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Robust AI-Based Flicker Estimation for Power Quality Applications

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Abstract

The present study proposes an original hybrid technique that combines H_∞ filtering with an adaptive linear neuron (ADALINE) architecture to estimate flicker components in power distribution networks. By taking advantage of the H_∞ filter's strong immunity to uncertainty and noise, the approach first recovers the voltage envelope; subsequently, the ADALINE identifies with high precision the relative magnitudes ($\Delta V_i/V_t$) of the flicker constituents located at the discrete frequencies specified by IEC standards within that envelope. The resulting cooperation yields fast, reliable time-domain estimation that converges quickly and maintains performance even under heavy noise, thereby resolving the principal weaknesses of most frequency-domain solutions. In contrast to established procedures, this combined framework effectively processes complex power-system disturbances without requiring prior knowledge of noise statistics or prolonged learning phases. Performance evaluation relies on simulations aligned with IEC Standard 61000-4-15, reinforced by statistical metrics, Monte Carlo runs, and actual field recordings. Comparative outcomes reveal markedly better precision, greater tolerance to disturbances, and substantially lower computational requirements than estimators based on the Fast Fourier Transform (FFT) or the Discrete Wavelet Transform (DWT).

Keywords Flicker, Voltage fluctuations, Estimation process, H-infinity, Adaptive linear neuron, Neural network

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Introduction

Voltage fluctuation consists of repeated or sustained deviations in either the root mean square (RMS) value or the peak magnitude of the supply voltage. Power quality norms indicate that such deviations ordinarily do not exceed 10% of the rated voltage [1, 2]. These variations frequently produce light flicker — an effect experienced as oscillating brightness or alterations in the color spectrum emitted by lamps. The issue is particularly important in systems dominated by renewable sources, as the fluctuating output from wind turbines and photovoltaic arrays often causes rapid, unpredictable voltage swings that trigger flicker [3, 4]. Although voltage fluctuations constitute the fundamental origin of flicker in electrical networks, the degree to which flicker becomes noticeable depends critically on the type of luminaire employed. Because of thermal time constants, incandescent bulbs naturally suppress rapid voltage changes, whereas fluorescent tubes and especially LEDs fitted with inferior electronic drivers can transform quite small voltage perturbations into clearly perceptible luminance swings [5, 6]. Modern luminaires may also incorporate internal energy storage or active power-factor-correction circuits that either lessen or amplify flicker susceptibility. Voltage fluctuation is therefore a prerequisite — yet not by itself sufficient — for visible light flicker; the final perception emerges from the combined action of the voltage disturbance, the lamp's dynamic response, and the characteristics of human vision, all of which are codified in IEC 61000-4-15.

The standardized IEC flicker meter models the physiological response of the eye and brain to fluctuating light levels, with its central quantity being the short-term flicker sensation (S). IEC 61000-4-15 specifies four sequential processing stages for deriving S [5, 7-9]. Stage 1 scales the measured voltage waveform against a reference amplitude. Stage 2 squares the normalized signal. Stage 3 performs demodulation through a cascade that includes a 0.05 Hz high-pass filter, a 35 Hz low-pass filter, and a special weighting filter that emulates human flicker sensitivity. Stage 4 squares the filtered waveform once more and divides by the average value to produce the instantaneous flicker sensation S.

Despite its acceptance, the conventional IEC procedure demands continuous waveform processing and therefore entails considerable computational effort when implemented in real time. For this reason, numerous discrete-time alternatives have appeared. A significant portion of them employ the discrete Fourier transform (DFT) and thus belong to frequency-domain families [10-12]. Such DFT techniques, however, suffer from aliasing errors, picket-fence effects, and leakage that seriously compromise accuracy when noise or other disturbances are present [13]. Attempts to lessen leakage have included frequency-domain correction based on the Z-transform [14, 15]. Separately, mitigation hardware, such as Dynamic Voltage Restorers (DVRs) paired with Multi-Level Inverters (MLIs), has been developed to counteract sags, swells, and flicker. Advanced topologies, for instance, the 33-level asymmetrical MLI, offer superior Low Voltage Ride Through (LVRT) and High Voltage Ride Through (HVRT) behavior, as well as better handling of flicker and harmonic content [16]. Even so, these hardware-oriented solutions tend to lose effectiveness in the presence of strong noise or harmonic pollution.

Other researchers have combined the Z-transform with the Teager energy operator to achieve higher estimation fidelity [17, 18]. However, this improvement comes at the expense of very high sampling frequencies and the corresponding processing overhead. Moreover, most reported simulations in these works limit themselves to a small selection of harmonic and flicker frequencies. Recognizing the drawbacks of frequency-domain analysis, many investigators have turned to time-domain algorithms [19, 20]. These approaches are already widely applied for harmonic estimation tasks in power systems [21-24]. Because flicker appears as sideband frequencies located close to the fundamental, any successful time-domain estimator must demonstrate robust separation capability when dealing with closely spaced spectral components.

In [25-28], amplitude modulation (AM) techniques are examined for extracting flicker components in distributed generation (DG) systems using multiple filters. Although this strategy provides straightforward implementation, its precision depends heavily on the number of filters used, and real-world deployment can face obstacles due to higher processing demands, particularly when capturing intricate flicker patterns. Performance assessments of flicker meters grounded in IEC 61000-4-15 appear in [29-32]. These investigations typically process RMS voltage data in an offline setting, which suits preliminary design stages but restricts online usage. Validation occurs through simulations and on-site measurements alike; nevertheless, flicker meters generally deliver reliable results for lower-frequency inputs while showing reduced reliability at higher fluctuation frequencies [30].

Artificial neural networks (ANNs) serve as effective tools for optimization and parameter estimation and have been applied to identify flicker in electrical networks [33, 34]. Direct utilization of ANNs for deriving flicker indices, however, often increases the number of input nodes, thereby increasing processing overhead. To counteract this drawback, cascaded architectures incorporating preliminary processing layers have been developed [35]. While such configurations produce reasonable outcomes in selected cases, their deployment is predominantly confined to non-real-time contexts.

The Kalman filter (KF), along with its extensions, stands as a cornerstone technique for tackling diverse estimation challenges [26, 27]. Numerous works have adopted state-space models of nonlinear flicker signals to isolate flicker elements via various KF formulations [36-39]. KF-oriented strategies yield consistent estimates when restricted to a narrow set of flicker frequencies, yet their performance declines noticeably as the frequency span widens. Moreover, basic KF implementations are prone to divergence in environments with substantial noise or signal perturbations.

In the current study, a pioneering time-domain hybrid technique, the Hybrid Envelope Flicker System (HEFS), is introduced for determining flicker components from modulated voltage signals in electrical power networks [40]. The procedure unfolds across two phases: initially, a resilient H_∞ filter recovers the waveform envelope [41]; subsequently, an adaptive online neural network (for instance, ADALINE) computes the flicker constituents [42–44]. This framework stands out for its uncomplicated structure and strong resilience. The primary innovations of the research are outlined as follows:

Although flicker estimation has attracted considerable attention, prevailing techniques often struggle to maintain consistency in the presence of non-sinusoidal perturbations, such as harmonics, noise, and intricate modulation patterns that alter voltage profiles. Conventional ANN solutions often require large input vectors and lengthy training periods, whereas Kalman-based approaches falter under unmodeled uncertainties or impose stringent modeling constraints. These shortcomings drive the creation of an estimator that withstands uncertainty while remaining suitable for efficient real-time execution. The present contribution targets realistic disturbances, including voltage flicker, harmonic pollution, and additive white Gaussian noise, all of which commonly co-occur in actual power systems. The key advancements offered in this paper are highlighted below:

1. Adopts a straightforward H_∞ estimator that robustly identifies flicker within modulated voltage signals, even when noise characteristics remain unknown.
2. Incorporates the ADALINE neural network [45], an efficient adaptive estimator that processes multiple envelopes rapidly without any prior training requirement, delivering effective voltage fluctuation assessment in the presence of harmonic interference.
3. Presents an advanced voltage fluctuation representation that jointly accounts for harmonic and flicker elements, yielding a truer depiction of realistic power waveforms.
4. Isolates various flicker frequency components from oscillating voltage signals, encompassing every relevant frequency outlined in the IEC 61000-4-15 standard.
5. Advances a hybrid processing scheme that effectively decouples carrier and flicker frequencies of varying strengths, ensuring swift convergence independent of conventional filter banks.

Overall, the integration of H_∞ filtering and ADALINE forms an innovative dual-stage framework that enables precise, online determination of both harmonic and flicker components in full compliance with IEC 61000-4-15.

Materials and Methods

According to the IEC standard, voltage signals containing flicker are modeled as amplitude-modulated (AM) waveforms. Here, the fundamental power frequency (50 Hz or 60 Hz) functions as the carrier, while the flicker components correspond to the modulating (envelope) frequencies. In discrete-time representation, this is given by [2]:

$$Z^k = V_c \cos(2\pi f k \tau_s) \left\{ 1 + \sum_{i=1}^F \frac{\Delta V_i}{2V} \cos(2\pi F_i k \tau_s + \theta_i) \right\} \quad (1)$$

Where V_c denotes the carrier amplitude (corresponding to the nominal voltage), f is the power-system frequency, and the subscript $i = 1, 2, \dots, F$ indexes the individual flicker components. F_i and θ_i denote the frequency and phase of the i th flicker component, respectively, and $\Delta V_i/V_i$ represents the relative voltage change. The discrete-time model is realized using the sampling interval τ_s . The primary objective of the developed algorithm is to accurately determine the relative

amplitude fluctuation $\Delta V_i/V$ for each flicker component. Note that, throughout all equations in this work, the superscript k indicates the discrete time instant.

In practical power systems, nonlinear loads introduce waveform distortion, rendering the simple AM model of [Eq. 1](#) inadequate for describing realistic voltage signals. To overcome this shortcoming, the present paper proposes an enhanced voltage fluctuation model that simultaneously incorporates harmonic content and flicker components. Furthermore, realistic noise characteristics are better represented by including a high-frequency Gaussian noise term, yielding the following extended signal model:

$$Z^k = \sum_{n=1}^N V_n \cos(2\pi n f k \tau_s + \phi_n) \left\{ 1 + \sum_{i=1}^F \frac{\Delta V_i}{2V_t} \cos(2\pi F_i k \tau_s + \theta_i) \right\} + \sigma \cdot \text{randn}_k \quad (2)$$

Where $n = 1, 2, \dots, N$ indicates the harmonic order, V_n is the amplitude of the n th harmonic, ϕ_n is its phase angle, and $\sigma \cdot \text{randn}_k$ denotes zero-mean Gaussian noise with standard deviation σ controlling the noise intensity. The term

$V_t = \sqrt{\sum_{n=1}^N V_n^2}$ serves as the reference (base) voltage used to normalize the fluctuation amplitudes.

Because the model involves a large number of state variables exhibiting widely different magnitudes, superior flicker estimation performance is obtained by adopting hybrid processing strategies. The suggested hybrid procedure consists of two consecutive stages. In the first stage, the envelope of the modulated voltage waveform is recovered at each discrete time step k using the H_∞ filter. In the second stage, the extracted envelope is supplied to the ADALINE network, which computes the corresponding $\Delta V_i/V_t$ values for each flicker frequency at time k .

Envelope estimation using H_∞ method

The H_∞ filter constitutes a robust analytical estimation technique designed to minimize the maximum (worst-case) estimation error [\[46\]](#). It proves particularly effective for tracking time-varying signals under unknown disturbance and noise conditions, in contrast to Kalman filter approaches, which aim to minimize the expected (average) estimation error variance. To apply the H_∞ filter for envelope recovery, the modulated signal given in [Eq. 2](#) is recast in state-space form as follows:

$$Z^k = A_1 \{\text{Envelope}_1\} + A_2 \{\text{Envelope}_2\} + \dots + A_N \{\text{Envelope}_N\} + \sigma \cdot \text{randn}^k \quad (3)$$

Where:

$$\text{Envelope}_n = V_n + \sum_{i=1}^F \frac{V_n \Delta V_i}{2V_t} \cos(2\pi F_i k \tau_s + \theta_i) \quad (4)$$

The fundamental-frequency power components, $A_n = \cos(2\pi n f k \tau_s + \phi_n)$, are expressed via standard trigonometric expansions:

$$A_n = \cos(2\pi n f k \tau_s) \cos(\phi_n) - \sin(2\pi n f k \tau_s) \sin(\phi_n) \quad (5)$$

To accurately track the true power-system frequency — especially under conditions of frequency drift or deviation — a Phase-Locked Loop (PLL) module available in MATLAB is employed. Drawing on the formulation in Eq. 3, the corresponding linear state-space model suitable for the H- ∞ estimator is constructed as:

$$Z^k = H^k x + \omega^k \quad (6)$$

Where ω_k denotes the measurement noise vector, and the state vector x is defined as:

$$x = [\cos(\phi_1) \text{Envelope}_1 \sin(\phi_1) \text{Envelope}_1 \dots \cos(\phi_N) \text{Envelope}_N \sin(\phi_N) \text{Envelope}_N] \quad (7)$$

The state vector x encapsulates information about the signal envelopes. The corresponding observation matrix H_k is given by:

$$H^k = [\cos(2\pi f k \tau_s) - \sin(2\pi f k \tau_s) \dots \cos(2\pi N f k \tau_s) - \sin(2\pi N f k \tau_s)] \quad (8)$$

The state vector x is estimated in the time domain from the measurement Z_k according to the time-update recursion:

$$\hat{x}^k = \Phi \left(\hat{x}^{k-1} + K^k \left(Z^k - H^k \hat{x}^{k-1} \right) \right) \quad (9)$$

Where K_k and Φ represent the filter gain matrix and the state transition matrix, respectively. Given that the time-varying dynamics of the states are not known a priori, Φ is taken to be the constant identity matrix. The estimation error covariance matrix is updated recursively by minimizing the worst-case estimation error as follows:

$$P^k = \Phi P^{k-1} \left(I - \alpha P^{k-1} + H^{kT} R^{-1} H^k P^{k-1} \right)^{-1} \Phi^T \quad (10)$$

Where the scalar parameter α governs the weighting of past errors within the estimation procedure and is selected by the designer according to the characteristics of the specific application, R stands for the covariance matrix of the measurement noise. The gain matrix K_k is then calculated from the estimation error covariance:

$$K^k = P^k \left(I - \alpha P^k + H^{kT} R^{-1} H^k P^k \right)^{-1} H^{kT} R^{-1} \quad (11)$$

At every discrete time instant k , the envelope estimates are extracted directly from the state vector components:

$$\text{Envelope}_1 = \sqrt{x_1^2 + x_2^2}, \dots, \text{Envelope}_n = \sqrt{x_{N-1}^2 + x_N^2} \quad (12)$$

In summary, the H_∞ filter constitutes a robust state estimator that seeks to minimize the maximum (worst-case) estimation error across all admissible disturbances, in contrast to the Kalman filter, which minimizes the expected (average) error covariance. Its design goal is to ensure that the energy gain from disturbances to estimation errors remains bounded by a designer-specified threshold γ , that is,

$$\frac{\|e_k\|_2^2}{\|\omega_k\|_2^2} < \gamma^2 \quad (13)$$

Where e_k is the estimation error vector, and ω_k is the disturbance (noise) vector. This criterion provides guaranteed robustness even in the absence of precise knowledge about noise statistics. In operation, the filter iteratively refines the state estimate by assimilating measurement innovations while constraining the worst-case amplification of disturbances. The required gain matrix K_k (computed as shown above) guarantees stable convergence despite uncertainty and noise. Consequently, the H_∞ approach is particularly well suited to power quality monitoring tasks, where unmodeled effects and random disturbances frequently corrupt voltage waveforms.

The H_∞ estimator is characterized by straightforward computations and modest complexity, rendering it highly practical for real-time applications. At each time step, the envelope estimates are supplied to the ADALINE network for subsequent identification of the flicker component. This subsequent stage is described in detail in the following subsection.

Flicker components estimation using ADALINE

The time-varying envelopes, which represent the instantaneous amplitudes, are obtained at every discrete time instant via [Eq. 12](#). These recovered envelopes are subsequently supplied as input to an online ADALINE neural network designed for frequency decomposition. The principal benefit of the ADALINE architecture lies in its simple topology, which eliminates the need for a preliminary training phase and thereby supports rapid estimation. In addition, the proposed algorithm requires only a very small set of adjustable parameters, which enhances its ease of practical deployment. A block diagram of the ADALINE structure is presented in [Figure 1](#). The desired outputs (target values) for the ADALINE correspond to the flicker amplitude components located at the sideband frequencies $f \pm F_i$ Hz, where f denotes the fundamental power frequency and the values of F_i are those prescribed by IEC Standard 61000-4-15, as listed in [Table 1](#).

For flicker amplitude estimation, the envelope signal from the H_∞ filter is treated as the input to be decomposed, with the basis frequencies drawn from the set in [Table 1](#). The network architecture incorporates 74 input nodes, each associated with a constant (DC) term.

Table 1. Flicker frequencies F_i in Hz according to IEC Standard 61000-4-15.

Flicker frequencies F_i (Hz)					
0.5	3.5	6.5	10	14	20
1	4	7	10.5	15	21
1.5	4.5	7.5	11	16	22
2	5	8	11.5	17	23
2.5	5.5	8.8	12	18	24
3	6	9.5	13	19	25

The selection of these 74 discrete frequencies follows directly from IEC Standard 61000-4-15, which identifies the modulation frequency band (0.5–25 Hz) as most significant for human flicker perception. This fixed set of basis functions enables the ADALINE network to estimate the flicker amplitudes efficiently. Although the frequency grid is inherently discrete, the algorithm's adaptive mechanism approximates components that fall between grid points by distributing energy (via spectral leakage) into neighboring basis functions. Such an approach achieves a satisfactory compromise between frequency resolution and computational efficiency, without necessitating online adaptation of the basis set.

$$x_{ad}^k = [1, 0, \cos(2\pi 0.5k\tau_s) - \sin(2\pi 0.5k\tau_s) \dots \cos(2\pi 25k\tau_s) - \sin(2\pi 25k\tau_s)]^T$$

(14)

The weight vector associated with the n th envelope at a discrete time step k is expressed as:

$$w_n^k = [w_{1n}^k, w_{2n}^k, \dots, w_{73n}^k, w_{74n}^k] \quad (15)$$

These weights are iteratively adjusted according to the Widrow–Hoff learning rule:

$$w_n^{k+1} = w_n^k + \frac{\theta^k e_n^k x_{ad}^{kT}}{\lambda + x_{ad}^{kT} x_{ad}^k} \quad (16)$$

Where e_n^k denotes the instantaneous tracking error, and λ is a small positive constant introduced to prevent division by zero. The time-dependent adaptive learning rate θ^k is computed using the expression:

$$\theta^k = \frac{\theta^0}{1 + \frac{k}{\beta}} \quad (17)$$

In Eq. 17, the parameter β is a fixed scalar that governs how quickly the initial learning rate θ_0 decays over time. Once convergence is achieved, the steady-state weight values directly encode the flicker amplitude information. Ultimately, the amplitudes of both the harmonic and flicker components are recovered through the relation:

$$V_n = \sqrt{w_{1n}^2 + w_{2n}^2} \quad \text{and} \quad \frac{\Delta V_i}{2V_t} = \frac{\sqrt{w_{(2i+1)n}^2 + w_{(2i+2)n}^2}}{V_n}, \quad (18)$$

$$i = 1, 2, \dots, F$$

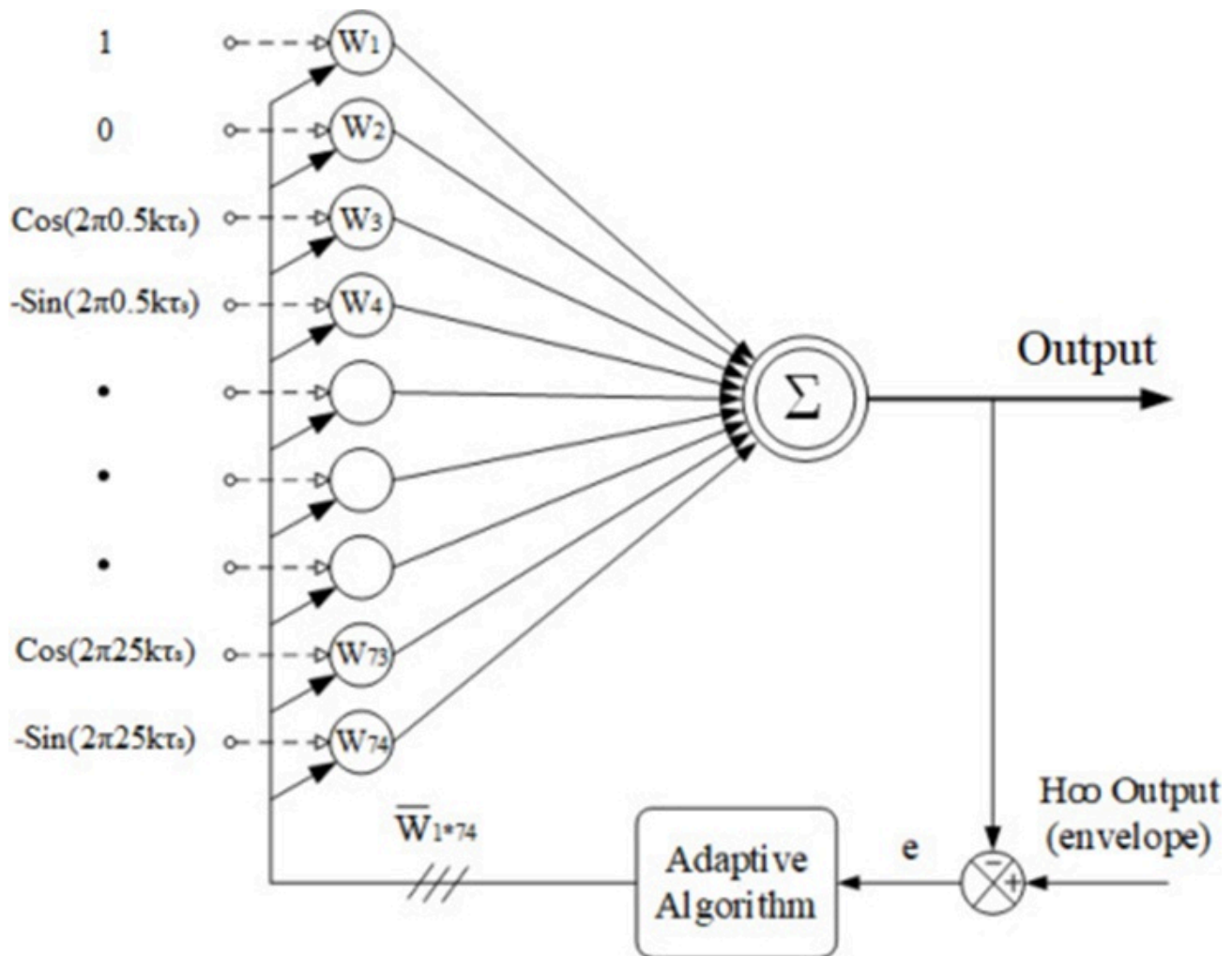


Figure 1. Schematic diagram of the ADALINE neural network employed for flicker frequency estimation.

The network receives a set of sinusoidal basis functions spanning the designated flicker frequency band. Each basis function is multiplied by an adjustable weight coefficient W_i , and the resulting weighted summation yields the ADALINE output. This output is then compared to the reference envelope provided by the H- ∞ filter. The difference, or error signal e , drives the Least Mean Squares (LMS) adaptation mechanism, which continuously adjusts the weight vector $W \rightarrow$ in real time to minimize the mean squared error and enable the network to follow multiple simultaneous flicker components.

The ultimate outputs of the ADALINE network are the relative flicker amplitudes $\Delta V_i/V_t$ associated with the standardized flicker frequencies F_i . These quantities correspond precisely to the physical flicker parameters specified in IEC 61000-4-

15 and serve as direct inputs for calculating the instantaneous flicker sensation (S) and other relevant standardized metrics. Consequently, the presented technique goes beyond mere frequency tracking by providing explicit estimates of the relative amplitudes of flicker components, which have clear physical meaning and directly relate to human perception.

Results and Discussion

A comprehensive set of simulation experiments was conducted to evaluate the performance of the proposed technique in recovering flicker components. The voltage waveform model described in Eq. 2 served as the basis for these tests. The frequency spectrum of the simulated waveform reflects typical conditions observed on industrial busbars, including harmonics from the 1st to the 11th orders. In addition, representative flicker components compliant with IEC Standard 61000-4-15 were superimposed onto the signal. To demonstrate the approach's resilience, the estimation task was deliberately applied to a severely distorted waveform containing five harmonic components and high-frequency additive noise.

Suitable parameter settings for the proposed algorithm were determined. The chosen values for both the H_∞ filter and the ADALINE neural network are summarized in Table 2.

I^* denotes the identity matrix, and 1^* is a column vector of ones. These parameter values were held constant across all simulation studies. The principal simulation scenarios examined in this work are outlined below:

Table 2. Parameter settings for H_∞ filter and ADALINE neural network simulations.

H ∞ method		ADALINE method		Simulation	
P0	$103 \cdot I * 2N \times 2N$	w0	$1 * * 2i + 2$	TS	1/1200
x^0	$1 * * 2N$	θ0	5	σ	0.02
α	8	λ	0.0001		
f	50	β	1000		
R	0.007				

1. Simulated waveform comprising the fundamental power harmonic plus a single flicker component.
2. Heavily distorted waveform containing five power harmonics and thirty-six flicker components. This scenario tests the proposed method's ability to accurately track flicker amid multiple interfering harmonics.
3. Monte Carlo (MC) simulation framework for performance evaluation of the proposed method. In this case, harmonic amplitudes and flicker parameters are randomly varied within the signal model to assess the algorithm's robustness and generalization capability.

Estimation of a waveform with power frequency and one flicker component

As an illustrative benchmark case, a voltage waveform consisting of the fundamental power-frequency component and a single flicker component was generated. The power frequency was set to 50 Hz and tracked using a Phase-Locked Loop (PLL) implemented via the MATLAB toolbox. To assess estimation accuracy under realistic conditions, Gaussian noise was superimposed on the signal according to the following expression:

$$Z^k = 1.5 \cos(2\pi 50k\tau_s + 80^\circ) \times \left\{ 1 + \frac{\Delta V_i}{2V_t} \cos(2\pi F_i k\tau_s + \theta_i) \right\} + 0.02 \cdot \text{randn}^k \quad (19)$$

Multiple simulation runs were performed, with each run injecting one of the flicker frequencies listed in [Table 1](#) into the waveform. The relative amplitude of the flicker component, $\Delta V_i/V_t$, was randomly drawn from the interval [0.001, 0.02]. Likewise, the phase angles θ_i were randomly selected from the range $[0^\circ, 90^\circ]$. The proposed algorithm was applied to estimate the relative flicker amplitudes. The estimated values were then compared against the known true values, and the absolute estimation error was computed. The error analysis results across the different simulation trials are depicted in [Figure 2](#). Although the absolute error increases modestly with increasing amplitude and frequency, the method consistently achieves amplitude estimates with errors of less than 1% for all tested flicker frequencies. Convergence behavior was also investigated, as illustrated in [Figure 3](#), revealing that satisfactory estimation accuracy is attained for every flicker frequency within a settling time of 0.3 s.

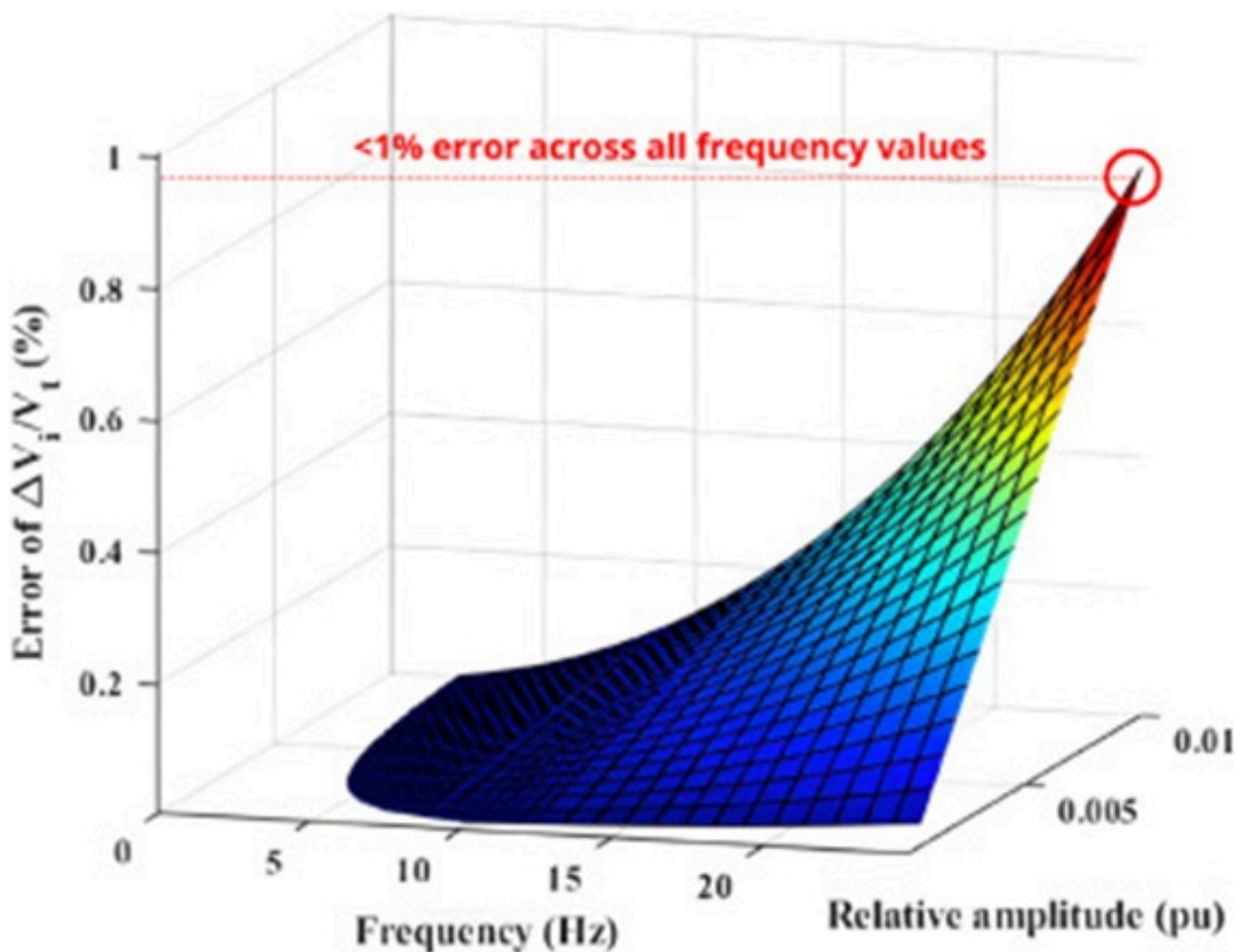


Figure 2. Absolute estimation error for $(\Delta V_i)/V_t$, considering a waveform that includes only the power frequency along with a single flicker component.

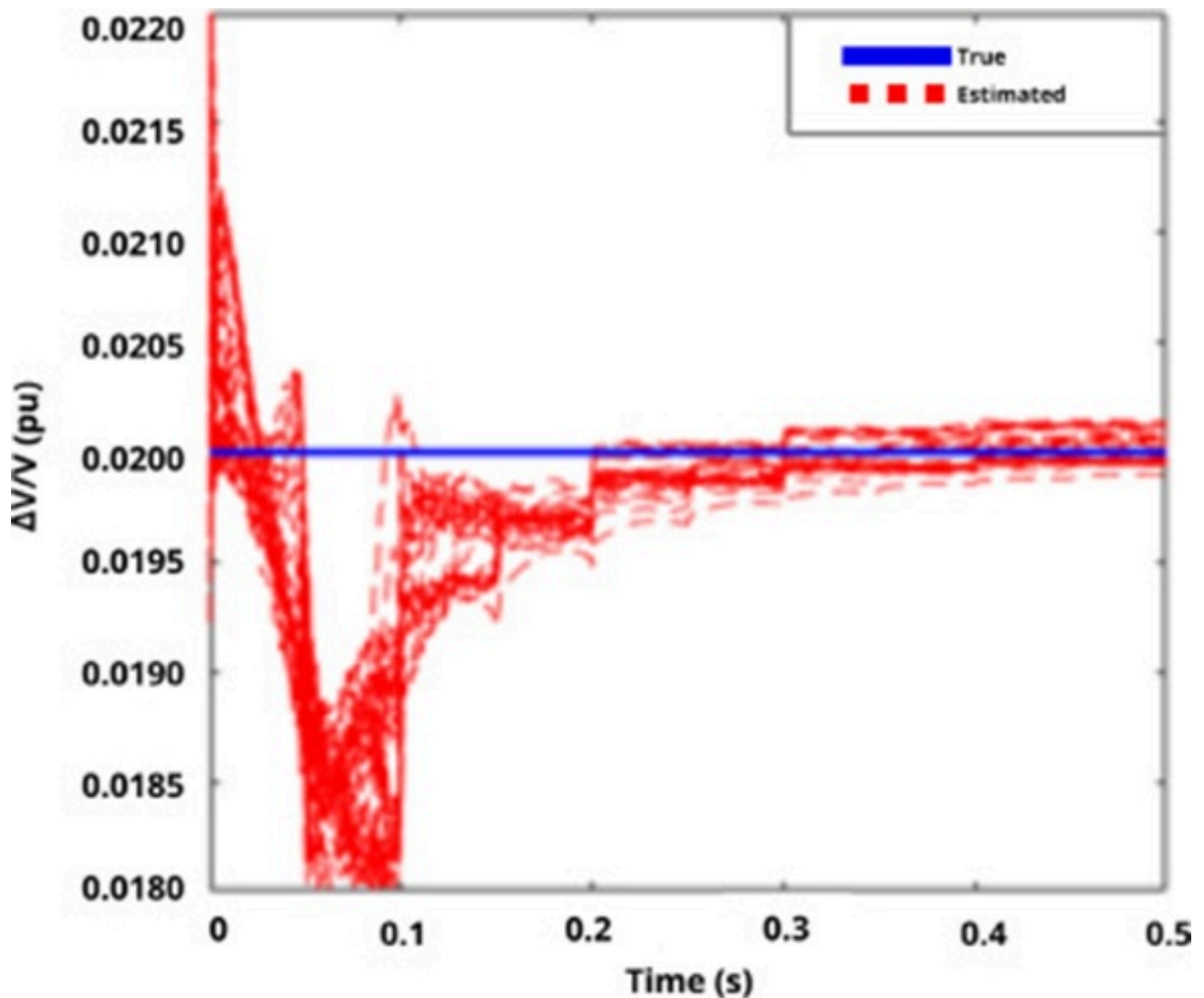


Figure 3. Convergence profile of the proposed estimation technique. The blue curve indicates the actual relative flicker amplitude set at $\Delta V/V = 0.02$ pu. The red curves depict the flicker amplitude estimates produced by the ADALINE neural network over time, obtained from several Monte Carlo trials.

The figure shows how the estimator converges when applied to a waveform containing the fundamental frequency and a single flicker component.

Estimation of distorted waveform with 5 power harmonics and 36 flicker components

Nonlinear loads and other current distortions commonly present on power lines cause real bus voltages to become non-sinusoidal, effectively resulting in a composite waveform made up of multiple harmonic orders. In this subsection, the flicker estimation task is tackled using a modulated voltage signal that incorporates several power harmonics. Moreover, to rigorously test the proposed method's capability when many flicker frequencies are simultaneously present, the modulated waveform includes all flicker frequencies specified in IEC Standard 61000-4-15. Accordingly, the disturbed signal described by Eq. 2 is constructed in the following manner [19, 23, 47, 48]:

$$\begin{aligned}
 Z^k = & [1.5 \cos(2\pi 50k\tau_s + 80^\circ) + 0.5 \cos(2\pi 150k\tau_s + 60^\circ) \\
 & + 0.2 \cos(2\pi 250k\tau_s + 45^\circ) \\
 & + 0.15 \cos(2\pi 350k\tau_s + 36^\circ) + 0.1 \cos(2\pi 550k\tau_s + 30^\circ)] \\
 & \left\{ 1 + \sum_{i=1}^F \frac{\Delta V_i}{2V_t} \cos(2\pi F_i k\tau_s + \theta_i) \right\} + 0.02 \cdot \text{randn}^k
 \end{aligned} \quad (20)$$

The corresponding flicker frequencies f_i together with their associated relative amplitudes $\Delta V_i/V_t$ are listed in **Table 3**. These amplitude values have been selected to produce a unity instantaneous flicker sensation for 230 V/50 Hz supply systems [38]. At every discrete time instant k , the H_∞ filter recovers the signal envelopes. In the scenario examined here, five harmonic components are included in the simulated waveform, requiring the H_∞ filter to estimate five separate envelopes. The estimation performance for envelope 1 is shown in **Figure 4**, where the proposed technique reaches the true envelope value within 1 fundamental period (0.02 s). Comparable rapid tracking is observed for the other four envelopes. As indicated by **Eq. 12**, the H_∞ filter simultaneously determines the phase angles of the power harmonic components. The phase estimation results for these harmonics are presented in **Figure 5**. Owing to minor inaccuracies in the PLL frequency tracking, phase convergence to the reference values occurs somewhat more slowly than envelope convergence.

Nevertheless, all harmonic phases stabilize within 0.03 s. Despite this minor delay, the H_∞ filter sustains reliable estimates thanks to its built-in robustness to measurement inaccuracies and model uncertainties. Further improvements could be achieved by fine-tuning the PLL parameters or by adopting more sophisticated PLL designs to reduce residual frequency-tracking errors.

During the second processing stage at each time step k , the envelopes delivered by the H_∞ filter serve as inputs to the ADALINE neural network, which then computes the flicker amplitudes $\Delta V_i/V_t$. The tracking performance of the flicker amplitudes obtained via the ADALINE network is illustrated in **Figure 6**. Because the network weights are initialized randomly, the early estimation transients exhibit some overshoot. By separating the estimation of harmonic and flicker components into distinct stages, the hybrid algorithm enables independent handling of parameters with significantly different magnitudes, thereby reducing the number of iterations required for convergence. Overall processing of the distorted waveform is completed within 0.6 s. Using the estimated flicker amplitudes, the envelopes can be reconstructed. Once the flicker components have converged to their correct values, the reconstructed envelopes closely match the true envelopes. The reconstruction accuracy for envelope 1, based on the ADALINE-derived flicker amplitudes, is shown in **Figure 7**; this level of agreement extends to the remaining envelopes as well.

Table 3. Flicker frequencies F_i and their corresponding relative amplitudes are employed for the distorted waveform estimation.

F	$\Delta V/V_t$	F	$\Delta V/V_t$	F	$\Delta V/V_t$
0.5	0.0234	6.5	0.003	14	0.00388
1	0.01432	7	0.0028	15	0.00432
1.5	0.0108	7.5	0.00266	16	0.0048
2	0.00882	8	0.00256	17	0.0053
2.5	0.00754	8.8	0.0025	18	0.00584
3	0.00654	9.5	0.00254	19	0.0064

3.5	0.00568	10	0.0026	20	0.007
4	0.005	10.5	0.0027	21	0.0076
4.5	0.00446	11	0.00282	22	0.00824
5	0.00398	11.5	0.00296	23	0.0089
5.5	0.0036	12	0.00312	24	0.00962
6	0.00328	13	0.00348	25	0.01042

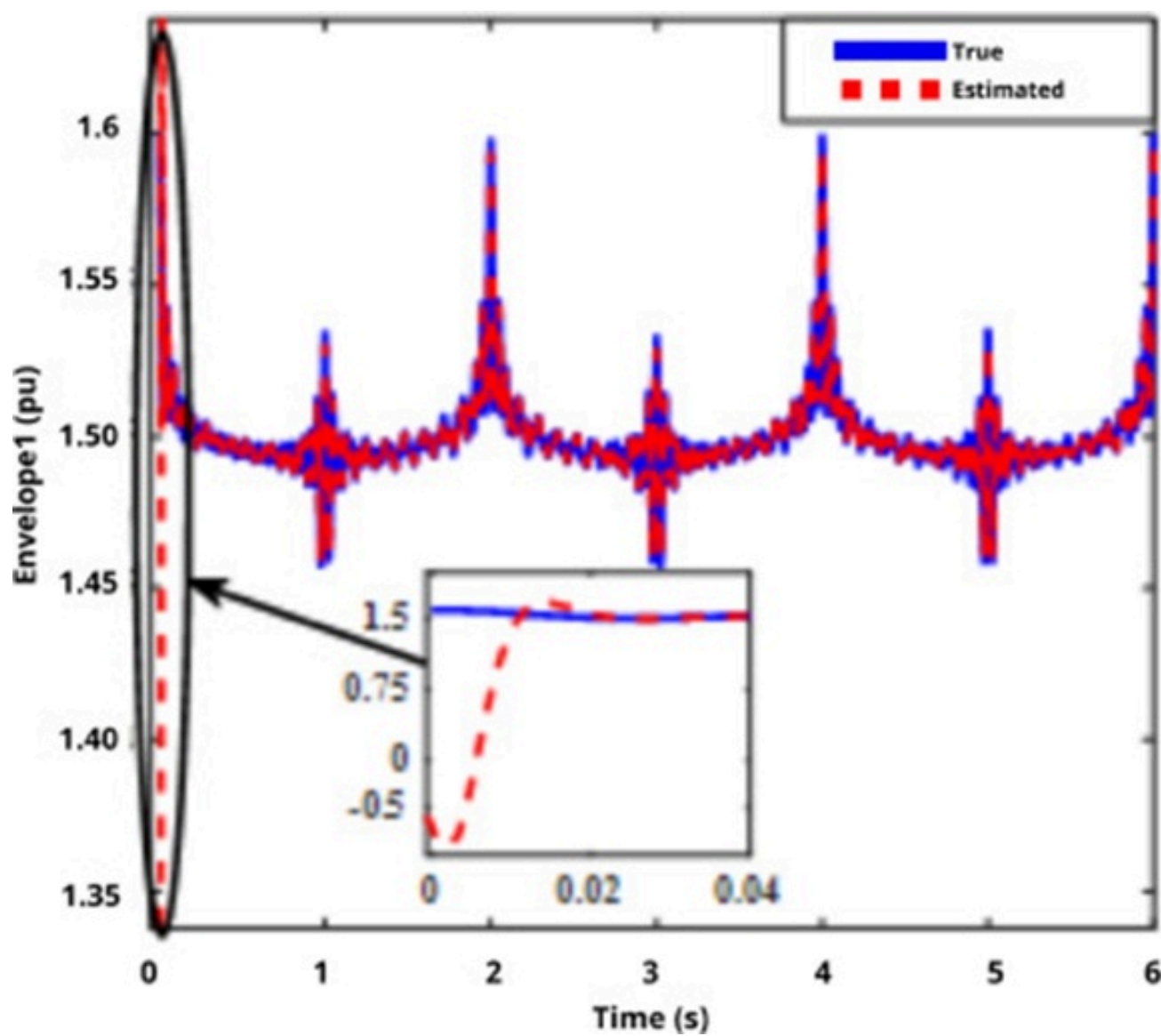


Figure 4. Estimation results for envelope 1 obtained with the H-∞ filter.

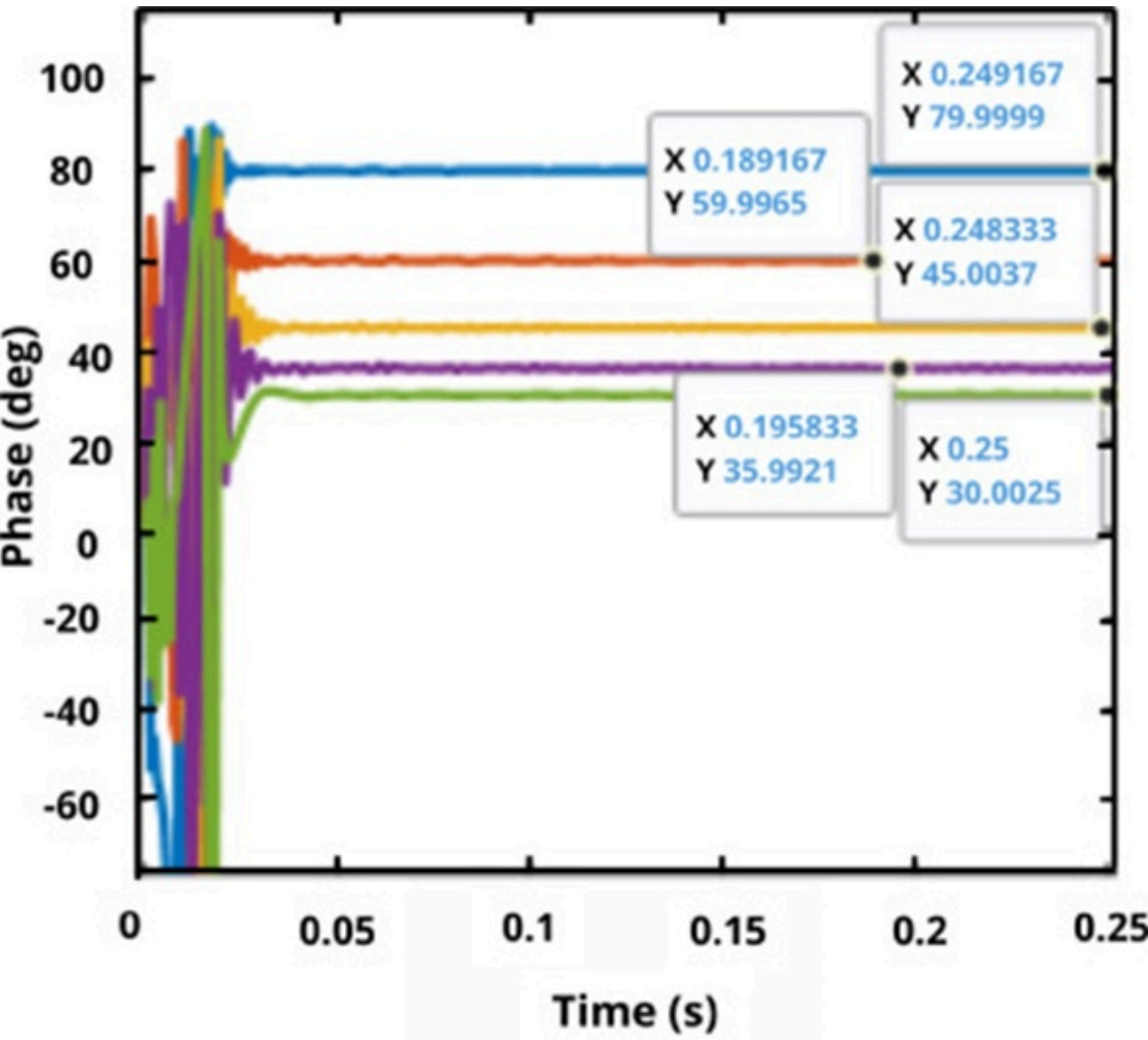


Figure 5. Phase estimation results for the power harmonics obtained with the H_{∞} filter. In blue the main components, in red the 3rd component, in orange the 5th component, in purple the 7th component, and in green the 11th component.

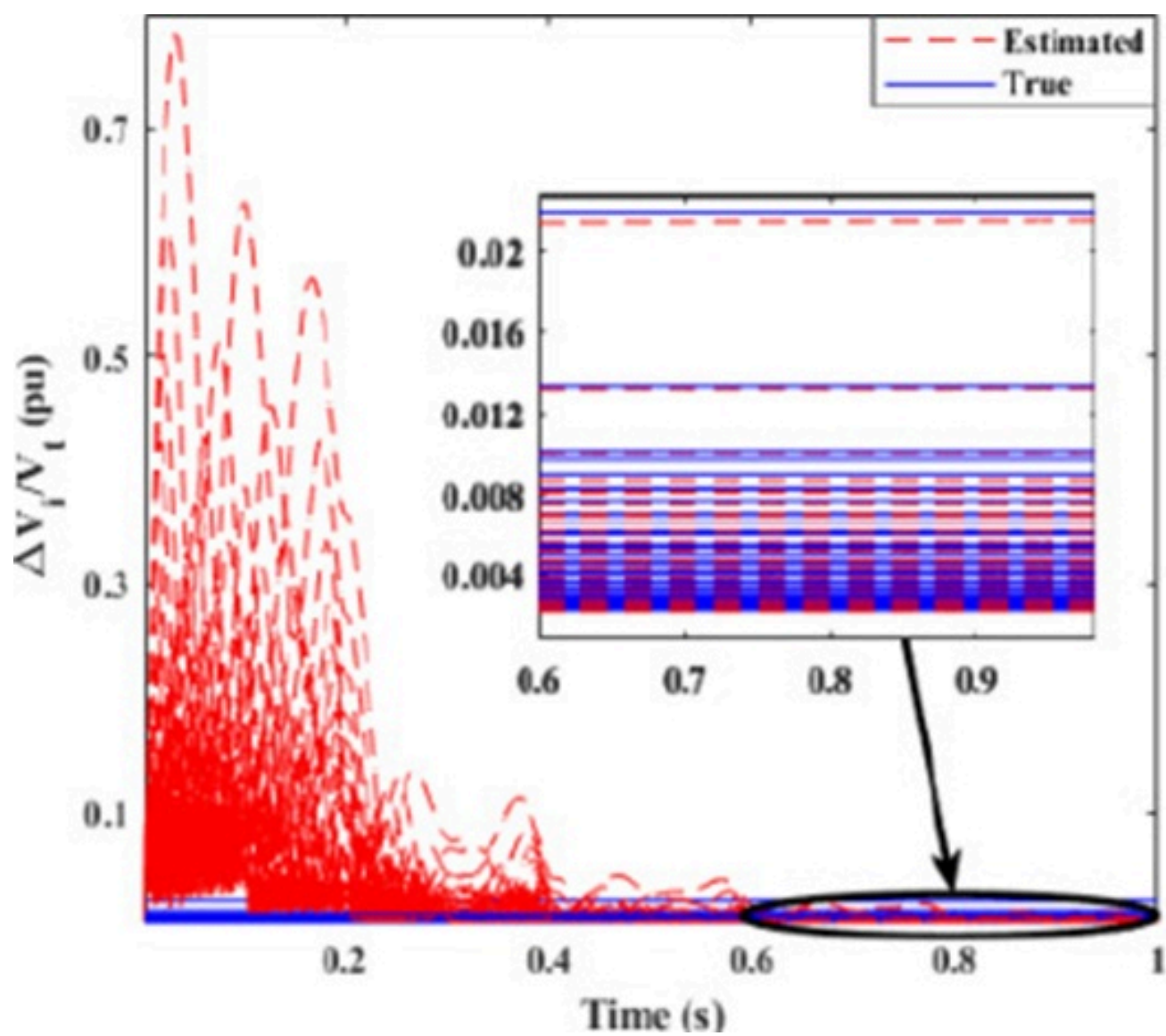


Figure 6. Estimation of relative flicker amplitudes $\frac{\Delta V_i}{V_t}$ performed by the ADALINE network.

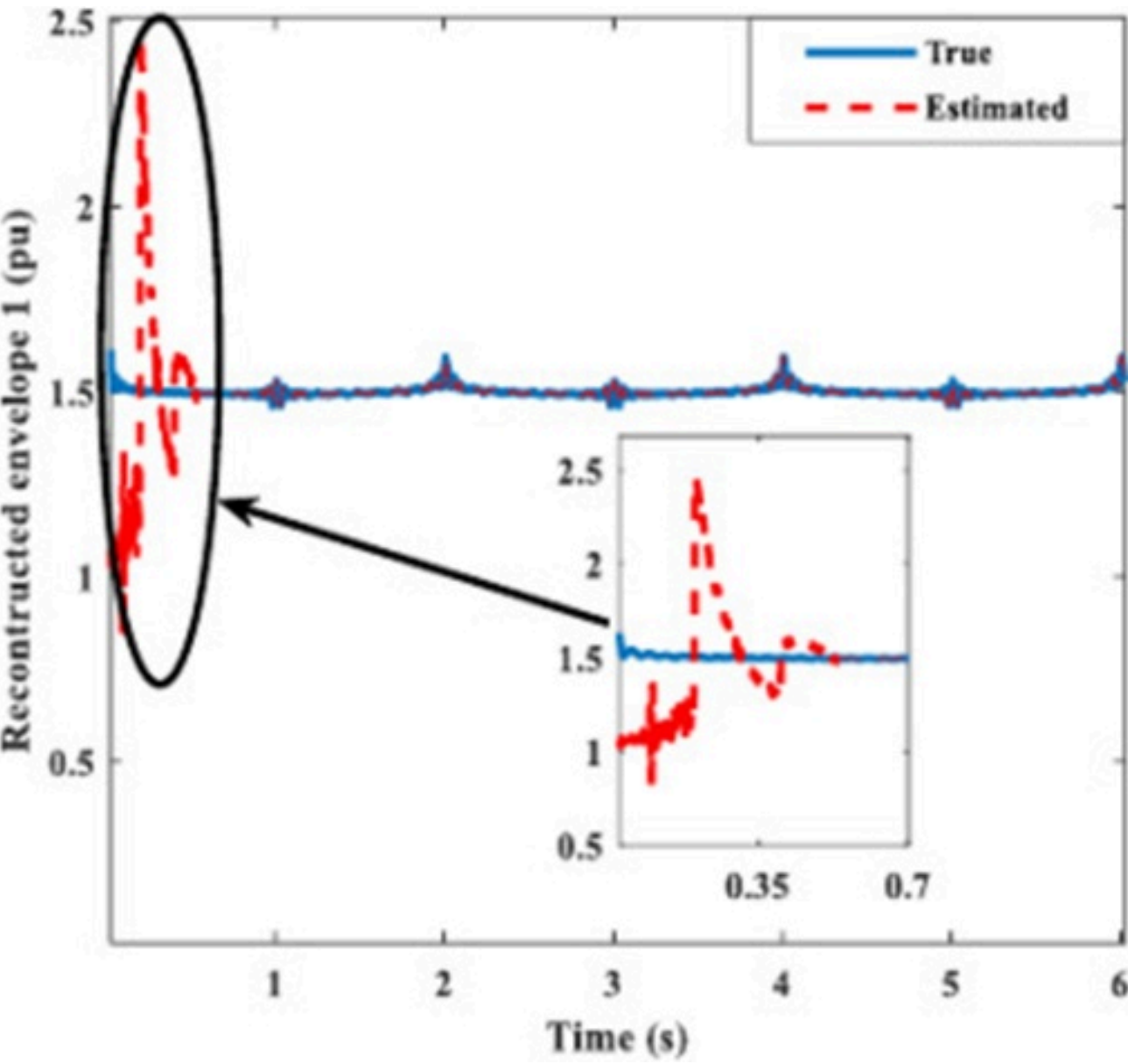


Figure 7. Reconstruction of envelope 1 based on the flicker amplitudes estimated by ADALINE.

As indicated in Table 4, when no frequency deviation is present, the envelope estimation error remains extremely small, with a mean value of 5.352×10^{-6} and a variance of 4.183×10^{-6} . In contrast, the introduction of a ± 0.5 Hz deviation in the fundamental frequency causes both the mean error and its variance to rise by more than one order of magnitude. This behavior underscores the well-known vulnerability of PLL-dependent methods to frequency offsets and highlights the superior robustness provided by the H_{∞} filter framework under comparable conditions.

Table 4. Estimation error for envelope 1 attributable to PLL inaccuracies.

Without frequency deviation		With frequency deviation of ± 0.5 Hz	
Mean	Variance	Mean	Variance
5.352e-6	4.183e-6	7.266e-5	8.419e-5

Impact of PLL errors and optimization strategies

As shown in **Table 4**, inaccuracies in the phase-locked loop (PLL) can lead to noticeable errors in the envelope estimation process, especially when the fundamental frequency deviates. Although the presented H_∞ -ADALINE hybrid scheme exhibits considerable robustness, its overall precision remains contingent upon the PLL's effectiveness in accurately following the fundamental frequency. To reduce the influence of this error source, more sophisticated adaptive PLL techniques can be adopted. Examples include second-order generalized integrator PLLs (SOGI-PLLs) and PLLs based on adaptive notch filters, both of which provide quicker locking times and superior performance during rapid or dynamic frequency changes [49].

Furthermore, an appropriate compromise between the PLL's bandwidth setting and its susceptibility to noise must be established to achieve accurate tracking and resilience against disturbances simultaneously. The incorporation of these enhanced PLL architectures into the proposed framework is anticipated to yield even greater dependability in non-stationary operating environments; this aspect will be investigated in future research efforts.

Monte Carlo (MC) analysis and results discussion

Monte Carlo (MC) methods constitute a broad class of computational approaches that rely on repeated random sampling to derive statistical properties of complex systems or algorithms [6, 19, 50-53]. A key application of MC techniques is assessing the robustness and reliability of estimation procedures when multiple sources of uncertainty are present. Within this investigation, the MC framework involves running a large number of independent simulations. In each simulation run, the amplitudes of the harmonic components and flicker components in the waveform model given by **Eq.2** are randomly selected. Specifically, harmonic amplitudes are drawn uniformly from the interval [0.8, 1.2], while flicker amplitudes are sampled uniformly from [0, 0.02]. The proposed estimation algorithm is then executed to recover the flicker amplitudes.

The quality of the estimation is quantified by computing the instantaneous flicker sensation (S), which acts as the principal performance metric for flicker severity [54, 55]. The contribution of each flicker frequency to the total S value is determined according to the expression:

$$S_i = \frac{\left(\frac{\Delta V_i}{V_t}\right)}{\left(\frac{\Delta V_i}{V_t}\right)_{IEC}} \quad (21)$$

Where $\left(\frac{\Delta V_i}{V_t}\right)_{IEC}$ corresponds to the standardized relative amplitude for flicker frequency F_i as listed in **Table 3**. The overall estimated flicker sensation S is obtained by summing the individual contributions S_i across all flicker frequencies. The percentage error between the estimated S and the true (reference) S value serves as the primary output statistic of each MC trial. The distribution of the error in S as a function of the root-mean-square harmonic content $\sqrt{\sum_{n=1}^N V_{2n}^2}$ and the root-mean-square flicker content $\sqrt{\sum_{i=1}^F \left(\frac{\Delta V_i}{V_t}\right)^2}$ is presented in **Figure 8**.

As illustrated in **Figure 8**, the error in the computed flicker sensation S stays below 0.25% across the entire range of randomly generated harmonic and flicker amplitude combinations. In addition, the algorithm's convergence characteristics are examined in both the frequency and time domains through extensive MC trials. To this end, a two-dimensional statistical distribution is analyzed, capturing the joint behavior of the error in S (a frequency-domain metric) and the error in the estimation of envelope 1 (a time-domain metric). These findings are shown in **Figure 9** and summarized numerically in **Table 5**. The results confirm not only the high accuracy of the proposed method in capturing the frequency-domain flicker characteristics (as reflected in the S values) but also its precision in reconstructing time-domain features, such as the voltage envelopes.

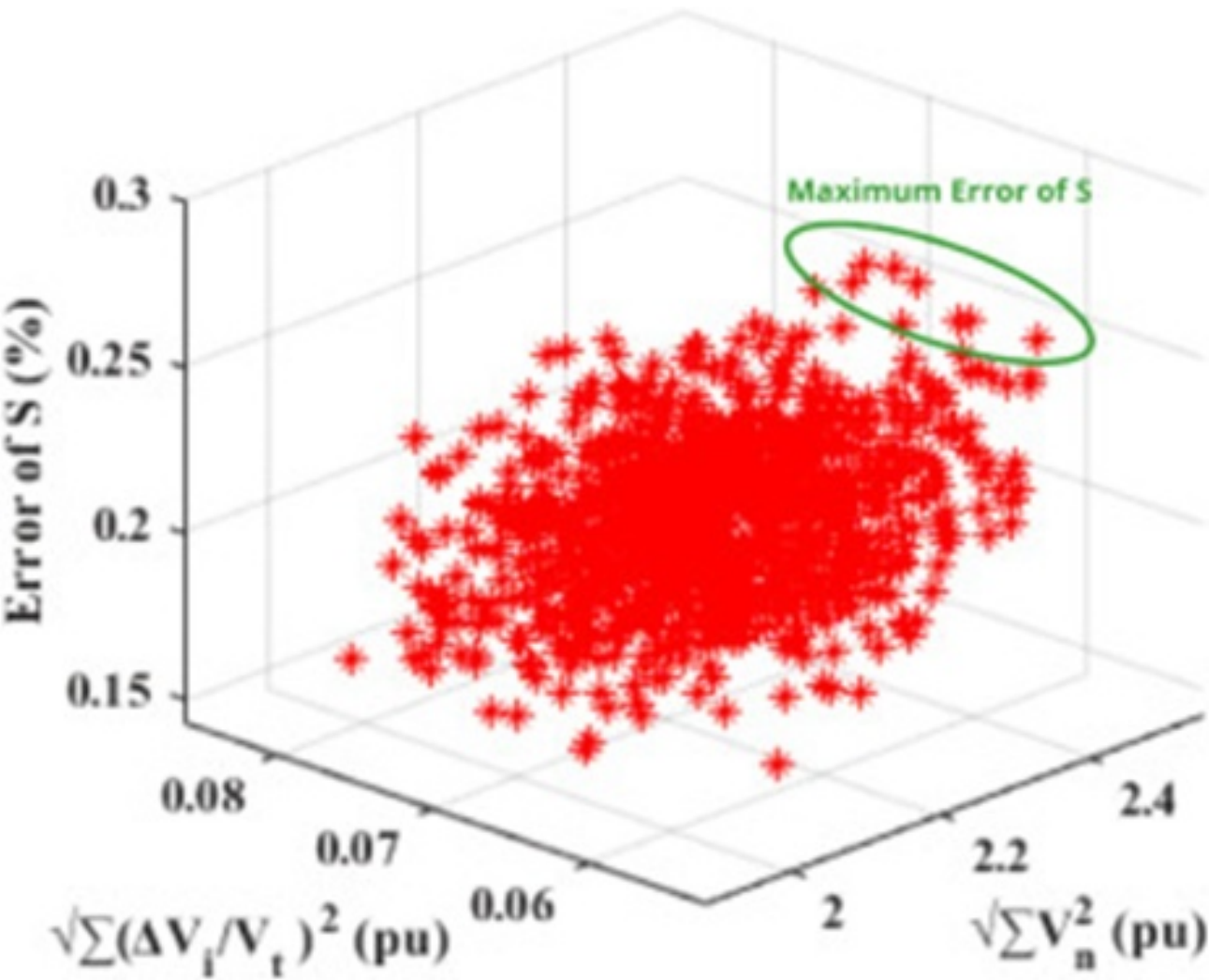


Figure 8. Monte Carlo analysis results showing the estimation error in the S level.

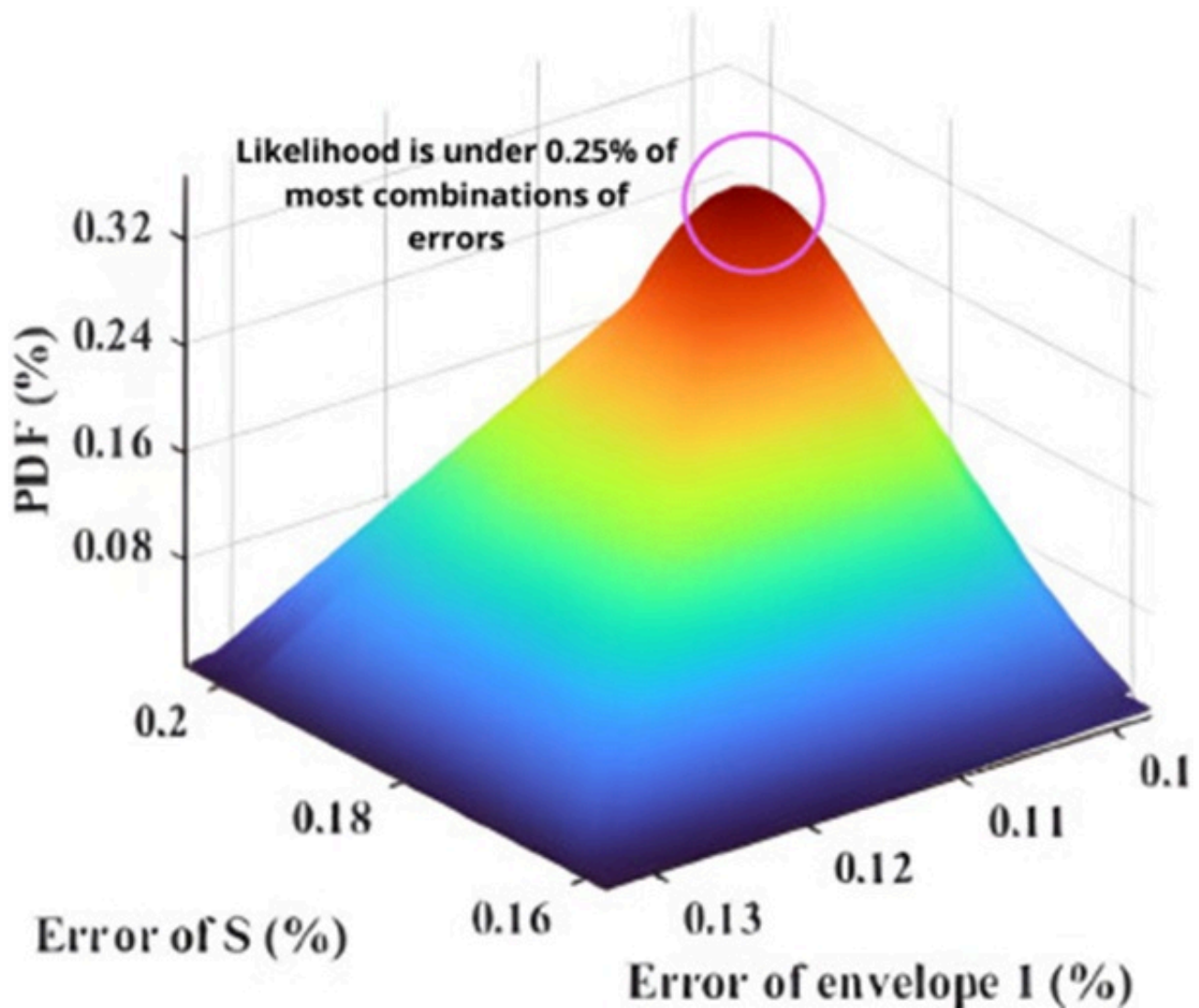


Figure 9. Statistical Monte Carlo analysis covering both frequency-domain and time-domain performance.

Table 5. Numerical summary of the Monte Carlo simulation outputs.

Empty Cell	Error of S (%)	Error of envelope 1 (%)
Mean	0.1832	0.1114
STD^a	0.0021	0.0038

^a: Standard deviation

Theoretical and practical insights

The theoretical effectiveness of the proposed technique has already been confirmed through an extensive series of simulation-based validations. The present section shifts focus to evaluate its practical viability in realistic operating environments. For comparative purposes, standard Fast Fourier Transform (FFT) and advanced Discrete Wavelet Transform (DWT) implementations — both sourced from MATLAB toolboxes — are applied to estimate flicker components under identical test conditions, and their outcomes are benchmarked against the proposed method.

A dedicated experimental platform was constructed to capture authentic voltage data from a fluctuating source. The voltage signal originates from a 400 V infinite bus supplying die-casting machines (with clamping forces of 160-1000 tons), electrostatic painting equipment, and oil circulation pumps at Mazinoor Lighting Industries Inc. The rapid, substantial load transients induced by die-casting machines cause sudden current surges, which in turn provoke noticeable voltage fluctuations on the supply side. Die-casting machines were deliberately chosen for this investigation because their highly dynamic and frequent load variations provide an effective means to demonstrate the proposed method's robustness and real-time estimation capabilities. To establish wider relevance, future investigations are encouraged to extend validation to inverter-fed loads — such as variable-frequency drives (VFDs) — and to induction motors, both of which are prevalent sources of harmonics and flicker in industrial settings.

The machine's supply voltage is measured using a high-speed voltage transducer (LV 25-P), with the analog signal digitized by an NI USB-6009 data acquisition card operating at a sampling frequency of 1200 Hz over a 6-second recording interval. The complete experimental arrangement is depicted in **Figure 10(a)**, while the data acquisition and logging configuration is illustrated in **Figure 10(b)**. Recorded data are subsequently analyzed offline in MATLAB using the proposed hybrid algorithm, along with the conventional FFT and DWT approaches. All processing was performed on a personal computer with a Core i5 processor running at 3.1 GHz and 8 GB of RAM.

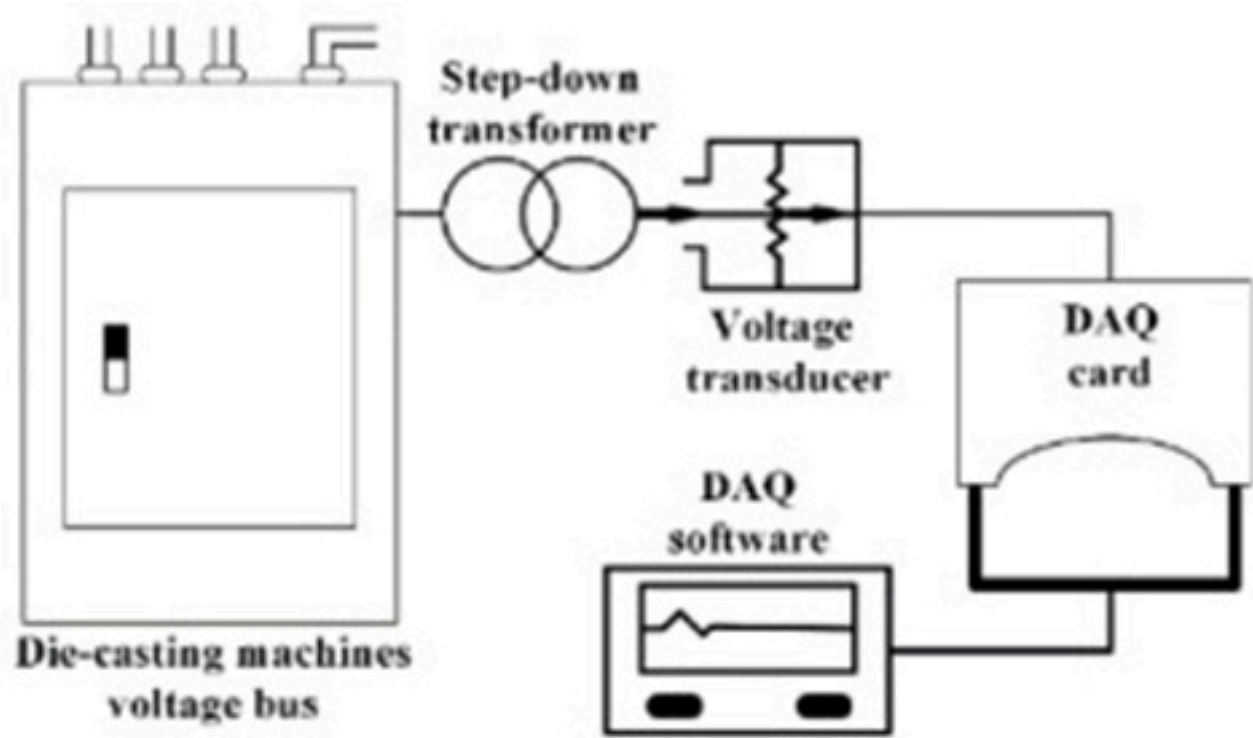
Comparative graphical results for envelope 1 obtained from the three estimation techniques are displayed in **Figure 11**. Despite the presence of pronounced notches in the measured waveform caused by abrupt load switching, the estimated envelope 1 produced by the proposed method closely tracks the actual signal envelope. For closer inspection, the undervoltage region of the waveform is enlarged, revealing that both the proposed algorithm and the DWT approach outperform the FFT method in accurately capturing the envelope during both steady-state and transient phases.

The reconstructed voltage waveform — generated by combining the estimated flicker amplitudes and harmonic parameters — is overlaid against the original measured signal for validation. Quantitative error metrics for the last two seconds of the recording (from 4 s to 6 s) across the FFT, DWT, and proposed methods are summarized in **Table 6**. Although the visual comparisons appear favorable, the numerical performance indicators indicate that the DWT method shows noticeably lower accuracy in real-world measurements. The main factor contributing to this degradation in the DWT time-frequency approach is the interference from high-frequency noise components inherent in field data, which introduce aliasing artifacts.

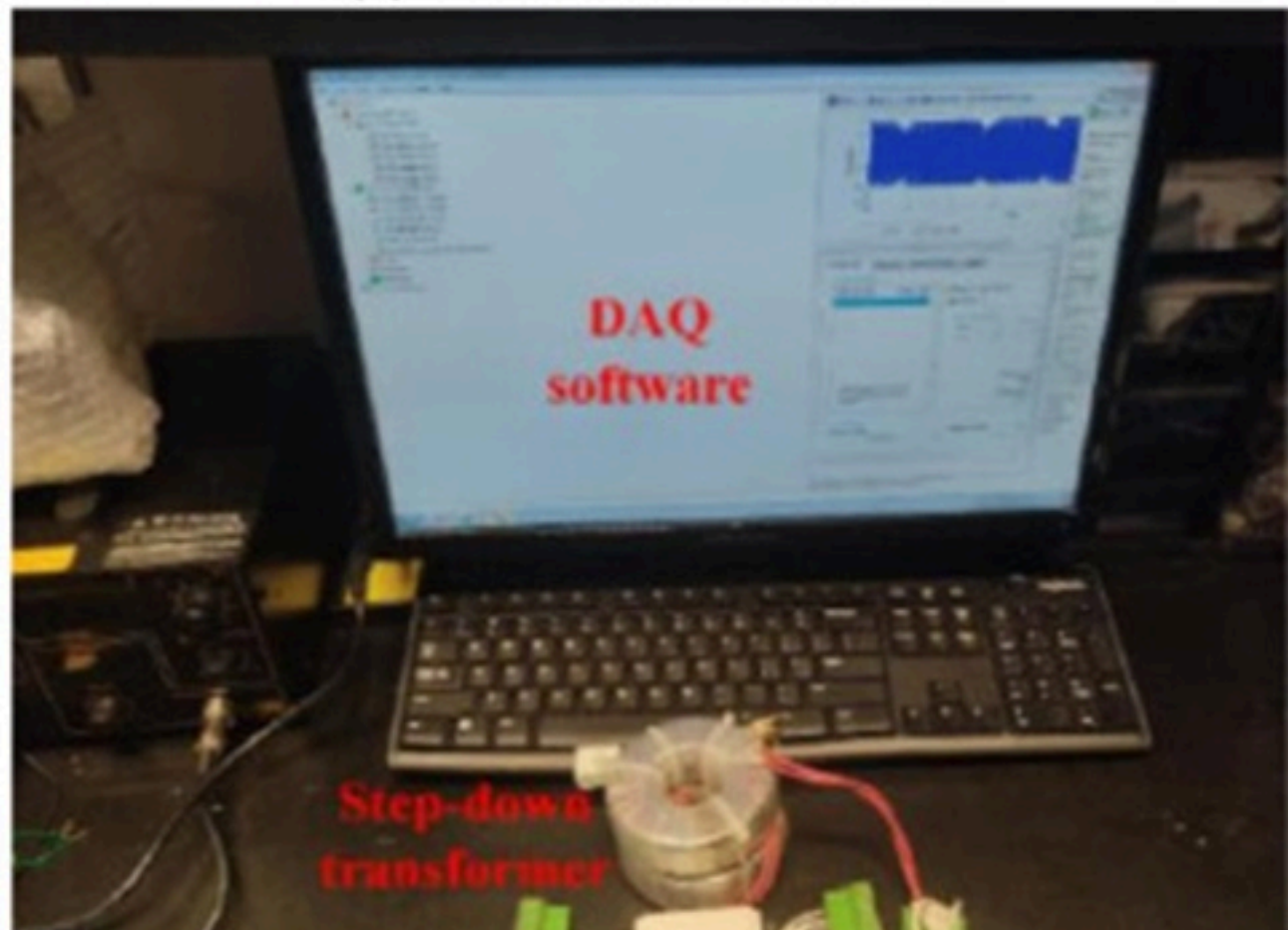
In a second experimental scenario, the utility feeder was intentionally disconnected, and a diesel emergency generator supplied the entire load bank. Under these isolated operating conditions, real-time monitoring revealed excursions in the fundamental frequency of ± 0.25 Hz during die-casting machine cycles. Such frequency deviations introduce bias into the PLL-based power-frequency estimation due to noise and narrowband disturbances, thereby affecting the accuracy of the proposed method to some extent. While all three techniques exhibit some performance degradation in this regime, the proposed hybrid approach maintains greater stability by separately decomposing voltage fluctuations and harmonic content, which effectively reduces the propagation of frequency-tracking errors into the final outputs. In contrast, the combined effects of aliasing and the picket-fence phenomenon substantially impair the FFT and DWT results.

Numerical performance details, including error statistics and computational requirements for the final two seconds of processed data, are compiled in **Table 6**. Under nominal grid-connected conditions (a stable feeder), the proposed method exhibits the best computational efficiency. When frequency deviations are present, however, its processing time slightly exceeds that of the FFT due to the need for additional adaptation iterations to reach satisfactory convergence. Although the DWT delivers accurate results in some respects, its significantly higher computational requirements make it less suitable for real-time deployment. The metrics reported in **Table 6** collectively demonstrate the proposed hybrid technique's ability to achieve both high estimation accuracy and practical computational efficiency in real-world field conditions.

Although the current investigation centers on flicker component estimation, the adaptive architecture underlying the hybrid method — which integrates H_∞ filtering with ADALINE neural networks — has potential for extension to the estimation of other power-quality disturbances, including voltage sags, swells, and interharmonics. Future studies should explicitly validate this broader applicability, possibly by modifying the signal model to accommodate the distinct frequency and amplitude characteristics associated with these additional disturbance types.



(a) Testbench schematic



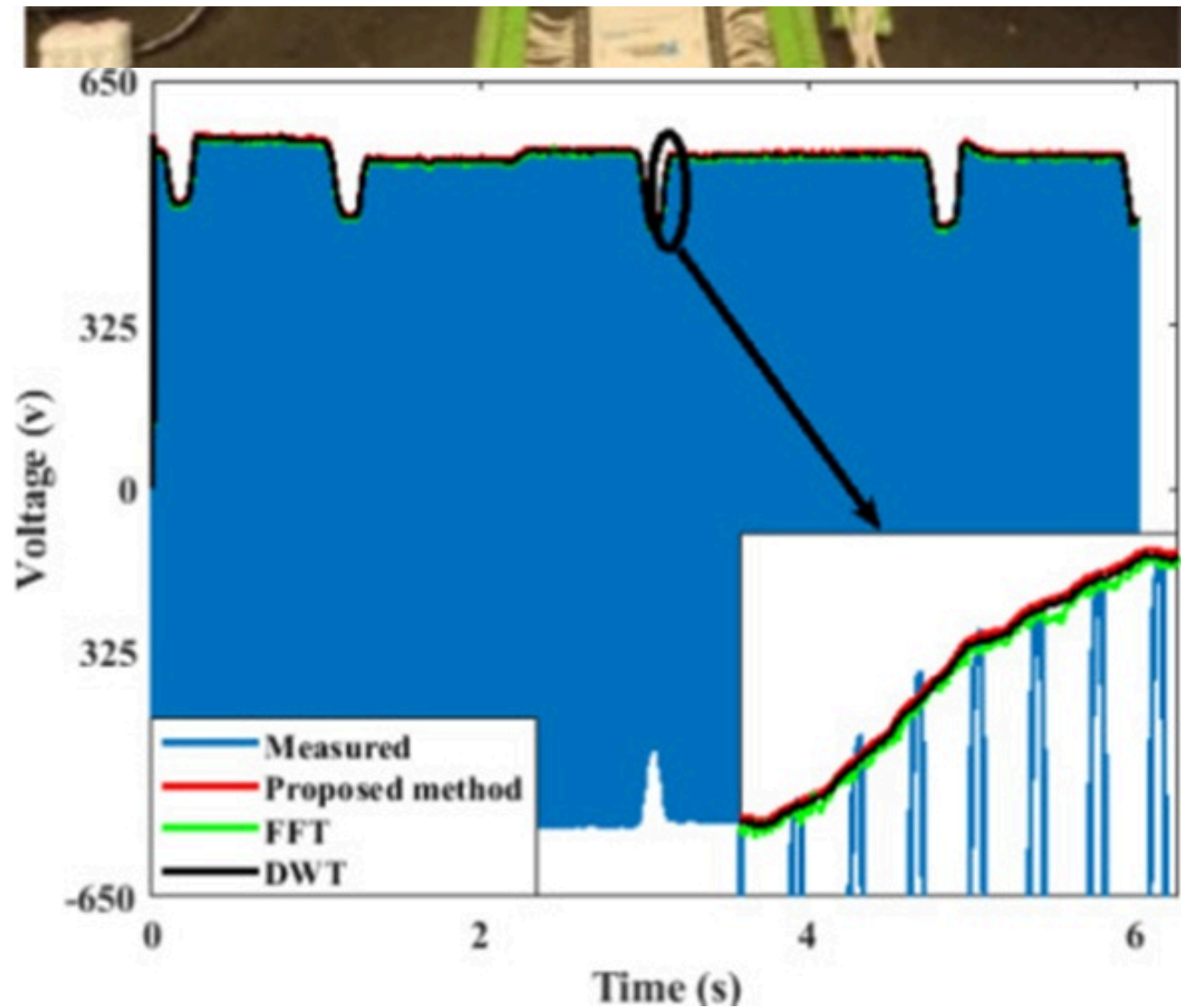


Figure 11. Comparative analysis of the experimental voltage signal processed by the different estimation methods.

Table 6. Quantitative performance evaluation based on real-world recorded data.

System	Approach	MSE	Variance	Computation Time
Infinite feeder	Proposed technique	7.776e−6	5.911e−6	0.3812 s
	FFT method	4.367e−5	1.019e−4	0.4182 s
	DWT method	7.8115e−6	7.381e−5	0.8338 s
Emergency diesel	Proposed technique	1.912e−4	4.54e−4	0.4290 s
	FFT method	3.007e−3	5.672e−4	0.4194 s
	DWT method	2.716e−4	4.705e−4	0.8627 s

Parameter selection and optimization

The effectiveness of the proposed H_∞ -ADALINE technique hinges on the careful selection of several critical parameters. For the H_∞ filter, the weighting matrices and the regularization parameter λ were determined in accordance with established design guidelines to strike an appropriate balance between strong resistance to measurement noise and guaranteed stability. The adopted values ensure that the estimation error remains bounded while maintaining adequate responsiveness to time-varying disturbances.

For the ADALINE network, the initial learning rate θ_0 and the decay factor β (Eq. 17) were adjusted based on a detailed sensitivity study. Higher values of θ_0 accelerate convergence but can lead to oscillatory or unstable behavior, whereas lower values promote greater stability at the expense of slower adaptation. The parameter set ultimately chosen in this work delivered a satisfactory compromise between speed and reliability, as confirmed through Monte Carlo simulation trials conducted in accordance with the test conditions outlined in IEC 61000-4-15.

Although manual parameter adjustment produced acceptable performance, more rigorous and systematic optimization techniques — including Bayesian optimization, genetic algorithms, or adaptive gain-scheduling strategies — could yield even greater robustness, particularly when scaling to large systems or operating under highly variable conditions. The integration of such automated tuning procedures is planned for consideration in subsequent research.

Scalability and feasibility considerations

Although the proposed H_∞ -ADALINE hybrid method has been thoroughly evaluated within the flicker frequency band specified by IEC standards (0.5–25 Hz), its inherently recursive and computationally lightweight structure indicates strong potential for scaling to extensive distribution networks. The H_∞ filter involves only iterative matrix operations at each time step. At the same time, the ADALINE network employs a straightforward single-layer design that requires no pre-training, making both components well aligned with the constraints of real-time power quality monitoring hardware.

That said, very large or highly interconnected power systems pose additional challenges, including intricate harmonic interactions, interharmonics, and asynchronous disturbances, all of which may compromise estimation precision. Furthermore, extending the method's scope to frequencies beyond 25 Hz — for example, into the supraharmonic range — would likely require adjustments to the ADALINE basis set or the incorporation of multi-resolution analysis techniques to resolve higher-frequency phenomena adequately.

Consequently, while the proposed approach is conceptually well-positioned for application at broader grid scales and elevated frequency regimes, forthcoming investigations will prioritize empirical testing with field measurements and further algorithmic refinements to improve robustness in complex network environments.

Conclusion

The present paper proposes an innovative algorithm specifically developed to accurately estimate the flicker frequency components embedded in voltage waveforms, effectively addressing the challenges posed by the large number of involved frequencies. The developed technique successfully separates the voltage signal into its envelope and harmonic constituents, thereby substantially simplifying the overall estimation task. A robust H_∞ filter is employed to reliably recover the envelopes, after which an online ADALINE neural network efficiently identifies the flicker components contained within them. In addition, a comprehensive voltage waveform model is introduced that simultaneously accounts for flicker, harmonic distortion, and additive white noise, enabling a thorough evaluation of the algorithm's performance.

Both graphical visualizations and quantitative metrics confirm the superior capability of the proposed method in faithfully tracking flicker phenomena in power systems. Extensive Monte Carlo simulations further substantiate its resilience across a wide range of harmonic and flicker conditions consistent with IEC Standard 61000-4-15. Real-world validation using recorded fluctuating voltage measurements from an industrial setting demonstrates that the proposed approach

surpasses conventional FFT and DWT techniques in terms of Mean Squared Error (MSE), error variance, and computational demand.

Among the principal advantages of the method are its strong immunity to measurement noise, fast convergence that supports real-time operation, and modest computational footprint well suited to resource-limited embedded devices. Taken together, these characteristics make the proposed technique highly suitable for deployment in industrial power-quality monitoring applications.

Notwithstanding these strengths, the method has certain limitations. The reliance on a predefined, standard-compliant frequency grid may limit precision when flicker components fall between grid points. Moreover, the experimental validation has so far focused on die-casting machine loads, limiting immediate generalizability to other industrial environments. The current model also does not explicitly account for the dynamic response characteristics of contemporary lighting technologies, particularly LED systems.

Directions for future research include investigations into the effects of higher-order harmonics, additional flicker components, and interharmonics. Exploring alternative online adaptive neural architectures — such as Recurrent Neural Networks (RNNs) operating in an online mode or Echo State Networks — may offer improvements in both estimation accuracy and processing speed. Furthermore, adapting the model to reflect better the flicker behavior induced by modern LED lighting systems is a valuable and timely research objective.

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Conflict of interest

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References

- IEEE application guide for IEEE standard for interconnecting distributed resources with electric power systems. IEEE Std 1547.2-2008. IEEE; 2008.
- Kuwalek P. Estimation of parameters associated with individual sources of voltage fluctuations. *IEEE Trans Power Deliv*. 2015;36:351-61.
- Farhan M, Reza TN, Badal FR, Islam MR, Muyeen SM, Tasneem Z, et al. Towards next generation internet of energy system: Framework and trends. *Energy AI*. 2023;14:100306.
<https://doi.org/10.1016/j.egyai.2023.100306>.
- Mitchell D, Blanche J, Harper S, Lim T, Gupta R, Zaki O, et al. A review: Challenges and opportunities for artificial intelligence and robotics in the offshore wind sector. *Energy AI*. 2022;8:100146.
<https://doi.org/10.1016/j.egyai.2022.100146>.
- Bucci G, Fiorucci E, Ciancetta F. The performance evaluation of IEC flicker meters in realistic conditions. *IEEE Trans Instrum Meas*. 2008;57:2443-9.
- Kukačka L, Dupuis P, Vik M, Richter A, Zissis G. Confidence intervals for luminous flicker measurements: Comparison of various approaches. *IEEE Trans Ind Appl*. 2021;57:5499-506.
- IEC. Electromagnetic compatibility (EMC)—Part 4-15 testing and measurement techniques—flickermeter—functional and design specifications. IEC Std. 61000-4-15. 2010:1-58.
- Wiczyński G. Estimation of Pst indicator values on the basis of voltage fluctuation indices. *IEEE Trans Instrum Meas*. 2017;66:2046-55.
- IEC Report: Flickermeter. Functional and Design Specifications. IEC 80 868-0. 1986.
- Li F, Ye M. Calculation of Flicker Parameters Using Voltage Interharmonics. In: 2012 Asia-Pacific Power and Energy Engineering Conference. Shanghai, China; 2012. P. 1-4.
- Zakaria D, Sunarno E, Anggriawan DO, Putra Ganda W. Real Time Voltage Flicker Detection Based on Fast Fourier Transform. In: 2019 International Electronics Symposium (IES). Surabaya, Indonesia; 2019. p. 164-9.
- Li Y, Gao Y, Feng Y, Cao Y, Zhu Y. Improved analytic energy operator and novel three-spectral line interpolation DFT method for parameter estimation of voltage flicker. *IEEE Trans Ind Inform*. 2024;20(1):327-36.
<https://doi.org/10.1109/TII.2023.3261885>.
- Chen MT. Digital algorithms for measurement of voltage flicker. *IEE Proc Gener Trans Distrib*. 1997;144:175-80.
- Marei MI, El-Saadany EF, Salama MMA. Estimation techniques for voltage flicker envelope tracking. *Electr Power Syst Res*. 2004;70:30-7.
- Abdel-Galil TK, El-Saadany EF, Salama MMA. Online tracking of voltage flicker utilizing energy operator and Hilbert transform. *IEEE Trans Power Deliv*. 2004;19:861-7.
- Falehi AD, Rafiee M. LVRT/HVRT capability enhancement of DFIG wind turbine using optimal design and control of novel PI λ μ -AMLI based DVR. *Sustain Energy Grids Netw*. 2018;16:111-25.

Li F, Gao Y, Cao Y, Iravani R. Improved Teager energy operator and improved chirp-z transform for parameter estimation of voltage flicker. *IEEE Trans Power Deliv.* 2016;31:245-53.

Yao W, Tang Q, Teng Z, Gao Y, Wen H. Fast S-transform for time-varying voltage flicker analysis. *IEEE Trans Instrum Meas.* 2014;63:72-9.

Enayati J, Moravej Z. Real-time harmonic estimation using a novel hybrid technique for embedded system implementation. *Int Trans Electr Energy Syst.* 2017;27:1-13.

Sun J, Aboutanios E, Smith DB, Fletcher JE. Robust frequency, phase, and amplitude estimation in power systems considering harmonics. *IEEE Trans Power Deliv.* 2020;35:1158-68.

Duda K, Zieliński TP, Bień A, Barczentewicz SH. Harmonic phasor estimation with flat-top FIR filter. *IEEE Trans Instrum Meas.* 2020;69:2039-47.

Dai Z, Lin W. Adaptive estimation of three-phase grid voltage parameters under unbalanced faults and harmonic disturbances. *IEEE Trans Power Electron.* 2017;32:5613-27.

Enayati J, Moravej Z. Real-time harmonics estimation in power systems using a novel hybrid algorithm. *IET Gener Transm Distrib.* 2017;11:3532-8.

Garanayak P, Naayagi RT, Panda G. A high-speed master-slave ADALINE for accurate power system harmonic and inter-harmonic estimation. *IEEE Access.* 2020;8:51918-32.

Saleh SA. Phaselet transform based approach for detecting voltage flickers due to distributed generation units. *IEEE Trans Ind Appl.* 2018;54:5278-92.

Saleh SA. The extended Newton–phaselet method for determining the reactive power from the active power in single-phase systems. *IEEE Trans Ind Appl.* 2016;52:1297-307.

Sun D, Gao Q, Lu Y, Zhu M. A sparse representation-based algorithm for the voltage fluctuation detection of power system. *Digit Signal Process.* 2016;48:259-68.

Kuwalek P. AM modulation signal estimation allowing further research on sources of voltage fluctuations, *IEEE Trans Ind Electron.* 2020;67:6937-45.

Yang X, Kratz X. Power system flicker analysis by RMS voltage values and numeric flicker meter emulation. *IEEE Trans Power Deliv.* 2009;24:1310-8.

Geiger DL, Halpin SM. Assessing voltage fluctuations and lamp flicker using RMS voltages. *IEEE Trans Power Deliv.* 2017;32:2481-8.

Balouji E, Salor O. Digital realisation of the IEC flickermeter using root mean square of the voltage waveform. *IET Gener Transm Distrib.* 2016;10:1663-70.

Cho SH, Park CH, Han J, Jang G. A waveform distortion evaluation method based on a simple half-cycle RMS calculation. *IEEE Trans Power Deliv.* 2012;27:1461-7.

Eghtedarpour N, Farjah E, Khayatani A. Intelligent identification of flicker source in distribution systems. *IET Gener Transm Distrib.* 2010;4:1016-27.

Moghadam BH, Abbasi M, Tousi B. A new method with minimum number of monitoring points for flicker source tracing by wavelet transform. *Int Trans Electr Energy Syst.* 2019;29:e12057.
<https://doi.org/10.1002/2050-7038.12057>.

Samet H, Khosravi M, Ghanbari T, Tajdinian M. A two-level neural network approach for flicker source location. *Comput Electr Eng*. 2021;92:107157.

<https://doi.org/10.1016/j.compeleceng.2021.107157>.

Kose N, Salor O, Leblebicioglu K. Kalman filtering based approach for light flicker evaluation of power systems. *IET Gener Transm Distrib*. 2011;5:57-69.

Al-Hamadi HM. Fuzzy logic voltage flicker estimation using Kalman filter. *Int J Electr Power Energy Syst*. 2012;36:60-7.

Salor N, Leblebicioglu O, Leblebicioglu K. Interharmonics analysis of power signals with fundamental frequency deviation using Kalman filtering. *Electr Power Syst Res*. 2010;80:1145-53.

Pramanik M, Routray A, Mitra P. A two-stage adaptive symmetric-strong-tracking square-root cubature Kalman filter for harmonics and interharmonics estimation. *Electr Power Syst Res*. 2022;210:108133.

Enayati J, Asef P, Yousefi A, Benoit A. A novel AI-driven hybrid method for flicker estimation in power systems. In: 7th International Conference on Smart Energy Systems and Technologies. Torino, Italy; 2024. (ResearchGate:

https://www.researchgate.net/publication/384062811_A_Novel_AI-driven_Hybrid_Method_for_Flicker_Estimation_in_Power_Systems

Li W, Jia Y. H-infinity filtering for a class of nonlinear discrete-time systems based on unscented transform. *Signal Process*. 2010;90(12):3301-7.

<https://doi.org/10.1016/j.sigpro.2010.05.023>.

Marei MI, El-Saadany EF, Salama MMA. An intelligent control for the DG interface to mitigate voltage flicker. In: Eighteenth Annual IEEE Applied Power Electronics Conference and Exposition (APEC '03). Miami Beach, FL, USA; 2003(1):179-83.

<https://doi.org/10.1109/APEC.2003.1179211>.

Sujith M, Padma S. Optimization of harmonics with active power filter based on ADALINE neural network. *Microprocess Microsyst*. 2020;73:102976.

<https://doi.org/10.1016/j.micpro.2019.102976>.

Zai Peng, Goh Radzi, Mohd Amran Mohd, Hizam Hashim, Abdul Wahab, Noor Izzri. A simple predictive method of critical flicker detection for human health precaution. *Math Probl Eng*. 2015:871826:10.

Dash PK, Swain DP, Routray A, Liew AC. Harmonic estimation in a power system using adaptive perceptrons. *IEE Proc Gener Transm Distrib*. 1996;143:565-74.

Simon D. Optimal state estimation: Kalman, H_∞ , and nonlinear approaches. Hoboken, NJ, USA: Wiley. ISBN: 978-0-471-70858-2. 2006.

Carbajala FB, Olvera RT. An adaptive neural online estimation approach of harmonic components. *Electr Power Syst Res*. 2020;186:106406.

Moravej Z, Enayati J. A hybrid least squares-clonal selection based algorithm for harmonic estimation. *Int Trans Electr Energy Syst*. 2014;12:1-15.

<https://doi.org/10.1002/etep.1676>.

Xu J, Qian H, Hu Y, Bian S, Xie S. Overview of SOGI-based single-phase phase-locked loops for grid synchronization under complex grid conditions. *IEEE Access*. 2021;9:39275-91.

Enayati J, Rahimnejad A, Gadsden SA. LED reliability assessment using a novel Monte Carlo-based algorithm. *IEEE Trans Device Mater Reliab*. 2021;21:338-47.

Enayati J, Sarhadi P, Rad MP, Zarini M. Monte Carlo simulation method for behavior analysis of an autonomous underwater vehicle. *J Eng Marit Environ*. 2015;230:481-90.

Matthews C, Clarkson P, Harris PM, Ihlenfeld WGK, Wright PS. Evaluation of flicker measurement uncertainties by a Monte Carlo method. *IEEE Trans Instrum Meas*. 2011;60:2255-61.
<https://doi.org/10.1109/TIM.2011.2139270>.

Almeida FS, Silveira FH, Visacro S. Stopping criterion for Monte Carlo method-based simulations of the lightning performance of transmission line. *Electr Power Syst Res*. 2023;214:108797.

Ferrero A, Salicone S, Toscani S. A fast, simplified frequency-domain interpolation method for the evaluation of the frequency and amplitude of spectral components. *IEEE Trans Instrum Meas*. 2011;60(5):1579-87.

Xu Y, Yi H, Zhang W, Xu H. An improved CZT algorithm for high-precision frequency estimation. *Appl Sci*. 2023;13:1907.
<https://doi.org/10.3390/app13031907>.