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Validation of the Orthogonal Fitting Results for Short-Circuit Impedance Identification

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Abstract

Background: Accurate transformer models are essential for electromagnetic transient (EMT) simulations, particularly for evaluating Transient Recovery Voltage (TRV) during switching operations. However, many transformer models used in simulation software rely on simplified parameter identification methods developed before the widespread availability of modern digital measurement techniques. A common approach combines low-signal frequency response measurements with Vector Fitting, producing pole-residue models without providing information on parameter uncertainty. This study investigates an alternative identification method based on orthogonal regression. Methods: The proposed approach applies orthogonal regression based on Koopmans–Levin method to identify the transformer short-circuit impedance from measurement data. The method is validated by comparing the identified model with reference measurements and assessing its suitability for TRV-oriented transient simulations. Results: The proposed identification procedure provides an accurate representation of the transformer short-circuit impedance while enabling the estimation of parameter uncertainty. Compared with conventional frequency-response-based identification, the method offers improved confidence in model parameters and better reflects measurement variability. Conclusions: Orthogonal regression is a promising alternative for transformer parameter identification in EMT studies. By incorporating parameter uncertainty into the identification process, the method enhances the reliability of transformer models used for TRV analysis and other transient simulations.

Keywords: identification; TRV; time response; orthogonal regression

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1. Introduction

Identifying the short-circuit impedance of a transformer is an essential aspect of understanding its performance, particularly in the context of power systems operations. The short-circuit impedance is a crucial characteristic involved in transient processes in a short-circuit condition [1].

In the field of research on power system transients, one can notice a huge development of simulation methods and tools, in contrast to the almost complete lack of progress in methods of obtaining (identifying) models of system elements. One of the possible ways to improve and make more flexible the mentioned identification is to use orthogonal regression of time courses obtained in specific tests of the input–output relationship of the object [2–5].

Power system models used to simulate transient processes are equivalent elements of separate network elements: transmission lines, cables, transformers, etc. The mod-

els of these elements are sufficiently precise for simple objects. More complex objects—transformers, electrical machines—are represented in simplified forms, determined on the basis of substitute research, including frequency response measurements. The remedy for these shortcomings may be direct measurements of transient processes in a real network excited by an appropriate source. One possible option is to measure the transient recovery voltage generated by the injection current with a half-sinusoidal time waveform.

Short-circuit impedance models (SIMs) are a fundamental element in advanced simulation of power system dynamics, going beyond standard steady-state analyses. Their indispensability in studying transient switching processes stems from the fact that these phenomena are rapidly changing and nonlinear, and span a wide frequency range, requiring precise representation of network elements in the frequency or time domain [6].

Unlike simplified short-circuit models used to determine maximum short-circuit currents in steady states (typically for a network frequency of 50/60 Hz), the analysis of transients, such as switching operations, requires the consideration of network parameters ranging from tens of hertz to several megahertz. In this context, traditional models based on symmetrical components and constant impedances are insufficient [7,8].

This article is devoted to the validation of the Orthogonal Fitting results for the identification of short-circuit impedance of power system components in the time domain. Its results can be used in simulations of transient processes in the system, at least comparatively to simulations carried out on models with characteristics obtained by other methods.

2. Materials and Methods

2.1. Experimental Research

The objective of the experimental study was to validate the Orthogonal Fitting (Ort-Fit) method for identifying the short-circuit impedance of a transformer from TRV measurements. The validation consisted of comparing the impedance model identified by the proposed time-domain approach with a conventional model obtained using the Vector Fitting (VF) technique based on frequency-response measurements.

The experiments were performed using a Recovery Voltage Indicator (RVI), which injects a controlled half-sinusoidal current pulse into the investigated transformer. The recorded current and voltage waveforms around the current-zero crossing were used to identify the transformer equivalent circuit. The obtained models were subsequently validated in independent simulation and measurement tests, including operation with a vacuum interrupter, to verify their capability to reproduce transient switching phenomena under conditions different from those used during identification.

2.2. Means

The experimental setup consisted of an RVI equipped with a capacitive current injection circuit, a laboratory transformer under short-circuit conditions, measurement probes for voltage and current acquisition, and a high-speed digital oscilloscope. The injected current was generated by discharging a capacitor through the tested circuit, producing a half-sinusoidal waveform representative of the final half-cycle of a short-circuit current.

Measured signals were processed using MATLAB2022b and Simulink. MATLAB was employed for signal preprocessing, Orthogonal Fitting, Vector Fitting, and parameter estimation, whereas Simulink was used to simulate the identified equivalent circuits and perform validation against experimental measurements. The reference impedance spectrum was additionally measured using an HP4192A impedance analyzer.

2.3. Measures

Two physical quantities were measured during each experiment: the injected current and the transient recovery voltage at the transformer terminals. The identification algorithm was applied to approximately 2000 samples recorded around the current-zero instant, where the transient response contains the highest information content.

Model quality was evaluated using the normalized root-mean-square mismatch between measured and simulated waveforms, expressed in decibels. This metric was calculated independently for current and voltage signals and served as the primary indicator of identification accuracy. Additional validation was performed by comparing frequency characteristics and transient responses obtained from simulations with experimental recordings.

2.4. Identification Procedure

The identification process consisted of four successive stages. First, current and voltage waveforms acquired during the RVI test were preprocessed and synchronized around the current-zero crossing. Second, the transformer parameters were estimated using the Orthogonal Fitting algorithm, which minimizes orthogonal distances between measured and simulated data while accounting for uncertainties in both variables. Third, an equivalent electrical circuit was synthesized from the identified parameters. Finally, for comparison purposes, an independent model was identified using the conventional Vector Fitting method based on frequency-response measurements obtained with an impedance analyzer. The resulting equivalent circuits were implemented in Simulink for further analysis.

2.5. Model Accuracy and Predictive Capability Assessment

Validation was carried out using two independent procedures. The first compared measured and simulated waveforms obtained under the same operating conditions as those used during identification, allowing direct assessment of the fitting accuracy. The second employed an external validation circuit incorporating a vacuum interrupter, introducing current-chopping conditions that were not included during model estimation. This approach enabled evaluation of the predictive capability and generalization of both the Orthogonal Fitting and Vector Fitting models.

The simulation results were assessed by comparing current and voltage waveforms, oscillation damping, transient frequency, and overvoltage amplitude with experimental recordings. The validation methodology made it possible to determine not only the numerical fitting accuracy but also the physical adequacy of the identified transformer models for transient electromagnetic simulations.

2.6. Mathematical Formulation of the Identification Problem

The identification process discussed in this publication concerns components that determine switching operations within the electric power grid—specifically their dynamics, associated risks, and risk mitigation strategies. These components include, in particular, transmission lines, switching devices, electrical machines, and transformers.

Simulating switching operations in the power grid requires models of its components that accurately replicate their behavior on a timescale ranging from a few microseconds to a millisecond, corresponding to a frequency range of 1 kHz to 1 MHz. This publication focuses on transformer modeling within this frequency range. A literature review presented in [9] covers transformer modeling for transient phenomena, particularly recovery voltages; however, that review identifies no method for deriving an equivalent circuit based on empirical observation of transformer behavior under actual or test switching conditions.

One experiment suitable for this purpose involves measuring the recovery voltage at the terminals of a specific transformer (or grid segment) using a device known as a current-injection Recovery Voltage Indicator [10]. Such an experiment yields the waveforms for the forcing current and the response of the one-port network (the short-circuited transformer). Identification of the transformer model for the transient regime is performed using a short segment of these waveforms—comprising up to 2000 samples with a 20 ns step (totaling 40 μs) in the studies described—that encompasses the current's decay to zero and the subsequent voltage relaxation. Such signals are equally susceptible to noise; therefore, identification must account for errors in both the model input (current) and output (voltage). To address this, system identification offers the state-variable method [10,11]; by focusing on identifying a model that incorporates the system's state variables, this approach requires, among other things, assumptions regarding the system's observability and the process's initial state. A simpler approach—known as the Koopmans–Levin method [12]—minimizes the total input and output estimation error by utilizing the singular value decomposition (SVD) of the model's regression matrix. Introduced for identification purposes by M. Levin [13] in 1964, this technique is known today as the Total Least Squares method [14,15]. The method estimates each signal value multiple times as it appears across successive model (regression) equations; this aspect may raise concerns regarding the bias of the resulting parameter estimates.

The identification method presented below also relies on minimizing the total input and output estimation error; however, this error is determined based on the properties of quadratic forms subject to linear constraints.

The subject of identification is a system model described by the transfer function (1)

$$\mathrm{G(q)} = \frac{b_1 q^r + b_2 q^{r-1} + \cdots + b_{r+1}}{a_1 q^r + a_2 q^{r-1} + \cdots + a_{r+1}} \tag{1}$$

where the model parameters are represented as a vector (2).

$$\theta = [b_1\ b_2\ b_{r+1}\ a_1\ a_2\ a_{r+1}] \tag{2}$$

The course of the identification experiment is contained in the recorded time series of current and voltage collected into a data record vector $\underline{\xi}$.

The values of the record vector were obtained by sampling the input and output signals, respectively; these are hereinafter referred to as the vector of collected undisturbed data (3).

$$\underline{x} = [x(1)\ x(2) \ldots\ x(p)\ y(1)\ y(2) \ldots y(p)] \tag{3}$$

The recorded data are subject to additive noise, such that the data vector takes the form (4).

$$\underline{\xi} = \underline{x} + \underline{e} \tag{4}$$

where $\underline{e} = \left[e_x(1) \ldots\ e_x(p)\ e_y(1) \ldots\ e_y(p)\right]$.

Identification is based on the weighted sum of squared fitting errors relative to a model $\underline{\theta}$ with assumed parameters $\underline{V}$ of a discrete signal approximating the recorded signal $\underline{\xi}$.

When the disturbances follow a multivariate normal distribution, the weight matrix $\underline{A}$ should be the inverse of their covariance matrix. However, this is a theoretical case. In real-world conditions, the model residuals do not represent the actual random disturbance but rather result from deterministic interference or an inadequate model structure—such as an incorrect model order or nonlinear effects.

In the study presented here, a diagonal matrix was used, with diagonal elements consisting of the reciprocals of the squared RMS values of the current and voltage signals.

3. State of the Art

After switching off the current, a transient recovery voltage (TRV) appears on the switch terminals. Typically, this voltage is considered in two successive time intervals: in the first one, where the TRV occurs, and then in the second one, during which the power frequency voltage itself occurs [16].

The driving-point impedance (DPI) function is simply the input impedance of the network as seen through the input terminals. The ratio of Laplace transform of the source voltage and source current is called driving-point impedance $Z(s)$ (5) [10,17].

$$Z(s) = \frac{U(s)}{I(s)} \tag{5}$$

For circuit breakers, an important network parameter indicating the possibility of using the device is the short-circuit impedance of the system. It applies to the switching processes occurring in operation of a switch. It is the DPI seen from terminals of the switch $Z_{sc}(s)$. In case of short current breaking—and under commonly assumed linearity of the short circuit—the voltage appearing at a breaker's terminals can be expressed as (6).

$$U_{\mathrm{TRV}}(s) = Z_{\mathrm{sc}}(s) I_{\mathrm{br}}(s) \tag{6}$$

$I_{br}(s)$ denotes the current which would flow if there is no break. In the case of a current break at zero, it is a sinewave of short circuit current, often—for a short period after current-zero—replaced by a linear ramp.

In the presented approach, $Z_{sc}(s)$ is a rational function with degree of numerator less than degree of denominator, so it can be defined by a set of zero-pole couples (7).

$$Z_{sc}(s) = \sum_{i=1}^{r} \frac{A_i}{s - p_i} \tag{7}$$

where r is the order of a system.

The Recovery Voltage Indicator (RVI), shown on Figure 1, is a device used to inject an electrical current repetitively into an electrical system. It is used primarily to tune test short-circuit circuits in terms of the parameters of the expected recovery voltage. The power system ideally may be modelled as a uniform transmission line, but in reality consists more often of an interconnection of cables, reactors, and transformers. Using RVI, a small amount of electric current (milliamperes) is injected into the system in the form of a half-sine wave, which represents the last half-cycles of the line current (e.g., large short-circuit current) before the breaker contacts open and the current is switched off. As a result, a recovery voltage is created at the switch contacts. In the standard RVI, the key element of the device is a diode that reproduces the operation of the contact switch. This is a non-linear element, making it difficult to analyze the received time courses [8].

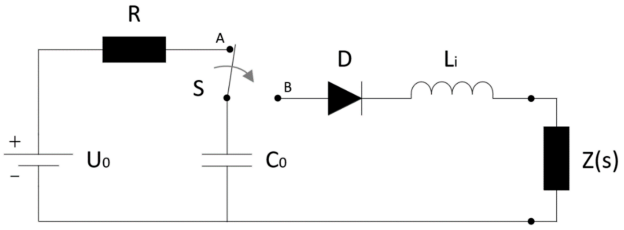


Figure 1. Structure of a 'capacitive current injection indicator': U_0—DC voltage source, R—charging resistor, Co—discharge capacitor, S—Two-position switch, D—impulse diode, Li—inductance of connection wires.

The identification of dynamic systems refers to the process of determining or estimating the parameters, structure, or behavior of a system that evolves over time [18]. Dynamic systems are systems whose state changes continuously or at least over a sequence of time points. This concept is widely used in various scientific and engineering disciplines, including control theory, signal processing, physics, economics, biology, and more.

The construction of a valuable model was described in [19]. Initially, it requires in-depth knowledge about the observed phenomenon. Then, an attempt is made to estimate the object's parameters, perform a check (simulation), and observe the results (Figure 2). Typically, the mere observation of the phenomenon under study requires performing a series of measurements, in both the time and frequency domains. Before identifying a dynamic system, it is crucial to develop a mathematical or computational model that represents the system's dynamics. This model may involve differential equations, transfer functions, state-space representations, or other mathematical formulations, depending on the nature of the system.

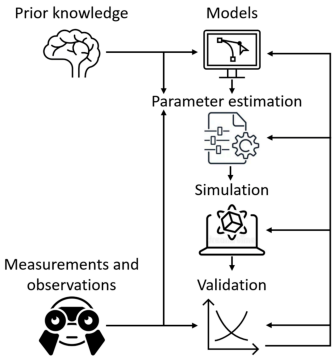


Figure 2. Typical course of the modeling, estimation, and simulation process.

The concept of an object model should be understood as a general representation of the studied properties of a real (or created) object in the expected form (e.g., mathematical, but not limited to that) [20]. The model is therefore a certain simplification (approximation) of reality, and the form of the model depends significantly on its purpose. It should externally behave like an object, although it may contain a different internal structure.

The choice of the identification method results precisely from the information available about the object from before the identification process. The information mainly concerns the structure of the object, the stochasticity of disturbances, and the stochasticity of the object's parameters. In many cases, the structure of the object itself is known, so the identification task involves determining the unknown parameters of the object. If the structure of the object is unknown, then one can adopt some alternative structures proposed arbitrarily and, by identifying all variants of structures, the optimal structure from the proposed ones is selected. Methods such as stochastic approximation, least sum of squares, or correlation functions require the least amount of a priori information. Other methods, e.g., maximum likelihood, require the greatest a priori information. A very extensive list of literature on identification methods is described in [21,22].

Data analysis, understood as an analysis of the processand the method of measuring characteristic data waveforms, together with the understanding of the occurrence of typical changes in these waveforms, is a process that is not very formalized and requires considerable experience and research intuition. Its essence is the discovery of, among others, what the nature of the examined process is, its linearity, the type and method of measuring physical quantities, possible disturbances and measurement errors, or the type of model for further identification. Unfortunately, there is no satisfactory method for automatically answering the above-mentioned issues.

It is obvious that transformer models are mainly created to test their behavior during possible failures or generally as important elements of the power system during, e.g., a short circuit. These situations can be analyzed using models developed using analytical methods, the finite element method (FEM), magnetic equivalent circuits (MECs), or reluctance networks [23].

Identification methods are classified mainly depending on the complexity of the test model. Models are generally characterized by using a non-parametric representation, e.g., impulse responses, transfer functions, covariance functions, spectral densities, and Volterra series, and by using a parametric model such as state models [24].

An appropriate mathematical model of a three-phase power transformer is required for the correct analysis of transient states in the power system [25]. Due to the nonlinearity of transformers' behavior, their modeling for the purpose of simulating such transients involves many challenges. Especially since these behaviors are strictly frequency-dependent. Some of the model parameters can be obtained quite easily based on standard factory tests. For the remaining parameters, only special tests or estimates allow obtaining their values [26].

4. Orthogonal vs. Vector Fitting

Orthogonal regression, to some extends similar to Total Least Squares regression or Errors-in-Variables regression, is a statistical technique used to fit a regression line to a set of data points in a way that minimizes the perpendicular (orthogonal) distances from the data points to the regression line [27]. Although orthogonal regression techniques have been successfully applied in fields such as physical chemistry [28], geophysics [29], and machine learning [30,31], their adaptation for identifying parameters in power system components—specifically short-circuit impedance—is novel. A review of current research on transformer modeling [1,6,25] reveals that standard industry practices rely heavily on frequency-domain methods, such as Vector Fitting. The research, supported by a comprehensive analysis of identification methodologies [21,22], demonstrates that this gap in the literature persists. By applying orthogonal regression to time-domain measurements, a methodology is established that moves beyond simplified frequency-response models and specifically addresses the limitations of standard least-squares approaches in the presence of measurement uncertainty.

The term 'Orthogonal Fitting' (Ort-Fit) originates from concept of 'Orthogonal Regression' [32]. It concerns the situation, when searching for mutual dependency of two random variables, it is impossible to distinguish independent and dependent variables. In such a regression, a line can be found such that the sum of distances from data points the regression line is minimal. In the context of a simple linear regression model (with two variables), the goal of orthogonal regression is to find the line that minimizes the sum of the squared orthogonal distances from each data point to the line. This is particularly useful when there is uncertainty or error in both the x and y coordinates of the data points. Orthogonal regression is especially useful when there are errors or uncertainties in both the independent and dependent variables and provides a more balanced approach to fitting a regression line under such conditions.

The Ort-Fit methosd determines the model parameters by minimizing the sum of squared orthogonal distances between measured data points and the fitted model. Unlike conventional least-squares regression, Ort-Fit does not assume that only one measurement variable is affected by error, treating the measured variables symmetrically. This makes the method suitable for identification of short-circuit impedance from voltage–current measurements. This approach is particularly suitable for impedance identification, where both

voltage and current measurements are subject to uncertainty. For a set of measured points (x_i, y_i) and a model $f(x, y, \theta) = 0$, the model parameters are determined by minimizing (8).

$$\theta^* = \arg\, min \sum_{i=1}^{N} d^i_{\perp,i} \tag{8}$$

where $d_{\perp,i}$ denotes the shortest distance between the i-th measurement point and the fitted model. In contrast to conventional least-squares fitting, OFM treats the variables symmetrically and therefore reduces the bias associated with choosing one variable as the independent variable. In the present study, this property is used for the identification of the short-circuit impedance from measured voltage–current data.

The Vector Fitting (VF) method was developed by Bjørn Gustavsen and Adam Semlyen in 1996, and today is implemented in Matlab as the 'rational fit' function [33]. It is an advanced and widely used numerical technique in electrical engineering for determining a rational approximation of frequency-domain data, such as impedances, admittances, or scattering matrices (S-parameters). The primary goal of the VF method is to transform discrete measurement results or electromagnetic simulations into a coherent analytical model expressed as a sum of simple fractions, i.e., as a rational function with precisely identified poles and residuals [34].

The advantage of Ort-Fit over the standard VF method, especially in the context of identifying circuit models from real measurements, is based on a more reliable approach to measurement uncertainty. The standard VF algorithm, based on the iterative least squares (LS) method, minimizes the fitting error only along the axis of the dependent variable (e.g., impedance magnitude or phase), implicitly assuming that the independent variable, frequency, has zero error. This simplification is statistically unjustified for precise measurements of passive components over a wide frequency band.

The conceptual applicability of the Errors-in-Variables (EIV) framework to RVI-based identification arises directly from the experimental measurement setup. In conventional parameter estimation techniques, the input signal is treated as a deterministic, noise-free variable, attributing all stochastic disturbances exclusively to the output response. However, during high-speed RVI transients, both the current waveform and the recovery voltage are simultaneously captured using independent wideband sensors and oscilloscope channels. As a result, both variables are subjected to unobserved measurement noise (including transducer bandwidth limits, ADC quantization, and high-frequency switching interference), satisfying the core premise of EIV modeling.

While initial experimental observations justify treating these disturbances as uncorrelated zero-mean random processes affecting both axes, an exhaustive statistical characterization of the noise distributions and their precise quantitative impact on the EIV parameter confidence bounds are currently under detailed investigation and will be presented in a subsequent dedicated study. In this work, the EIV formulation implemented via Orthogonal Fitting serves as a robust baseline to minimize parameter bias caused by dual-channel measurement uncertainties.

5. Validation

Validation involves subjecting the DUT (Data Under Test) to a series of tests in an external, different test circuit (external validation circuit), whose configuration—terminating impedances and inputs—differ from the circuit used to initially identify the model. Next, the current and voltage waveforms (in the time domain) predicted by the model, embedded in the simulation of this new circuit, are compared with the actual measurement waveforms. A positive validation result confirms that the model is not only a statistically accurate representation of the input data but also a standalone, authentic macromodel,

capable of faithfully reproducing transient switching processes such as recovery voltage, overcurrents, and fast pulse propagation in any configured power system.

Identification methods based on fitting empirical time series to a model of a specific class produce results with a calculable margin of confidence only when the model class is correct and the interference satisfies assumed statistical properties. In the presented identification case, this is not the case due to the physical complexity and nonlinearity of the identified object, which make it impossible to assume a model structure of reasonable complexity. Registration interference is a second factor leading to uncontrollable identification errors. In this situation, the resulting identification model must be verified by an experiment to determine the extent to which the model's simulation predictions agree with the experimental data. The two experiments presented below were used in the presented research.

To validate the approximation method, an experiment was designed based on an RVI with a vacuum chamber (Figure 1). The validation circuit with an ideal switch (Matlab) is shown in Figure 3.

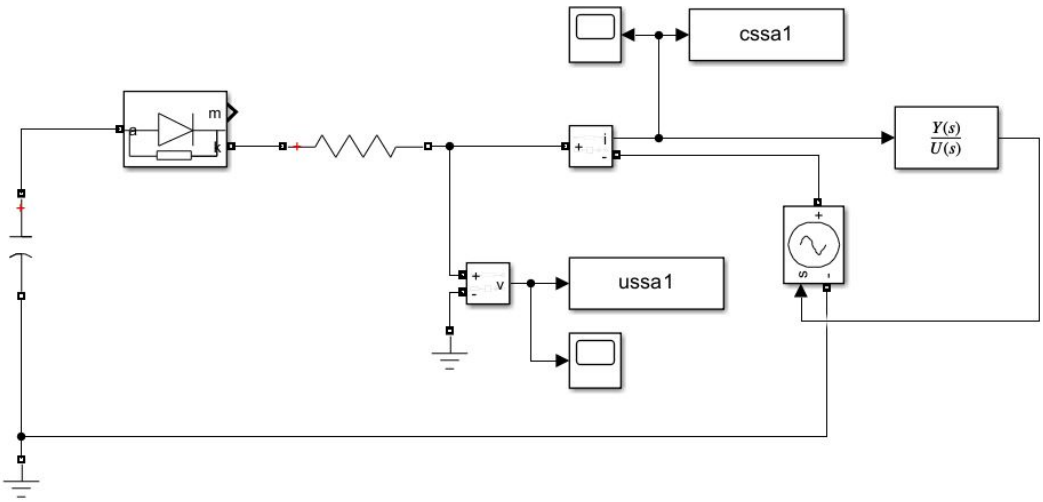


Figure 3. Matlab Simulink model scheme for validating models obtained from the TRV indicator.

6. Model Validation

VF identification involves determining the distribution of short-circuit impedance into simple fractions based on its frequency response. In this work, the response was measured using an HP impedance analyzer. The obtained response and the identification result are shown in Figure 4.

The Ort-Fit identification of the impedance model is performed based on the current and voltage waveforms obtained during the indicator test. Due to the computational time required, the fitting applies to a portion of the indicator test limited to 2000 samples of current and voltage waveforms around the current-zero crossing. An example of the fitting is shown in Figure 5. The synthetic measure of the mismatch 'ss' between the simulation and the simulation measurement was taken as the ratio of the RMS value of the difference between the simulated and recorded signal and the RMS value of the recorded signal.

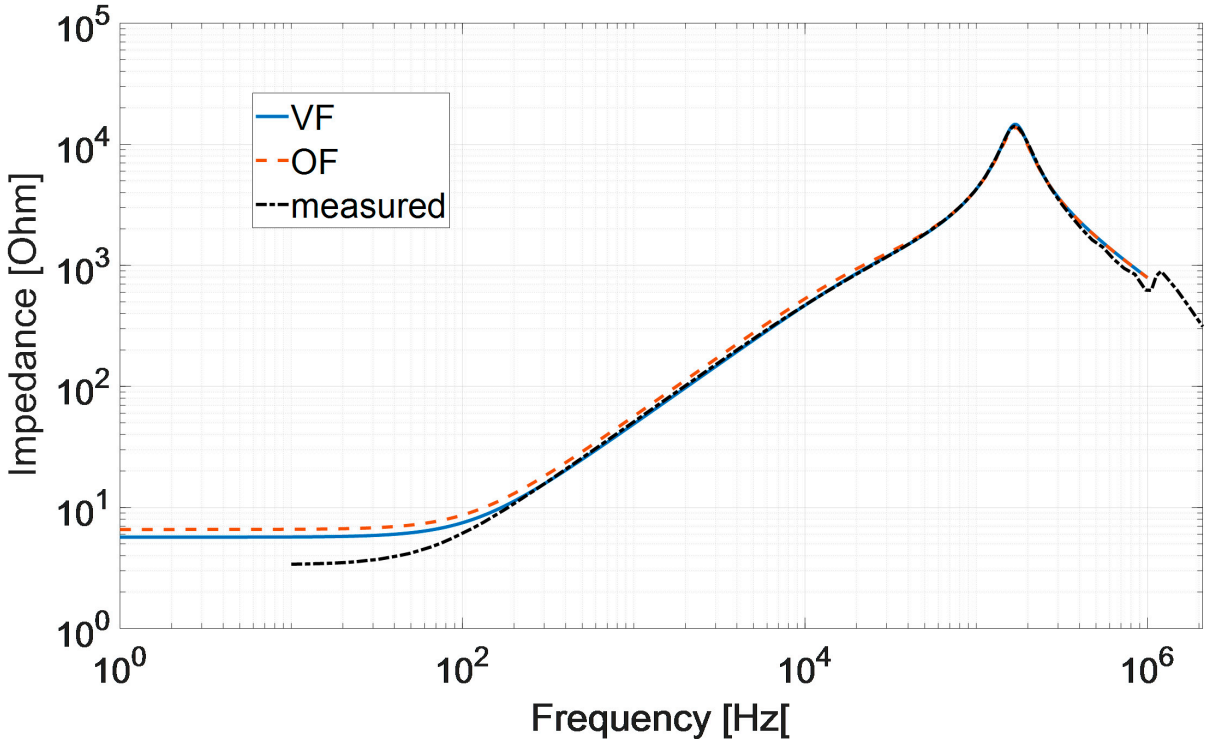


Figure 4. Frequency characteristics of the impedance of a short-circuited transformer: black dashed line—measured with an impedance analyzer, blue line approximated by the VF method, red dashed line impedance model obtained by the OF method.

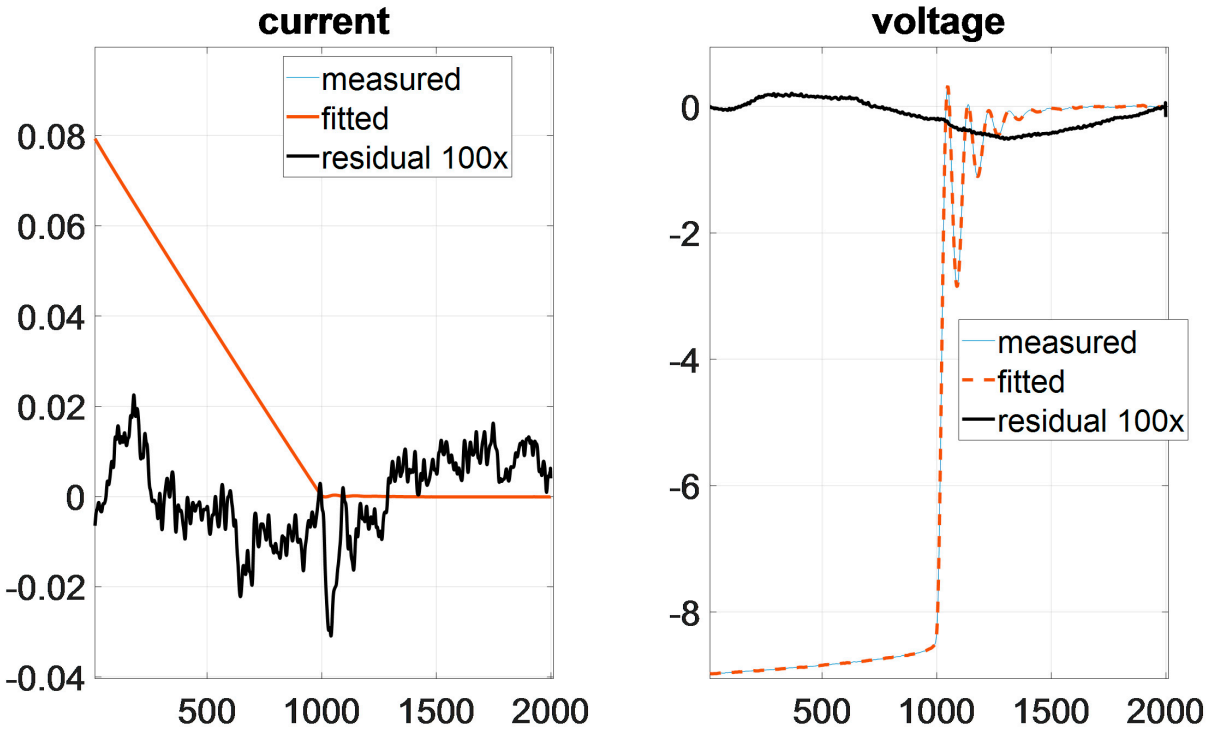


Figure 5. Example of signal fitting in OF identification: left pic/ current—ss = −55.4 dB mismatch, right pic/ voltage—ss = −85.0 dB mismatch.

The impedance model obtained in this test corresponds to the equivalent circuit shown in Figure 6. Its impedance spectrum is shown in the previous Figure 4.

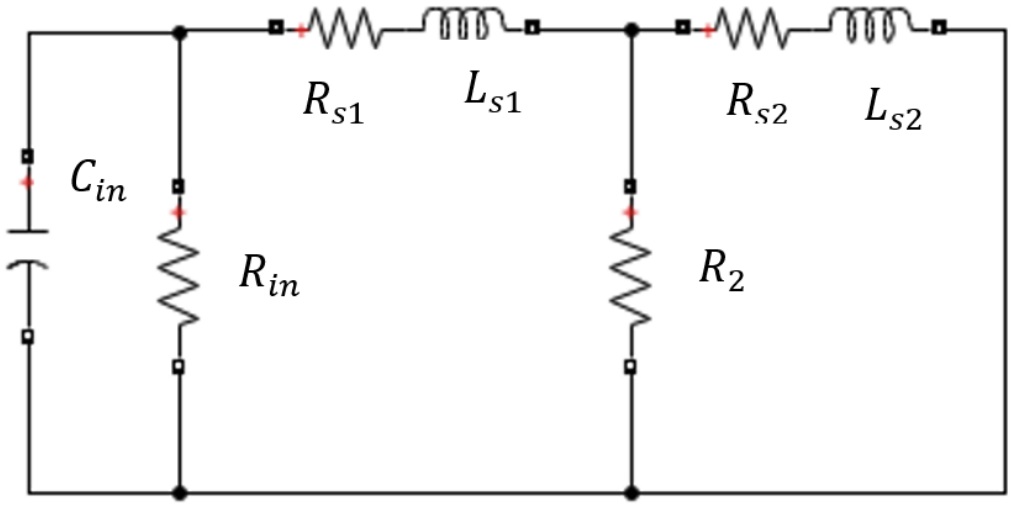


Figure 6. Equivalent impedance diagram of a short-circuited transformer according to the Ort-Fit model.

Table 1 shows the parameters obtained from fitting models using the VF and Ort-Fit methods.

Table 1. Parameters obtained from fitting models using the VF and Ort-Fit methods.

Parameter	C_{in}	R_{in}	L_{s1}	R_{s1}	R_2	L_{s2}	R_{s2}
Units	pF	µS	mH	Ω	µS	mH	Ω
VF model from analyzer spectrum	207.2	41.13	4.28	1.05	1.68	3.50	4.72
Ort-Fit model	158.6	93.15	5.57	1.30	2.31	3.32	3.12

A. Validation based on the waveforms used in identification

Validation involves comparing the current and voltage waveforms used in identification with those from an indicator test simulation in the circuit with the model being verified. Simulations are run in the Simulink package on the circuit shown in Figure 3.

Two models were subjected to this verification:

- VF model—results shown in Figure 7.
- Ort-Fit model—results shown in Figure 8 and a zoomed-in view of the current-zero region—in Figure 9.

B. Validation based on TRV indicator waveforms with current interruption

The simulation results derived from the tested model were compared against current and voltage waveforms obtained from an indicator test. This test utilized a circuit in which the diode was replaced by a vacuum chamber gap near current-zero. Example current and voltage waveforms recorded during such a test are shown in Figure 10.

The current-choke test waveforms were specifically compared with simulation results generated in the 'Simulink' package (Figure 3), which employed the VF impedance model.

The full comparison results are shown in Figure 10, and the extended zero-current region is detailed in Figure 11. As can be seen, the VF model correctly reproduces the transformer's natural frequency but simulates less damping. Consequently, the model exhibits higher overvoltage during current-choke.

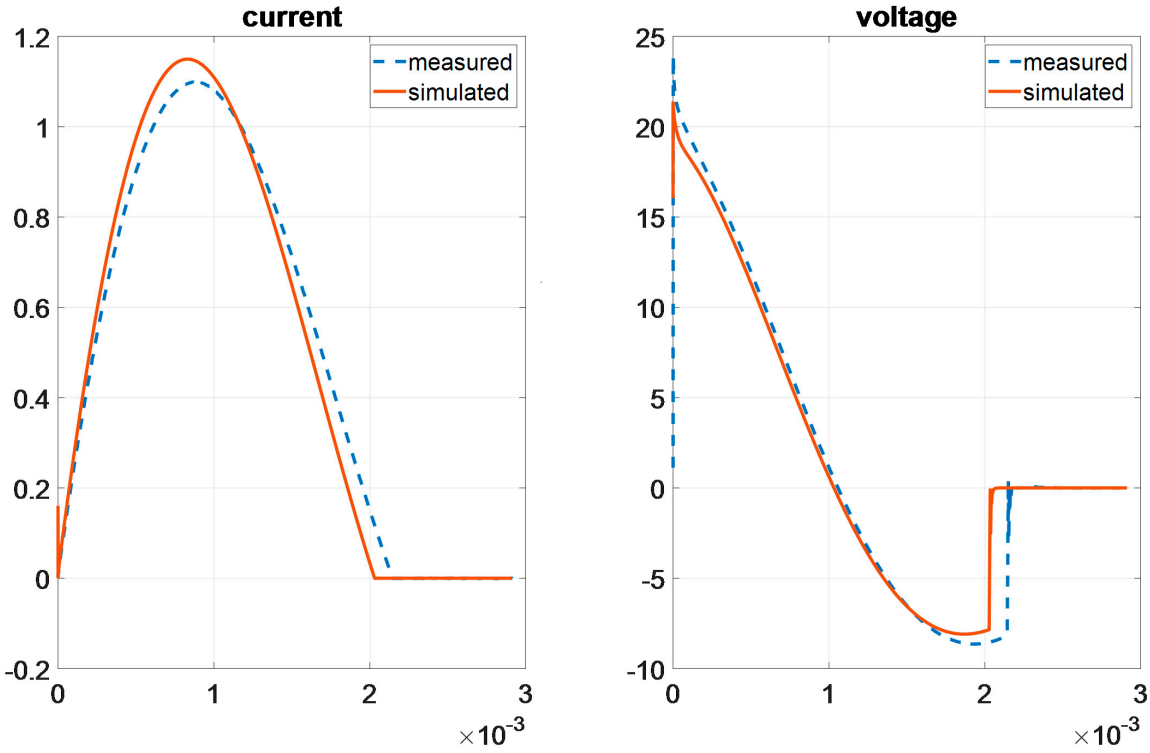


Figure 7. VF model validation result.

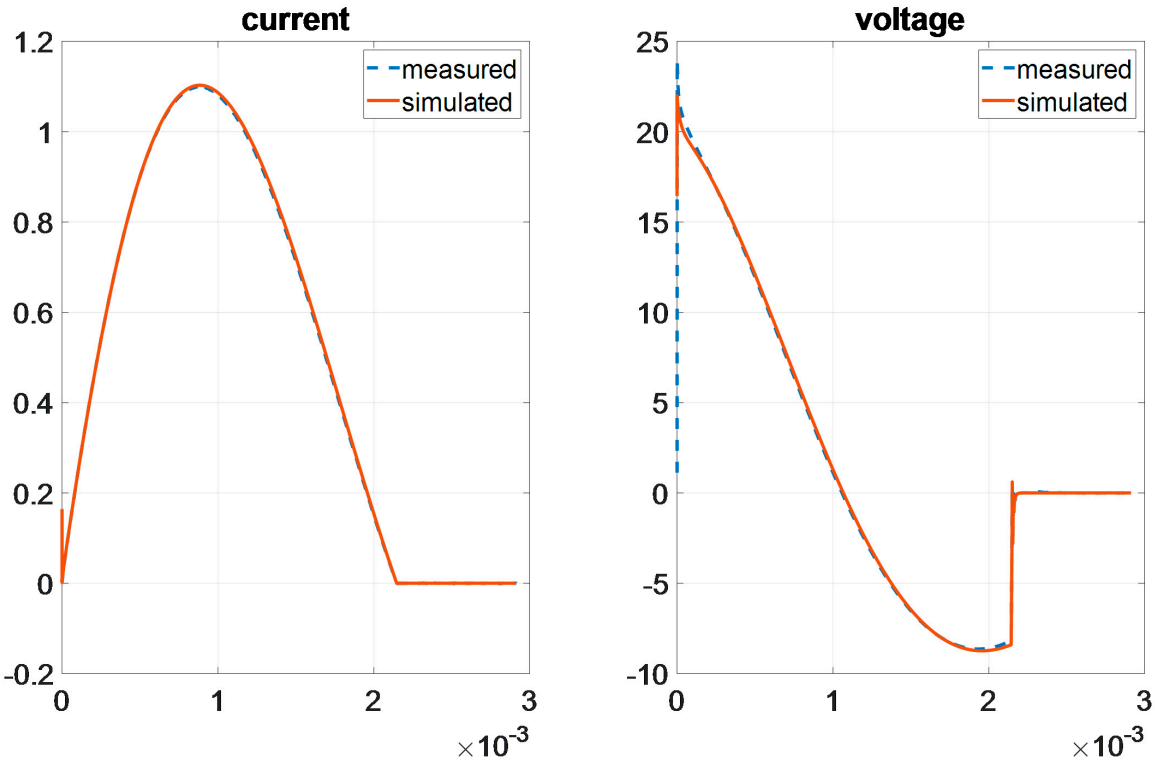


Figure 8. The result of the OF model validation on the TRV indicator waveforms over the full time scale.

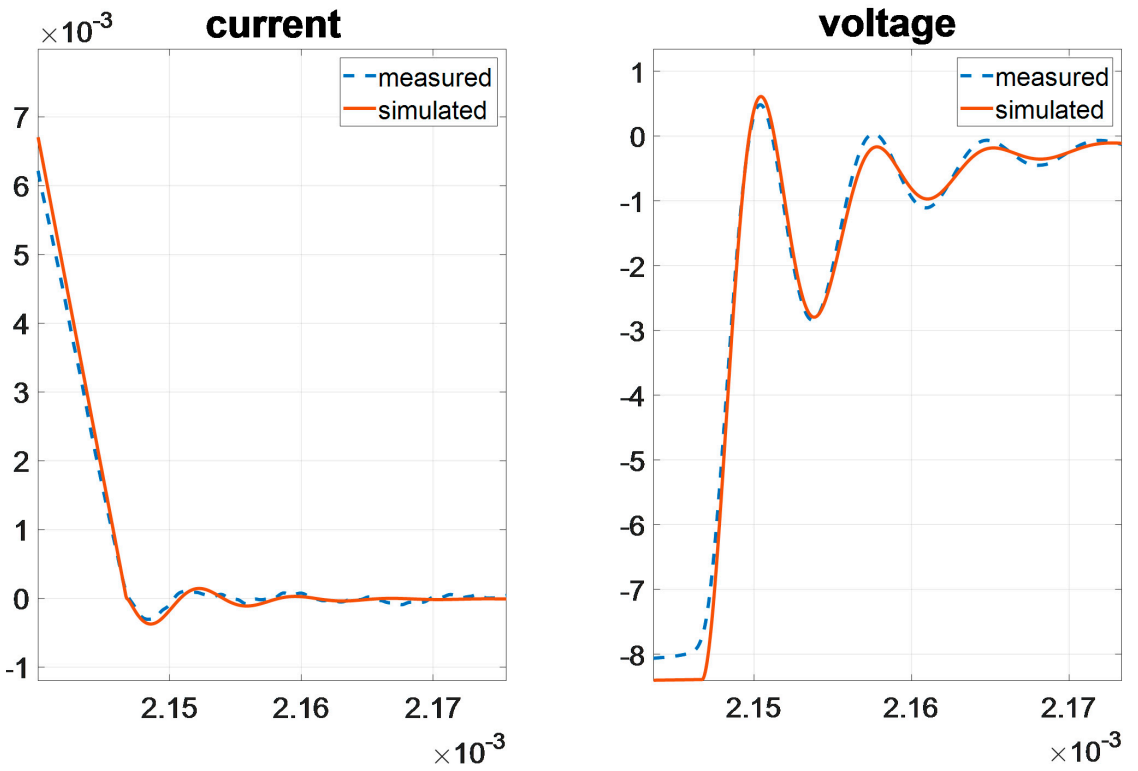


Figure 9. The result of the Ort-Fit model validation on the TRV indicator waveforms around current-zero.

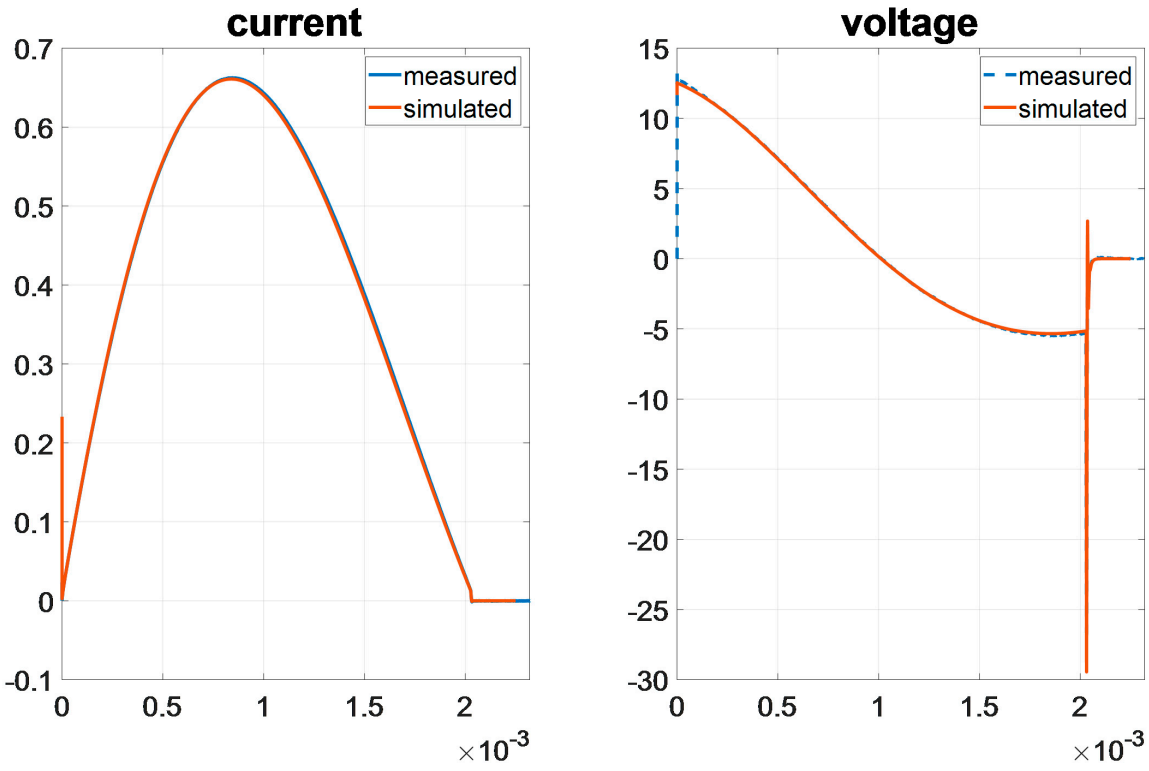


Figure 10. Validation result of the Ort-Fit model in a circuit with full-time-scale current shedding.

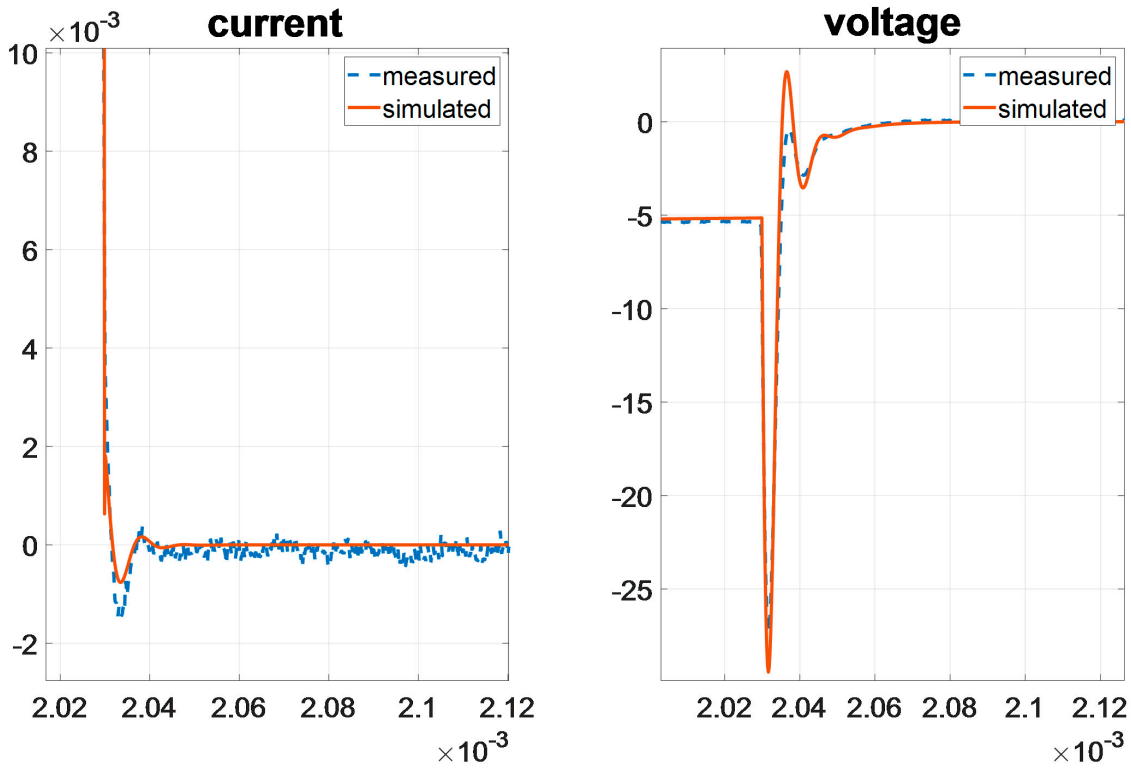


Figure 11. Validation result of the Ort-Fit model in a circuit with current ripping near zero current.

In the literature, identification accuracy is assessed in statistical terms; model inaccuracy is attributed to random disturbances in empirical data, and identification results are analyzed regarding the probability of model parameter deviations.

In the case presented here, the inaccuracy stems from the assumed model structure and from deterministic—albeit unknown—disturbances in the current and voltage records. This is evidenced by the clearly time-ordered nature of the fitting error (residual) waveforms (Figure 5).

In this context, validation of the identification results can involve assessing the model's practical applicability. The results of model verification for two processes are presented below:

A—an indicator test simulated in the Simulink environment (Figure 3), where the transformer under study was represented as a voltage source driven by the impedance of the tested model.

B—a current chopping test. This test was conducted using the indicator setup, but with the diode replaced by a vacuum interrupter opened near the current zero-crossing, yielding waveforms characteristic of current chopping (Figures 10 and 11).

7. Conclusions

The presented material is part of broader, ongoing research into the feasibility of using the Ort-Fit method to precisely identify transformer short-circuit impedance. Despite its theoretical similarity to the most reliable frequency-domain identification methods, this method tends to generate ambiguous results. This ambiguity is strongly dependent on the nature and frequency band of the measurement signals used. Therefore, a key need has arisen to develop effective validation tools for the resulting models. To mitigate this ambiguity and guarantee consistent, unambiguous parameter identification across diverse transformer designs, the current injection signals must be systematically optimized and standardized.

The low-frequency mismatch observed in the slowly varying time components highlights a structural limitation of the present linear Ort-Fit formulation, which assumes time-invariant parameters and omits core magnetization dynamics. To overcome this limitation and dynamically account for magnetic saturation, several mathematical calibration extensions to the Ort-Fit algorithm are currently under investigation.

The analyses conducted revealed the following key conclusions regarding the suitability of the individual models:

(1) Inadequateness of the VF-based model.

It was demonstrated that the impedance model identified using the standard VF method significantly deviates from the actual transformer characteristics. Its structure is overly simplified, resulting in the inability to correctly represent key dynamic parameters across the entire frequency range tested.

(2) Satisfactory performance of the Ort-Fit model in the TRV indicator circuit, taking into account nonlinearity.

The model determined using the Ort-Fit method was able to satisfactorily describe the transformer's behavior in the circuit used to measure the TRV. However, a significant mismatch was observed in the range of slowly varying time-varying components (low frequencies). This significant deviation is likely the result of the magnetic nonlinearity of the tested object, requiring further model calibration to account for this effect.

(3) Limitations of the Ort-Fit model under current chopping conditions and additional phenomena.

The high computational complexity of the Ort-Fit algorithm currently necessitates restricting the parameter identification window to approximately 2000 samples centered around the current-zero crossing, where signal dynamics and information density are highest. Extending the algorithm to process full-duration waveforms or larger experimental datasets requires targeted optimization strategies, such as adaptive non-uniform time-grid sampling, analytical gradient evaluation for Jacobian matrices, parallel GPU-accelerated computing, and hierarchical multi-stage parameter estimation. However, implementing such numerical simplifications while strictly preserving parameter uniqueness, numerical stability, and physical fidelity is a delicate endeavor that demands significant time, meticulous algorithmic refinement, and comprehensive empirical validation. Consequently, the development and rigorous verification of these computationally efficient Ort-Fit variants are the focus of active ongoing research by the authors and will be presented in a subsequent study.

The Ort-Fit model proved insufficient in tests simulating current shedding, especially in the context of oscillation damping. The discrepancy in damping suggests that the abrupt current shedding conditions reveal additional dynamic phenomena that were not properly accounted for in the identification process. Potential causes of this phenomenon include, among others, a significant increase in eddy currents in the transformer windings and magnetic core, which strongly influence the model's damping parameters.

Comprehensive uncertainty quantification, covariance analysis, and sensitivity evaluation are the subject of ongoing research and will be addressed in a subsequent study.

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Abbreviations

The following abbreviations are used in this manuscript:

DPI	Driving Point Impedance
TRV	Transient Recovery Voltage
RVI	Recovery Voltage Indicator

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