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A Method for Reconstructing Transient Process Parameters in Critical Infrastructure Security Applications

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Abstract. *This paper addresses the reconstruction of transient process parameters from their oscillograms in the context of critical infrastructure security. It is shown that under real operating conditions the only available information on the dynamic state of electrical systems is often limited to recorded oscillograms, while the parameters of circuit elements may be unknown or vary over time. An engineering-oriented method for determining transient process parameters in first- and second-order circuits is proposed. The method is based on separating the forced and natural responses, forming a time series of the natural response, and subsequently estimating its parameters using logarithmic transformations, the least squares method, and numerical approximation techniques. The method is implemented as specialized software developed in Microsoft Excel using VBA. Numerical testing on a first-order circuit example demonstrated exact parameter recovery for noise-free oscillograms and maintained an accuracy of approximately 1% in the presence of disturbances simulating measurement errors. The obtained results confirm the practical applicability of the proposed approach for non-destructive testing, diagnostics, and improving the security of critical technical systems.*

Keywords: *transient process, oscillogram, natural response, forced response, least squares method, critical infrastructures, security, VBA programming, Microsoft Excel, programmable logic controllers.*

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Introduction

Ensuring the security of critical infrastructures largely depends on the ability to timely detect degradation processes, anomalies, and hidden defects in technical systems under conditions of limited access to equipment. Under real operating conditions, the parameters of elements in electrical circuits and systems are often unknown or vary due to aging, temperature effects, or damage, while the only available information consists of oscillograms of transient processes recorded by measurement and data acquisition devices. This circumstance has led to the formation of a broad research direction in the scientific literature devoted to reconstructing transient process parameters directly from oscillograms, without constructing a complete physical model of the object, which confirms both the practical significance and the complexity of this problem [1], [3].

In electric power engineering, oscillograms of transient processes following disturbances represent a primary source of information for assessing dynamic stability and analyzing the security of operating modes. Classical and recent studies demonstrate that the parameters of oscillatory and aperiodic components reconstructed from oscillograms are directly related to power system stability and are used to prevent the development of hazardous operating conditions [1], [2], [5]. At the same time, it is emphasized that real oscillograms contain noise, distortions, and are limited in duration, which complicates reliable parameter estimation and necessitates the development of specialized reconstruction methods specifically oriented toward practical operating conditions [2], [5].

A similar problem is characteristic of transmission lines and distribution networks, where oscillograms of voltages and currents during fault conditions are used to estimate line parameters, localize faults, and analyze failure causes. Studies devoted to parameter reconstruction of lines from fault oscillograms show that such information is critical for improving network reliability and security, since the actual line parameters at the moment of a fault are generally inaccessible by other means [8], [9]. In industrial systems and electric drives, oscillograms of start-up transient processes are used to reconstruct parameters of electrical machines without dismantling them, which is of direct importance for safe operation and equipment diagnostics [6], [7].

In automation and telemechanic systems, particularly within Smart Grid and PMU-oriented monitoring frameworks, oscillograms of transient processes form the basis for real-time condition assessment and detection of hazardous deviations in operating modes. Review studies indicate that modern modal identification algorithms are specifically oriented toward oscillogram analysis, as these data are available in real time and can be used for security-related decision-making [3], [5]. Furthermore, parameters reconstructed from oscillograms are considered informative features for anomaly detection in cyber-physical systems, thereby extending their role in comprehensive critical infrastructure security tasks [15].

From the perspective of non-destructive testing, the analysis of transient process oscillograms represents a typical non-invasive approach to assessing the technical condition of objects. Review works on non-destructive testing emphasize that modern condition monitoring methods are based on reconstructing parametric characteristics of systems from measured signals without interfering with equipment design [11]. This is confirmed by the application of frequency- and time-domain diagnostic methods for transformers, such as SFRA [12], as well as Time Domain Reflectometry techniques for cable networks, where the oscillogram of the reflected signal is used to detect defects [4], [13]. Taken together, these studies demonstrate that the ability to reconstruct transient process parameters from oscillograms is a key component of non-destructive testing and contributes to improving the security of critical infrastructures by enabling early detection of potentially hazardous states and reducing the risk of sudden failures.

Reconstruction of transient process parameters from oscillograms is also important for industrial controllers, including programmable logic controllers (PLCs), distributed control systems (DCS), and embedded control modules used at critical infrastructure facilities. During switching operations, fault conditions, load changes, or cyber-physical disturbances, industrial controllers typically record only time-domain responses of voltages, currents, or internal control signals, while information about object parameters or internal states may be unavailable. Analysis of such transient processes makes it possible to indirectly determine dynamic characteristics of controlled objects, such as effective time constants, damping factors, and dominant modes, without interfering with normal system operation. This makes transient parameter reconstruction an effective tool for non-destructive diagnostics, verification of controller settings, and early detection of degradation or abnormal behavior in industrial automation systems. In security-related applications, these capabilities enhance the resilience and reliability of control systems by enabling assessment of their dynamic state based on recorded oscillograms.

Thus, reconstruction of transient process parameters in devices and systems of critical infrastructures is an actual problem. The aim of this paper is to develop engineering methods for reconstructing transient process parameters from their oscillograms.

1 State of the Art

In contemporary research, the problem of reconstructing transient process parameters from oscillograms is considered as part of a broader challenge of analyzing the dynamic state of technical systems under conditions of incomplete information about their parameters and structure. For critical infrastructures, this formulation is of fundamental importance, since under real operating conditions oscillograms obtained from event recorders, digital measuring devices, or embedded monitoring systems are often the only available source of information about system behavior during transient and emergency regimes. At the same time, element parameters may be unknown, vary over time, or differ from nominal values, which makes the direct application of classical model-oriented approaches for security assessment impractical.

One of the modern directions for addressing this problem is the application of compressed sensing methods, in which a transient process is interpreted as a signal having a sparse representation in a certain basis (exponential, harmonic, or combined). It has been shown that due to this property it is possible to reconstruct parameters of harmonic and transient components even with a limited number of oscillogram samples or in the presence of significant noise [16]. For critical infrastructure security tasks, this is an important advantage, as it enables processing of short or partially lost oscillograms that are typical for emergency events. At the same time, the practical implementation of compressed sensing methods in security monitoring systems is limited by high computational complexity, the need to select an appropriate basis, and the lack of guaranteed reproducibility of results under varying measurement conditions.

Another approach aimed at improving the reliability of transient parameter reconstruction from oscillograms involves explicitly accounting for the properties of the measurement system. Studies devoted to the identification and compensation of frequency and nonlinear characteristics of sensor chains in broadband transient measurements demonstrate that a significant portion of reconstruction errors is caused precisely by distortions introduced by the measurement path [17]. Compensation of these distortions makes it possible to substantially increase the accuracy of estimating damping factors, frequencies, and amplitudes from oscillograms. From the standpoint of critical infrastructure security, this approach is of particular importance, since incorrect interpretation of oscillograms may lead to erroneous conclusions regarding system stability or technical condition. However, the need for detailed calibration of the measurement system and the availability of additional information about its parameters complicate the application of this approach in field conditions and during crisis situations.

For the analysis of complex, nonstationary, and nonlinear transient processes, adaptive signal decomposition methods are widely used, including the Hilbert–Huang Transform and related empirical mode decomposition algorithms. These methods allow an oscillogram to be decomposed into a set of intrinsic mode functions, each characterized by its own instantaneous frequency and amplitude [18]. Such an approach is attractive for critical infrastructure security applications because it does not require assumptions about linearity or stationarity and can be applied to real emergency oscillograms with rapidly changing structures. At the same time, the decomposition results strongly depend on algorithm parameters and oscillogram quality, and the absence of unified criteria for selecting modal components complicates the use of the obtained parameters as formalized security indicators.

A separate group of methods comprises automatic detection of disturbance onset moments and reconstruction of step changes in transient oscillograms. These approaches are used to accurately determine the start of an event, which is critically important for correct reconstruction of transient parameters and subsequent analysis of incident causes [19]. In the context of critical infrastructure security, such methods enhance the reliability of post-event analysis and localization of hazardous events. Their limitations are related to sensitivity to noise and measurement artifacts, which may lead to incorrect detection of disturbance onset and, consequently, to biased estimates of transient process parameters.

An important direction directly related to nondestructive testing is represented by methods for reconstructing transient processes from indirect measurements, in particular estimating currents from voltage oscillograms. Such approaches make it possible to recover hidden dynamic parameters of a system without installing additional sensors, thereby reducing the invasiveness of monitoring and increasing the reliability of operation of critical facilities [20]. For security applications, this constitutes a significant advantage, as it expands the informational basis for analysis without physical intervention in the system. At the same time, these methods usually rely on physical models and computationally intensive processing algorithms, which limits their applicability in real-time regimes.

Finally, theoretical and applied studies of transient processes in power supply systems demonstrate that a substantial portion of hazardous operating conditions is associated with transient currents in the medium-frequency range, whose parameters are difficult to determine using standard analysis methods [21]. Oscillograms of such processes contain information that is critically important for assessing electromagnetic compatibility, reliability, and equipment security. Nevertheless, existing methods are often oriented toward specialized scenarios and do not provide a unified engineering toolkit for systematic reconstruction of transient process parameters from oscillograms.

Thus, the analysis of contemporary studies shows that existing approaches to reconstructing transient process parameters from oscillograms cover a wide range of methods – from optimization-based and time-frequency techniques to adaptive and model-oriented approaches. However, for critical infrastructure security applications they share com mon limitations related to sensitivity to noise, complexity of tuning, dependence on oscillogram quality, and insufficient unification of procedures. This substantiates the need for the methods proposed in this paper, which are aimed at robust, reproducible, and engineering-oriented reconstruction of transient process parameters from oscillograms, taking into account the requirements of non-destructive testing and the assurance of critical infrastructure security.

2 Characteristics of Transient Process

Determination of transient process parameters based on oscillograms has a number of fundamental features that directly affect the accuracy and reliability of the obtained results and therefore must be taken into account in engineering analysis and in the assessment of technical system security. By its nature, an oscillogram represents a graphical or discretized depiction of a continuous process, in which the values of the measured quantity and time are presented with limited resolution along the x- and y-axes. This implies that any transient process parameters identified from an oscillogram are inherently approximate, since the source data consist not of exact instantaneous values but of discrete samples or visually read estimates.

Limited resolution along the time axis leads to errors in determining characteristic moments of the transient process, such as the disturbance onset, rise time, oscillation period, or decay time. Even when digital oscillograms are used, time quantization errors are governed by the sampling frequency and synchronization algorithms, while analysis of graphical oscillograms additionally introduces errors associated with visual reading and scaling. As a result, parameters related to time derivatives, frequencies, or roots of the characteristic equation are particularly sensitive to inaccuracies along the x-axis, which may cause systematic bias in the estimated damping factors or natural frequencies.

Similar limitations apply to the y-axis, which corresponds to the amplitude of voltage or current. A real oscillogram represents signal values with limited vertical resolution determined by the bit depth of the analog-to-digital converter or by the accuracy of graphical rendering. This leads to errors in determining initial conditions, integration constants, and amplitudes of both forced and natural components of the transient process. These effects become especially pronounced at low signal levels, where the relative measurement error increases, or under saturation of the measurement chain, which distorts the oscillogram shape at peak values.

A further important feature is that an oscillogram typically contains a superposition of forced and natural responses, as well as noise and parasitic disturbances. Under conditions of limited accuracy along the x- and y-axes, this complicates correct separation of the components, since even small errors in estimating the steady-state level or the parameters of sinusoidal excitation may lead to significant errors in reconstructing the natural response. Consequently, measurement errors tend not only to propagate into the identification results but also to accumulate and mutually reinforce each other during mathematical processing of oscillograms.

Another characteristic feature is the dependence of parameter estimation accuracy on the selected segment of the oscillogram. In real transient processes, the initial segments often contain steep fronts with large derivatives, where the influence of quantization and noise is maximal, whereas at later stages the signal may approach the noise floor. This creates a trade-off between using an informative but noisy part of the oscillogram and a cleaner but less informative segment. The choice of the analysis interval under such conditions directly affects the stability and reproducibility of the estimated transient parameters.

An additional important aspect is the influence of oscillogram scaling and a priori assumptions regarding the system order and the type of excitation. Since an oscillogram does not contain direct information about the structure of the electrical circuit, any parameter reconstruction is performed within the framework of a chosen mathematical model. Given the limited accuracy of the input data, oscillogram errors may mask a mismatch between the adopted model and the real object, which complicates the physical interpretation of the identified parameters.

Thus, determination of transient process parameters from oscillograms always represents an inverse and ill-conditioned problem, in which the accuracy of the results strongly depends on the resolution and quality of the oscillogram along the x- and y-axes, the noise level, the correctness of component separation, and the adequacy of the adopted model.

At the same time, modern digital oscilloscopes provide not only on-screen visualization of oscillograms but also the ability to store transient processes in the form of time series suitable for further numerical analysis. For example, Tektronix TBS2000B series oscilloscopes support saving oscillograms in SPREADSHEET/CSV format to a USB device, enabling acquisition of a discrete time series of the transient process [22]. Similar functionality is described in the documentation of SIGLENT SDS1000X-E series oscilloscopes, which explicitly indicates the possibility of saving waveforms in

CSV files for subsequent off-instrument processing [23]. RIGOL DS1000Z series oscilloscopes also support saving oscillograms in CSV format, which is a standard tool for transferring data into the Excel environment [24].

Awareness of these features is a necessary condition for the correct application of identification methods in engineering practice, especially in tasks related to reliability analysis and the security of complex technical systems and critical infrastructures.

3 Method for Determining Transient Process Parameters

Let the oscillogram of a transient process be represented as a time series of discrete points. $\{t_i, a(t_i)\}, i = 1, \dots, N$, where t – time instants, a $a(t)$ – the measured quantity (voltage or current). In a linear system, the total process is represented as the sum of the forced component $a_f(t)$ and the natural component $a_n(t)$:

$$a(t) = a_f(t) + a_n(t).$$

Subsequently, the parameter identification procedure is expediently organized into three sequential steps: first, the forced component $a_f(t)$ is estimated from the oscillogram; next, the time series $a_n(t)$ is numerically formed as the difference between the total process and the estimated forced component; finally, the parameters of the natural component are determined with explicit consideration of errors in the discrete data.

Determination of the parameters of the forced component under constant excitation is based on the fact that in the steady state $a_f(t)$ is a constant value, that is,

$$a_f(t) = \lim_{t\to\infty} a(t).$$

In practice, $a_f(t)$ is estimated from the final segment of the oscillogram, where the exponential natural component has already decayed to a level comparable with the noise floor and the signal fluctuates around a steady value. To improve robustness with respect to noise and quantization along the amplitude axis it is advisable to apply averaging over the interval $[t_k,\ t_N]$ where t_k is chosen such that the process is visually close to the steady state:

$$a_f(t) = \frac{1}{N-k+1} \cdot \sum_{i=k}^{N} a(t_i).$$

In this expression, N – denotes the total number of discrete samples (data points) of the time series obtained from the oscillogram.

Under sinusoidal excitation, the forced component in the steady state is harmonic and can be expressed as:

$$a_f(t) = A_f \cdot sin(\omega t + \psi_f),$$

where ω is known from the excitation conditions (or can be determined from the oscillogram based on the period T), while the amplitude A_f and the phase ψ_f are estimated from the steady-state portion of the oscillogram. The amplitude A_f is determined from the peak values in the steady-state oscillation interval, for example as one half of the difference between the averaged estimates of the upper and lower extrema over several periods. The initial phase ψ_f is conveniently determined from the time shift Δt between the instant at which the signal crosses zero (or another fixed phase reference) and the corresponding instant of the sinusoidal excitation, that is, $\psi_f = \omega \cdot \Delta t$ To reduce the error in determining t it is advisable to apply interpolation between two adjacent discrete samples between which the zero crossing occurs. In cases where the oscillogram contains noise or a significant natural component, estimation of A_f and ψ_f should be performed on a segment sufficiently far from the switching instant, where the influence of the natural component is minimal, since any error in estimating the forced component directly propagates into the error of the reconstructed natural component.

After estimating the parameters of the forced component, the natural component is numerically isolated as the difference between the total signal and the reconstructed forced component evaluated at the same time instants. The resulting time series $\{t_i, a(t_i)\}$ serves as the basis for determining the parameters of the natural component. It is important to emphasize that errors in discrete time (limited sampling frequency, trigger or synchronization inaccuracies, rounding during data export) as well as amplitude errors (ADC quantization, noise, scale error, and nonlinearity of the measurement chain) introduce uncertainties into the values of the natural component. Therefore, the parameters of the natural component are not determined from individual data points but are obtained as the result of approximating a model to the entire data interval, which makes it possible to reduce the influence of random errors.

For a first-order circuit, the natural component has an exponential form:

$$a_n(t) = A \cdot e^{-\frac{t}{\tau}}, \tag{1}$$

where A – is the integration constant and τ – is the time constant of the transient process.

For discrete values of $a_n(t)$ the model is linearized by logarithmic transformation (1):

$$ln|a_n(t_i)| = ln|A| - \frac{t_i}{\tau}.$$

By introducing $z_i = ln|a_n(t_i)|$, a linear regression model is obtained

$$z_i \approx \alpha + p \cdot t_i,$$

where $\alpha = ln[A]$, and $p = {}^{1}/_{\tau}$ – is the root of the characteristic equation of the circuit.

Estimation of α and p can be performed using the least squares method, which ensures physically consistent linearization. Once α and p, are obtained, the exponential parameters are determined as

$$\tau = \frac{1}{p}, A = \pm e^{\alpha},$$

with the sign of the integration constant chosen to be consistent with the sign of the natural component in the initial segment of the process.

This procedure is more robust than determining the time constant using a tangent-based method, since it averages random errors along the amplitude ax a nd partially compensates for time-axis errors by exploiting the entire set of samples.

For a second-order circuit, the natural component in the general case is represented either as the sum of two exponentials (for the aperiodic regime) or as exponentially damped oscillations (for the oscillatory regime). In the aperiodic case,

$$a_n(t) = A_1 \cdot e^{p_1 t} + A_{21} \cdot e^{p_2 t}$$

and direct logarithmic transformation no longer yields a linear relationship. Therefore, in this case the parameters of the natural component are determined numerically as a nonlinear approximation problem by minimizing the squared residual between the measured and model-predicted values. From a practical standpoint, it is expedient to employ iterative nonlinear least squares algorithms, such as the Gauss–Newton or Levenberg–Marquardt methods, in which the parameters are updated at each iteration based on linearization of the model around the current estimate.

Thus, the practical procedure for identifying transient process parameters from an oscillogram consists of sequentially reconstructing the steady-state parameters from the steady portion of the record (a constant level for DC excitation or harmonic parameters for sinusoidal excitation), forming the time series $a_n(t)$ as the difference between the measured signal and the reconstructed forced component, and subsequently determining the parameters of the natural component with explicit consideration of errors in the discrete data. For first-order systems, this can be efficiently implemented via logarithmic transformation of the exponential response followed by linear approximation, whereas for second-order systems, represented by a sum of exponentials or damped oscillations, numerical methods of nonlinear parametric identification are required to consistently fit the model to the oscillogram under measurement uncertainties. the model to the oscillogram under measurement uncertainties.

4 Practical Implementation of the Method

For the practical implementation of the method for determining transient process parameters from their oscillograms, specialized software was developed in the Microsoft Excel environment using the VBA programming language. The choice of Microsoft Excel as the implementation platform is justified by a combination of accessibility, functional adequacy, and engineering convenience. Modern digital oscilloscopes directly export oscillograms in CSV or XLSX formats, which makes it possible to work with time series data in Excel without additional data conversion. Built-in spreadsheet tools, graphical visualization capabilities, and standard mathematical functions provide clear verification of each stage of oscillogram processing, which is critically important for engineering interpretation of the results. The use of VBA enables automation of parameter estimation algorithms, implementation of the least squares method, and numerical approximation techniques without relying on external software packages, while preserving transparency and reproducibility of the computations. In addition, Excel is a widely adopted standard in measurement and operational practice, which facilitates the integration of the developed software into tasks of analysis, diagnostics, and security assessment of critical technical systems without the need for specialized proprietary software. The appearance of the Microsoft Excel worksheet is shown in Fig. 1.

The software is designed for engineering analysis of experimental time series and operates directly on oscillograms represented in tabular form, which ensures straightforward integration with measurement results obtained from modern digital oscilloscopes.

The input data consist of columns containing the time series, including time instants and the corresponding values of the investigated process. The number of samples is not fixed in advance and is automatically determined based on the actual number of populated cells, which allows the software to handle both short and long oscillograms without prior data preprocessing. This eliminates the need for manual specification of array sizes and reduces the risk of errors during the processing of experimental data.

The type of the forced component of the transient process is specified by the user via interface control elements. A choice between a constant and a sinusoidal forced component is provided through.

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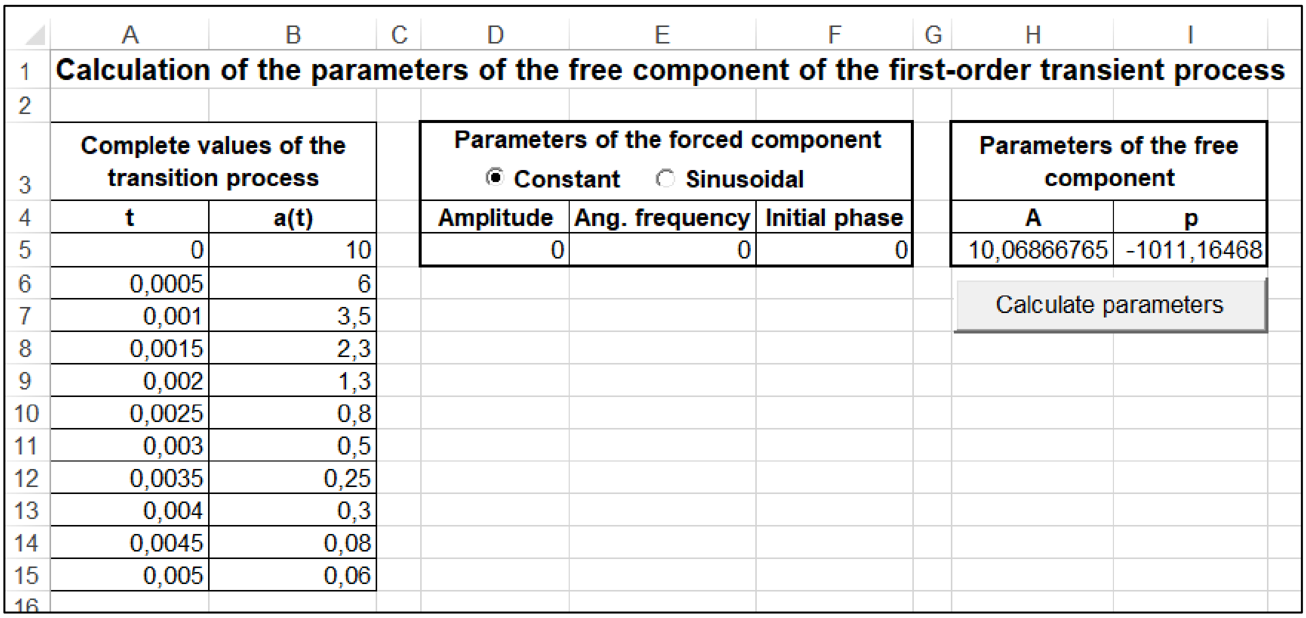

	A	B	C	D	E	F	G	H	I
1	Calculation of the parameters of the free component of the first-order transient process								
2									
3	Complete values of the transition process			Parameters of the forced component ◉ Constant ◯ Sinusoidal				Parameters of the free component	
4	t	a(t)		Amplitude	Ang. frequency	Initial phase		A	p
5	0	10		0	0	0		10,06866765	-1011,16468
6	0,0005	6						Calculate parameters	
7	0,001	3,5							
8	0,0015	2,3							
9	0,002	1,3							
10	0,0025	0,8							
11	0,003	0,5							
12	0,0035	0,25							
13	0,004	0,3							
14	0,0045	0,08							
15	0,005	0,06							

Fig. 1 - Software for determining the parameters of transient processes

The input data consist of columns containing the time series, including time instants and the corresponding values of the investigated process. The number of samples is not fixed in advance and is automatically determined based on the actual number of populated cells, which allows the software to handle both short and long oscillograms without prior data preprocessing. This eliminates the need for manual specification of array sizes and reduces the risk of errors during the processing of experimental data.

Radio Button controls. In the case of constant excitation, the forced component is interpreted as a steady-state level, whereas under sinusoidal excitation it is represented by a harmonic function with known excitation parameters. This approach ensures consistency between the oscillogram processing algorithm and the physical nature of the investigated process.

After selecting the type of the forced component and preparing the input data, the user initiates the computation by pressing the “Calculate” button. In response, the program automatically executes all stages of the algorithm: it estimates the parameters of the forced component from the oscillogram, numerically isolates the natural component as the difference between the total signal and the reconstructed forced component, and determines the parameters of the natural component based on its time series.

For this purpose, logarithmic transformations and the least squares method are applied for first-order circuits, while numerical approximation procedures are used for more complex models, ensuring robustness of the results with respect to discretization errors and measurement noise.

The program outputs numerical values of the integration constant and the characteristic equation root, which describe the dynamic properties of the circuit or system and can be used for analysis, diagnostics, or security assessment. The interface supports English and Ukrainian languages, and the software provides a transparent and reproducible implementation of the method, combining the clarity of the Excel environment with automated numerical processing for real experimental data.

To verify the proposed method for determining transient process parameters from their oscillograms, numerical testing was performed using a first-order electrical circuit as an example. A circuit implemented in the Multisim environment was used as a reference model, which made it possible to obtain an oscillogram of the transient process with a priori known circuit element parameters and, consequently, with precisely known theoretical values of the transient process parameters. The circuit used for the study is shown in Fig. 2.

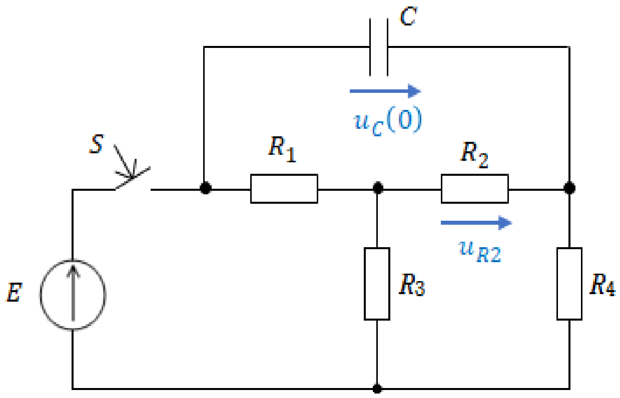

Fig. 2 - Circuit used for testing the method

For the parameter values $R_1 = 20\,\Omega, R_2 = 15\,\Omega, R_3 = 25\,\Omega, R_4 = 10\,\Omega,\ C_2 = 100\,\mu F,$ $u_C(0) = 10\,V,\ E = 100\,V,$
the voltage across resistor u_{R2} is given by
$u_{R2} = 23{,}077 - 42{,}86 \cdot e^{-1383t},\ V.$

The oscillogram of the transient process was generated using time-domain simulation and exported as a tabular time series, which was subsequently used as input data for the analysis (Fig. 3).

At the first stage of testing, the analysis was carried out for the case of exact oscillogram values, that is, without taking into account discretizationerrors, noise, or distortions of the measurement chain. For this purpose, the forced component of the transient process was determined from the oscillogram,

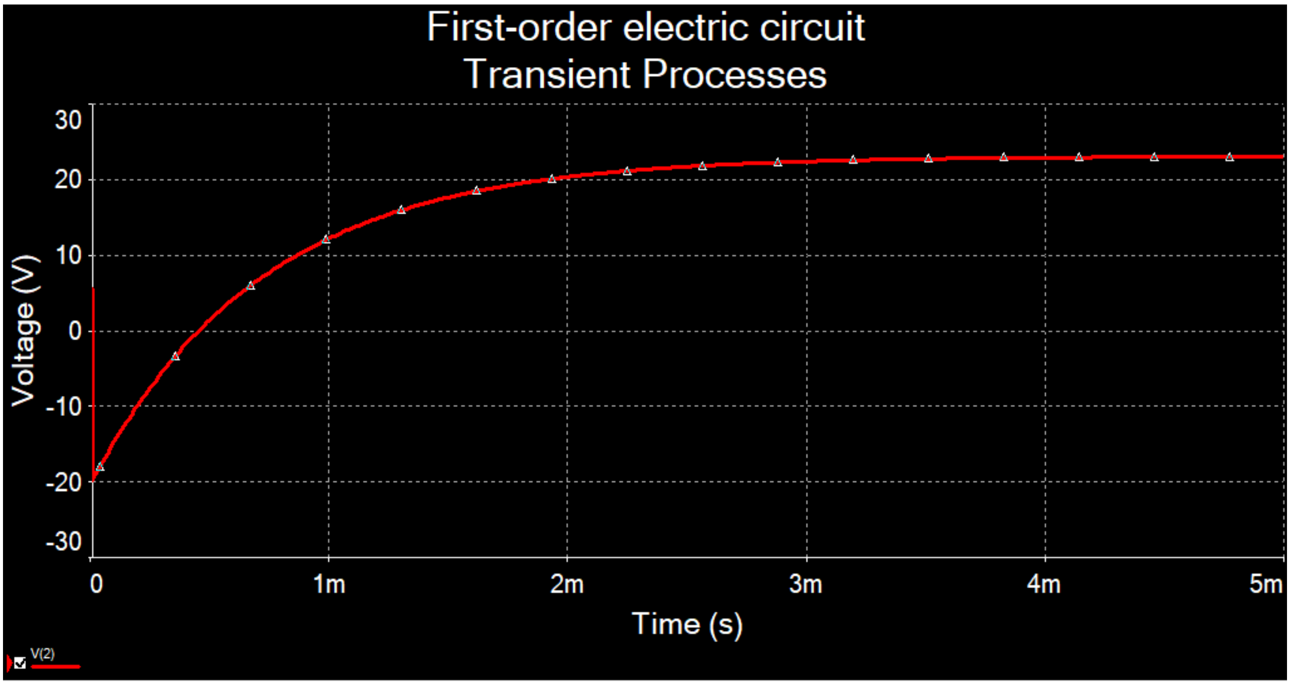

Fig. 3 - Oscillogram of the transient process

corresponding to the steady-state operating condition of the circuit after completion of the transient. Then, based on the known value of the forced component and the initial signal values, the integration constant of the natural component was calculated, and the time constant of the transient process was determined. The obtained parameter values fully coincided with the theoretical values calculated directly from the circuit parameters, which confirmed the correctness of the algorithm under ideal conditions and its consistency with the analytical solution of the linear nonhomogeneous first-order differential equation.

At the next stage of testing, the performance of the method was investigated under conditions of approximate oscillogram values that simulate real errors in experimental data acquisition. For this purpose, artificial disturbances were introduced into the exact time series to model errors in both the time axis and the amplitude of the transient process. Such disturbances are typical of real oscillographic measurements. Under these conditions, direct graphical determination of transient process parameters leads to significant discrepancies, making it impossible to obtain reliable results without the use of specialized data processing methods.

To improve the accuracy of estimating the parameters of the natural component in the presence of approximate data, the least squares method was applied, which makes it possible to fit the exponential model of the natural response to the entire set of experimental oscillogram points. The application of this approach ensured stable estimation of the integration constant and the root of the characteristic equation even in the presence of noise and discretization errors.

Using the proposed method and the developed software, the following parameter values were obtained: the forced component of the transient process $u_{R2\,f} \approx 23\ V$, the integration constant $A \approx -42{,}8\ V$, and the time constant $\tau \approx 0{,}000722\ s$ (corresponding to the characteristic equation root $p = -1385\ s^{-1}$).

Comparison with theoretical values shows that the relative error of the reconstructed transient parameters does not exceed 1%, confirming the high accuracy and robustness of the proposed method under conditions close to real experimental practice.The results demonstrate complete reconstruction of first-order transient parameters for exact oscillograms and preservation of high accuracy in the presence of measurement-like disturbances due to approximation techniques and the least squares method. This substantiates the applicability of the method to real oscillograms obtained in both simulation environments and physical measurements, as well as its suitability for engineering diagnostics and dynamic analysis of first-order electrical circuit.

5 Conclusions

In this work, a method for determining transient process parameters from their oscillograms is proposed and verified, with a focus on practical application in engineering problems related to the analysis of electrical circuits and systems. The method is based on decomposing the complete transient process into forced and natural components, followed by reconstruction of the parameters of the natural component from a time series formed on the basis of the oscillogram. Numerical experiments in the Multisim environment for a first-order circuit showed error-free reconstruction of transient parameters for exact oscillograms and a relative error not exceeding 1% under simulated measurement disturbances, confirming the robustness and practical applicability of the method. Future work includes extending the approach to higher-order circuits and complex excitations, automating oscillogram interval selection, improving noise-robust filtering, and enhancing numerical identification and uncertainty estimation, thereby broadening its use in analysis, diagnostics, and security assessment of technical systems.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study, as well as the results reported in this paper.

Financing

The study was conducted without financial support.

Data availability

All data are available, either in numerical or graphical form, in the main text of the manuscript.

Using artificial intelligence

The authors declare the use of an artificial intelligence tool: the ChatGPT model (OpenAI GPT-5, version 2025), release number 5.0.1. The artificial intelligence tool was used exclusively for language editing and grammar checking. The outputs provided by the artificial intelligence tool reduced the impact of human grammatical errors during the preparation of the manuscript.

Author`s contribution

Dmitry Maevsky: scientific supervision, conceptualization, methodology development;
Elena Maevskaya: software, investigation;
Vitaliy Kvitchuk: experimental studies;
Vyacheslav Lavrynenko: writing of the original draft.

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Метод відновлення параметрів перехідних процесів в задачах безпеки критичних інфраструктур

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Анотація. *Статтю присвячено задачі відновлення параметрів перехідних процесів за їх осцилограмами в контексті забезпечення безпеки критичних інфраструктур. Актуальність роботи зумовлена тим, що в реальних умовах експлуатації електротехнічних систем параметри елементів часто є невідомими або змінюються внаслідок старіння, пошкоджень чи зовнішніх впливів, тоді як доступною інформацією залишаються лише осцилограми перехідних процесів, зафіксовані вимірювальними засобами. Показано, що відновлення параметрів перехідних процесів безпосередньо за осцилограмами та погано обумовленою задачею, точність розв'язання якої залежить від похибок дискретизації за часом і амплітудою, а також від коректного розділення вимушеної та вільної складових процесу. Запропоновано інженерний метод визначення параметрів перехідних процесів, який базується на послідовному відновленні вимушеної складової за усталеною частиною осцилограми, формуванні часового ряду вільної складової та подальшому оцінюванні її параметрів із використанням логарифмічних перетворень і методу найменших квадратів або чисельних методів нелінійної апроксимації. Розроблено спеціалізоване програмне забезпечення в середовищі Microsoft Excel із використанням мови VBA, що забезпечує автоматизовану обробку осцилограм, експортованих у табличному вигляді з цифрових осцилографів. Проведено чисельне тестування методу, яке показало повне відтворення параметрів за точних даних осцилограми та збереження точності на рівні близько 1 % за наявності збурень, що моделюють реальні похибки вимірювань. Отримані результати підтверджують ефективність і практичну придатність запропонованого підходу для задач неруйнівного контролю, діагностики та підвищення безпеки критичних технічних інфраструктур.*

Ключові слова: *перехідний процес, осцилограма, вільна складова, вимушена складова, метод найменших квадратів, критичні інфраструктури, безпека, програмування на VBA, Microsoft Excel, програмовані логічні контролери.*

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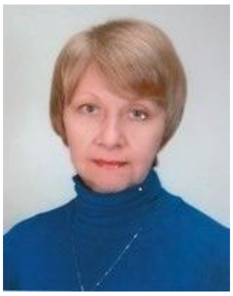

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