on some undetermined constant parameters, thus (1) can be transformed to a regression model.

The primary fault current $i_p(t)$ is the superposition of a sinusoidal waveform (*i.e.*, the phasor of the fault current) and an exponentially decaying DC-offset, which is determined by the factors: source voltage, circuit impedance, fault inception angle and X/R ratio of the primary fault path. It can be expressed as

$$i_p(t) = A\sin(\omega t + \theta) + Be^{-\tau t}, \tag{2}$$

where A is the amplitude, ω is the angular speed, and θ is the inception angle. B and τ are respectively the initial value and the time constant of the DC-offset. By respectively applying trigonometric expansion and first-order Taylor series expansion on the cosine term and the exponential term of the equation, a linear approximation can be obtained:

$$\begin{aligned} i_p(t) &= A\cos\theta\sin(\omega t) + A\sin\theta\cos(\omega t) + B - \tau t \\ &= a_1\sin(\omega t) + a_2\cos(\omega t) + a_3 + a_4 t, \end{aligned} \tag{3}$$

where $a_1 - a_4$ are unknown parameters.

The magnetizing current $i_m(t)$ is a function of CT core flux $\varphi(t)$. The function is also called the magnetization curve of the CT. It can be converted from the secondary-excitation curve of the CT provided by CT manufacturers. A high-order power series based model introduced in [10] provides an accurate approximation to the curve. The typical expression of the model is

$$i_m(t) = k_1\varphi(t) + k_2\varphi(t)^5 + k_3\varphi(t)^{33}, \tag{4}$$

where $k_1 - k_3$ are the magnetizing characteristic of the CT. $\varphi(t)$ and $i_s(t)$ have a relationship described in

$$\frac{d\varphi(t)}{dt} = R_s i_s(t) + L_s\frac{di_s(t)}{dt}. \tag{5}$$

Integrating it from t_0 to t yields

$$\varphi(t) = R_s\int_{t_0}^{t} i_s(t)dt + L_s(i_s(t) - i_s(t_0)) + \varphi(t_0). \tag{6}$$

Substitute $\varphi(t)$ in (4) with (6) and set remanent flux $\varphi(t_0)$ as an unknown parameter a_5, $i_m(t)$ can be represented as a function F_{im}.

$$i_m(t) = F_{im}([i_s(t_0), i_s(t_1)\cdots i_s(t)], a_5), \tag{7}$$

where $[i_s(t_0), i_s(t_1)\cdots i_s(t)]$ denotes the samples of the secondary current between t_0 and t. Then a nonlinear regression model (8) is obtained by substituting (8) and (7) into (1).

$$\begin{aligned} i_s(t) = &\ a_1\sin(\omega t) + a_2\cos(\omega t) + a_3 + a_4 t \\ &- F_{im}([i_s(t_0), i_s(t_1)\cdots i_s(t)], a_5). \end{aligned} \tag{8}$$

Inside, parameters $a_1 - a_5$ are unknown. The regression analysis based on this model aims to estimate $a_1 - a_5$ using the sampled secondary fault current.

3. SNLLS based regression scheme

A nonlinear regression function $\mathbf{f}_i(\mathbf{a})$ can be formed by shifting all the terms in (8) to the right side of the equation. This gives

$$\begin{aligned} \mathbf{f}_i(\mathbf{a}) = &\ i_s(t_i) + F_{im}([i_s(t_0)\cdots i_s(t_i)], a_5) - (a_1\sin(\omega t_i) + a_2\cos(\omega t_i) \\ &+ a_3 + a_4 t_i), \end{aligned} \tag{9}$$

where $\mathbf{a}$ is the vector of unknown parameters $a_1 - a_5$. Applying (9) to m samples of secondary fault current yields

$$\mathbf{f}(\mathbf{a}) = \mathbf{i_s} + \mathbf{F_{im}}(a_5) - \mathbf{L}\mathbf{a}_{(1-4)}, \tag{10}$$

where $\mathbf{f}(\mathbf{a}) = [\mathbf{f}_0(\mathbf{a})\,\mathbf{f}_1(\mathbf{a})\ldots\mathbf{f}_{m-1}(\mathbf{a})]^T$, $\mathbf{i_s} = [i_s(t_0)\,i_s(t_1)\ldots i_s(t_{m-1})]^T$, $\mathbf{F_{im}}(a_5) = [F_{im}([i_s(t_0)], a_5)\ldots F_{im}([i_s(t_0), i_s(t_1)\cdots i_s(t_i)], a_5)]^T$, $\mathbf{a}_{(1-4)} = [a_1\,a_2\,a_3\,a_4]^T$, and

$$\mathbf{L} = \begin{bmatrix} \sin(\omega t_0) & \cos(\omega t_0) & 1 & t_0 \\ \sin(\omega t_1) & \cos(\omega t_1) & 1 & t_1 \\ \vdots & \vdots & \vdots & \vdots \\ \sin(\omega t_{m-1}) & \cos(\omega t_{m-1}) & 1 & t_{m-1} \end{bmatrix}.$$

Then, the least squares problem of the regression model can be expressed in a matrix format as

$$r_{NLLS}(\mathbf{a}) = \mathbf{f}(\mathbf{a})^T\mathbf{f}(\mathbf{a}). \tag{11}$$

Nonlinear least squares (NLLS) problems do not have analytical form solutions and normally solved by iterative refinement. The computational load needed to solve a NLLS problem mainly depends on its convergence speed and the load of each iteration. The computational load needed to solve (11) can be greatly reduced by exploiting the partial nonlinear characteristic of (10). Inside, only a_5 relates to the nonlinear function $\mathbf{F_{im}}(a_5)$, and $\mathbf{a}_{(1-4)}$ have linear relationships with $\mathbf{L}$. By using SNLLS method [11], the 5-dimension NLLS problem, $r_{NLLS}(\mathbf{a})$, can be converted to a one-dimension NLLS problem and a 4-dimension LLS problem. First,(10) turns to a LLS

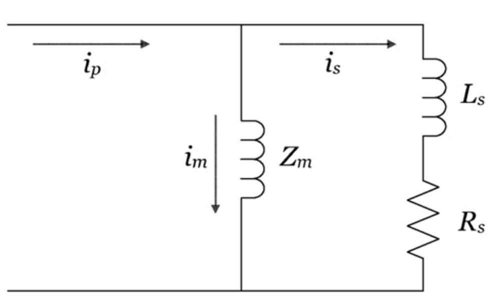

Fig. 1. Simplified equivalent circuit of a CT.