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RESEARCH ARTICLE

Multi-Objective Optimization of Passive Filters in DG-Integrated Distribution Networks Utilizing Dynamic EMT-Based Co-Simulation

AHMED TALEB MOHAMED¹, AHMED F. ZOBAA², (Senior Member, IEEE),
AHMED TELBA³, (Senior Member, IEEE), AND MOHAMED MAHMOUD SAMY⁴

¹Department of Electrical Power Engineering, Faculty of Engineering, Cairo University, Giza 12613, Egypt

²College of Engineering, Design and Physical Sciences, Brunel University of London, UB8 3PH Uxbridge, U.K.

³Department of Electrical Engineering, College of Engineering, King Saud University (KSU), Riyadh 11421, Saudi Arabia

⁴Department of Electrical Engineering, Faculty of Engineering, Beni-Suef University, Beni-Suef 62511, Egypt

Corresponding author: Ahmed F. Zobaa (azobaa@ieee.org)

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ABSTRACT The increasing penetration of distributed generation (DG) introduces variability in network impedance and harmonic emissions that can degrade the performance of passive harmonic filters designed for nominal operating conditions. This paper develops a reliability-oriented C-type filter synthesis framework that couples the Secretary Bird Optimization Algorithm (SBOA) with MATLAB–PSCAD electromagnetic transient (EMT) co-simulation. Candidate filter parameters are evaluated directly from simulated point-of-common-coupling (PCC) voltage waveforms under Monte Carlo realizations of grid impedance, background harmonic distortion, DG harmonic injection, and component tolerances. Probabilistic constraints are imposed on total and individual voltage harmonic distortion, while a conditional value-at-risk metric and lifecycle cost are considered as optimization objectives. The resulting design is compared with conventional and optimization-based benchmark filters under a common EMT-based evaluation framework. For the investigated medium-voltage distribution system, the optimized filter reduces PCC total voltage harmonic distortion (TVHD) to approximately 2.5%, with no limit violations observed in the considered Monte Carlo samples, while also improving power factor and reducing system and filter losses. The results indicate that incorporating EMT-based scenario evaluation into filter synthesis can improve harmonic-compliance margins under the uncertainties considered in this study.

INDEX TERMS Dynamic co-simulation optimization, distributed generation, electromagnetic transient analysis, passive harmonic filters, secretary bird optimization.

NOMENCLATURE

R	Filter damping resistance.
L	Filter inductance.
C_m	Main filter capacitance.
C_a	Auxiliary filter capacitance.
Z_{tl}	Transmission-line impedance.
Z_d	Demand-side impedance.
Z_f	C-type filter impedance.
V_g	Background grid harmonic voltage.

I_{dg}	DG harmonic-current injection.
$V_{PCC,1}$	Fundamental-frequency PCC voltage.
Q_c	Filter reactive-power rating.
Q_f	Filter quality factor.
n_t	Filter tuning order.
$\mathbf{x}$	Filter decision vector.
ξ	Uncertainty scenario vector.
$\mathcal{H}$	Considered harmonic-order set.
N_{MCS}	Number of Monte Carlo scenarios.
Ψ	Required chance-constraint satisfaction probability.
α	CVaR upper-tail fraction.

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$\hat{P}_T$	Empirical TVHD satisfaction probability.
$\hat{P}_D$	Empirical DVHD satisfaction probability.
f_1	Harmonic-risk objective.
f_2	Lifecycle-cost objective.
IC	Filter investment cost.
CE	Filter operating cost.
PL	Transmission-line power loss.
FPL	Filter power loss.
N_{pop}	Population size.
N_{iter}	Maximum iteration number.
N_w	Number of parallel EMT workers.
λ	Normalized sensitivity perturbation.

I. INTRODUCTION

The increasing penetration of power-electronic interfaces, nonlinear loads, and renewable energy-based distributed generation (DG) has intensified harmonic distortion in modern power systems. Harmonic currents generated by nonlinear devices and converter-interfaced resources can deteriorate power quality, increase system losses, accelerate equipment thermal aging, and contribute to electromagnetic interference [1], [2], [3], [4], [5]. Additional DG-related harmonic emissions may also contribute to cable derating, transformer overheating, increased losses, and malfunction of sensitive equipment [6], [7], [8]. Consequently, voltage harmonic distortion at the point of common coupling (PCC) must be assessed using standardized total and individual harmonic indices in accordance with applicable requirements such as IEEE Standards 519 and 1547 [9], [10].

Passive harmonic filters remain an economically attractive and widely adopted solution for harmonic mitigation [11], [12]. Conventional synthesis procedures generally determine filter parameters for specified network conditions and harmonic spectra; however, their performance can deteriorate when actual operating conditions deviate from those assumed during design [13]. Treating network impedance and harmonic spectra as fixed quantities [14] may therefore produce filter parameters that are sensitive to subsequent operating-point variations [15], particularly in DG-integrated networks.

This sensitivity has motivated probabilistic and uncertainty-aware filter-design approaches [16], [17], [18], consistent with harmonic-assessment frameworks that account for variations in emissions and operating conditions [10], [19], [20]. Probabilistic synthesis based on statistical harmonic modeling was investigated in [21], while stochastic filter optimization was considered in [22]. Renewable DG effects on harmonic-constrained filter design were further examined in [23]. In addition to system-level uncertainty, deviations between designed and implemented component values arising from manufacturing tolerances, environmental effects, measurement uncertainty, and numerical approximation can alter filter tuning and damping characteristics [24].

Metaheuristic techniques have also been increasingly applied to passive-filter design and harmonic mitigation. The crow spiral-based search algorithm and Dragonfly Algorithm have been employed for passive-filter parameter optimization and combined harmonic-power-factor objectives [25], [26], while other population-based methods have been developed to improve exploration and exploitation in nonlinear optimization problems [27], [28]. More recent passive-filter studies have incorporated multi-objective and uncertainty-aware formulations [29], [30], [31], [32], [33]. Despite these advances, candidate performance in most reported approaches is still determined using static or harmonic-domain representations rather than by directly evaluating the corresponding EMT response under simultaneous network, harmonic-source, and component uncertainties.

EMT-based and hybrid co-simulation frameworks provide a means of incorporating detailed time-domain responses into system-level analysis and parameter synthesis. Foundational studies established the numerical basis for coupling detailed EMT models with complementary simulation domains, including synchronization, boundary representation, and data exchange [34], while more recent work has examined the accuracy and sensitivity of EMT co-simulation with respect to interface configuration, synchronization settings, and FFT-based data transformation [35]. Synchronized MATLAB–PSCAD loops have also been employed for iterative parameter optimization using EMT feedback [36], [37]. In particular, [36] applied closed-loop EMT evaluation to C-type passive-filter parameter optimization, whereas [37] demonstrated the same EMT-in-the-loop design principle for optimized shunt compensation. However, reliability-oriented passive-filter synthesis in which candidate feasibility and optimization objectives are determined directly from EMT responses under simultaneous network, harmonic-source, and component uncertainties remains insufficiently addressed.

To address this gap, this paper couples the Secretary Bird Optimization Algorithm (SBOA) with synchronized MATLAB–PSCAD co-simulation for C-type passive-filter synthesis in DG-integrated power systems. Each candidate design is evaluated through PSCAD EMT simulation under sampled realizations of grid impedance, background harmonic distortion, DG harmonic injection, and component tolerances. The resulting EMT-in-the-loop implementation, referred to as dynamic SBOA (DSBOA), retains the underlying SBOA search mechanism while determining candidate feasibility and objective values from the corresponding time-domain responses. Probabilistic harmonic constraints, CVaR-based tail-risk assessment, and lifecycle cost are incorporated into the multi-objective formulation. The main contributions of this work are summarized as follows:

- 1) A synchronized MATLAB–PSCAD EMT-in-the-loop framework that evaluates candidate C-type filter parameters directly from PCC time-domain responses.
- 2) A probabilistic formulation that incorporates uncertainties in grid impedance, background harmonic distortion, DG harmonic injection, and filter-component

parameters through Monte Carlo evaluation and chance constraints.

- 3) A multi-objective DSBOA formulation that combines CVaR-based harmonic tail-risk assessment and lifecycle cost while directly optimizing the physical C-type filter parameters.
- 4) A comparative evaluation of the proposed and benchmark designs under a common EMT-based assessment procedure considering harmonic distortion, limit exceedance, power factor, losses, and economic performance.

II. SYSTEM REPRESENTATION AND HARMONIC DISTORTION CHARACTERIZATION

This section defines the studied network, C-type filter model, harmonic-performance indices, and uncertainty representation used in the subsequent optimization. Harmonic performance is evaluated at the PCC shown in Figure 1 using total voltage harmonic distortion (TVHD) and individual voltage harmonic distortion (DVHD), with the corresponding limits adopted from [9], [10], [19], [20]. Variations in network impedance, harmonic-source characteristics, and filter-component parameters are represented probabilistically.

The system architecture and its harmonic-domain equivalent are illustrated in Figs. 1 and 2, respectively. The upstream network and connected demand are represented by the transmission-line impedance $Z_{tl}(n)$ and demand-side impedance $Z_d(n)$. To account for variations associated with operating-point changes, network reconfiguration, and parameter estimation, these impedances are bounded as $Z_{tl}(n) \in [Z_{tl}^-(n), Z_{tl}^+(n)]$ and $Z_d(n) \in [Z_d^-(n), Z_d^+(n)]$. The upstream background harmonic voltage is similarly represented by $V_g(n) \in [V_g^-(n), V_g^+(n)]$, while the DG harmonic-current injection is bounded as $I_{dg}(n) \in [I_{dg}^-(n), I_{dg}^+(n)]$. These intervals define the uncertainty ranges considered in the subsequent probabilistic evaluation. The filter impedance $Z_f(n)$ is determined by the main capacitor C_m , auxiliary capacitor C_a , inductor L , and damping resistor R . Their tolerance-induced variations are represented by δC_m , δC_a , δL , and δR , such that $Z_f = f(R + \delta R, L + \delta L, C_m + \delta C_m, C_a + \delta C_a)$, with $Z_f(n) \in [Z_f^-(n), Z_f^+(n)]$. The C-type topology has been widely applied in high-voltage direct-current installations, including the France–England interconnection and the Intermountain–Quebec–New England corridors [38], [39], [40]. At the fundamental frequency, the auxiliary capacitor C_a and inductor L are tuned to resonance, providing a low-impedance bypass around the damping resistor and thereby limiting its fundamental-frequency power loss. At harmonic frequencies, the branch impedance changes, allowing the damping resistor to contribute to harmonic attenuation and resonance suppression.

Accordingly, the C-type topology combines tuned filtering and damping characteristics [40], [41], [42], [43]. Let n denote the harmonic order, with X_{C_m} and X_{C_a} representing the

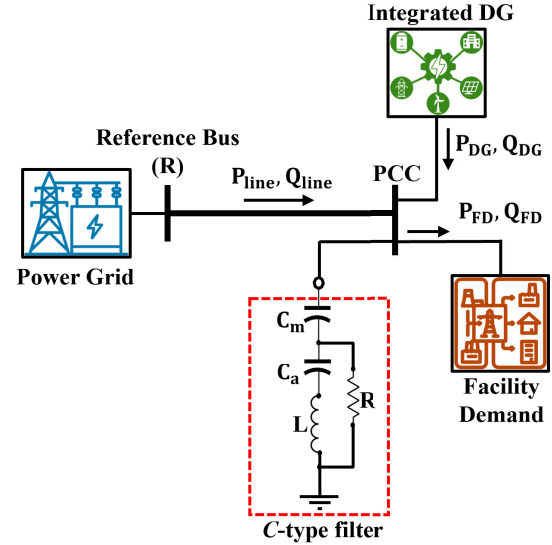


FIGURE 1. Simplified representation of the distribution system.

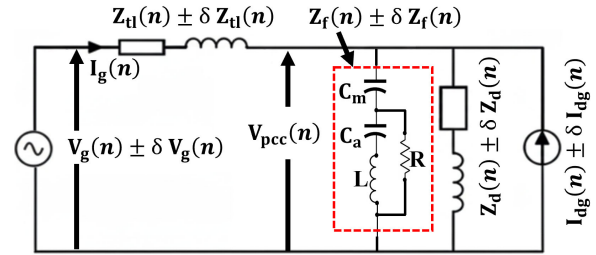


FIGURE 2. Harmonic-domain equivalent circuit of the studied network incorporating bounded uncertainties in grid voltage, system impedance, DG harmonic injection, and C-type passive filter parameters.

fundamental-frequency reactances of the main and auxiliary capacitors, respectively. Since C_m is connected in series with the parallel combination of the damping resistor and the tuned C_a - L branch, the resulting filter impedance is expressed as

$$Z_f(n) = -j \frac{X_{C_m}}{n} + \frac{RjX \left(n - \frac{1}{n} \right)}{R + jX \left(n - \frac{1}{n} \right)}. \quad (1)$$

The filter parameters are derived according to established C-type design principles [44], [45]. Resonance between the inductor and auxiliary capacitor at the fundamental frequency is imposed through

$$jX_L - jX_{C_a} = 0, \quad (2)$$

which gives $X_{C_a} = X_L = X$. The main capacitor C_m is selected according to the reactive power required for the desired displacement power-factor (DPF) correction:

$$X_{C_m} = \frac{V_{PCC,1}^2}{Q_c}, \quad (3)$$

where

$$Q_c = P_1 \left[\tan \left(\cos^{-1}(\text{DPF}_{\text{act}}) \right) - \tan \left(\cos^{-1}(\text{DPF}_{\text{des}}) \right) \right]. \quad (4)$$

Here, $V_{PCC,1}$ is the root-mean-square fundamental PCC voltage, P_1 is the corresponding active power, and DPF_{act} and DPF_{des} denote the actual and desired displacement power factors, respectively.

For a selected tuning order n_t , the harmonic tuning condition is

$$jn_t X - j\frac{X}{n_t} - j\frac{X_{C_m}}{n_t} = 0, \quad (5)$$

which yields the fundamental-frequency reactance

$$X = \frac{X_{C_m}}{n_t^2 - 1}. \quad (6)$$

The damping resistor R is then determined from the quality factor Q_f as

$$R = \frac{n_t X}{Q_f}. \quad (7)$$

Thus, Q_c , n_t , and Q_f govern the compensation level, tuning location, and damping characteristic of the filter, respectively.

Using the uncertainty bounds introduced above, the grid voltage is represented as a Thevenin source containing the fundamental component and bounded background harmonics:

$$V_g = V_g(1) + (A_{BGH} + \delta A_{BGH}) \sum_{n>1} V_s(n), \quad (8)$$

where $A_{BGH} \in [A_{BGH}^-, A_{BGH}^+]$ denotes the bounded background harmonic-distortion factor. The transmission-line and demand-side impedances are represented compactly as

$$Z_i(n) \in [Z_i^-(n), Z_i^+(n)], \quad i \in \{tl, d\}. \quad (9)$$

The DG harmonic-current components are modeled as

$$I_{dg}(n) = (A_n + \delta A_n) I_{dg}(1), \quad n > 1, \quad (10)$$

where $A_n \in [A_n^-, A_n^+]$ denotes the corresponding harmonic-current ratio obtained from FFT-based harmonic characterization.

The resulting PCC voltage distortion is quantified using TVHD

$$TVHD = \frac{\sqrt{\sum_{n>1} V_{PCC}^2(n)}}{V_{PCC,1}}, \quad (11)$$

and the individual voltage harmonic distortion at harmonic order n

$$DVHD_n = \frac{V_{PCC}(n)}{V_{PCC,1}}, \quad n > 1. \quad (12)$$

The corresponding deterministic harmonic constraints are

$$TVHD \leq TVHD_{\max}, \quad DVHD_n \leq DVHD_{\max}. \quad (13)$$

The adopted limits are $TVHD_{\max} = 5\%$ and $DVHD_{\max} = 3\%$, respectively [29].

Under the sampled uncertainties, these deterministic limits are imposed probabilistically. The TVHD chance constraint is

$$P(TVHD \leq TVHD_{\max}) \geq \Psi, \quad (14)$$

where $\Psi = 95\%$ is the adopted satisfaction probability. The corresponding per-order DVHD constraint is

$$P(DVHD_n \leq DVHD_{\max}) \geq \Psi, \quad n > 1. \quad (15)$$

The optimization therefore searches for the filter parameters $\{R, L, C_a, C_m\}$ that satisfy the prescribed probabilistic harmonic constraints while balancing harmonic-performance risk and lifecycle cost, as formulated in Section III.

III. DSBOA-DRIVEN EMT CO-SIMULATION FRAMEWORK

The filter-synthesis problem is formulated with two competing objectives: harmonic-performance risk and filter lifecycle cost. The physical C-type filter parameters are generated by SBOA and evaluated under sampled realizations of the network, harmonic-source, and component uncertainties defined in Section II. Unlike conventional candidate evaluation based solely on nominal or harmonic-domain conditions, each candidate-scenario pair is assessed directly through the PSCAD EMT model.

Optimization techniques previously applied to passive-filter design include Artificial Bee Colony (ABC) [29], Teaching-Learning-Based Optimization (TLBO) [30], particle swarm optimization (PSO) [31], Interactive Forest Algorithm (IFA) [32], and SBOA [33]. In the proposed framework, the underlying SBOA search mechanism is retained, while its candidate-evaluation stage is replaced by the EMT-Monte Carlo procedure described below. This EMT-in-the-loop implementation is referred to as DSBOA.

SBOA is a population-based metaheuristic that alternates between exploration and exploitation stages to search the admissible solution space [28]. The exploration stage promotes movement toward different candidate regions, whereas the exploitation stage refines the search around better-performing solutions. In the present implementation, the decision variables are defined directly in terms of the physical C-type filter parameters:

$$\mathbf{x} = [R, L, C_a, C_m]^T. \quad (16)$$

For each candidate $\mathbf{x}$, the uncertain quantities are assembled into the scenario vector ξ . Consistent with the uncertainty representation introduced in Section II, one realization is expressed as

$$\xi = [Z_{tl}(n), Z_d(n), V_g(n), I_{dg}(n), \delta R, \delta L, \delta C_a, \delta C_m]^T, \quad n \in \mathcal{H}. \quad (17)$$

where $\mathcal{H}$ denotes the set of dominant harmonic orders considered for the per-order DVHD constraints and the corresponding tail-risk assessment. In this study,

$$\mathcal{H} = \{5, 7, 11, 13\}. \quad (18)$$

TVHD is evaluated from the complete nonfundamental spectrum included in the FFT analysis, whereas the individual DVHD constraints are imposed for $n \in \mathcal{H}$.

For a given pair $(\mathbf{x}, \xi)$, the candidate filter parameters and uncertainty realization are transferred to PSCAD, where the

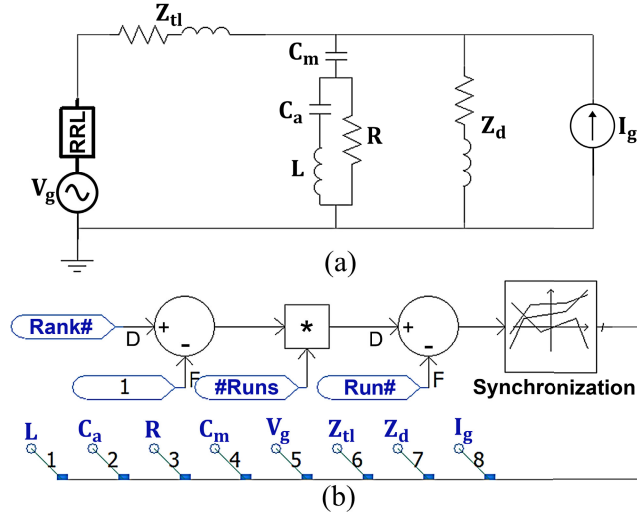


FIGURE 3. Closed-loop MATLAB-PSCAD EMT co-simulation framework: (a) DG-integrated system with the C-type filter and uncertain network parameters; (b) synchronization and data exchange for transferring candidate and scenario parameters to PSCAD and returning EMT-based performance indices to MATLAB.

corresponding EMT simulation is executed using the system shown in Figure 3(a). The PCC voltage $v_{PCC}(t)$ is recorded, and FFT analysis is applied to a steady-state segment to obtain the fundamental component $V_{PCC,1}$ and the nonfundamental harmonic components. The resulting distortion indices are

$$TVHD(\mathbf{x}, \xi) = \frac{\sqrt{\sum_{n>1} V_{PCC,n}^2}}{V_{PCC,1}}, \quad (19)$$

$$DVHD_n(\mathbf{x}, \xi) = \frac{V_{PCC,n}}{V_{PCC,1}}, \quad n \in \mathcal{H}. \quad (20)$$

All candidate-scenario evaluations use identical EMT and harmonic-extraction settings. The PSCAD simulation time step is $83.33 \mu\text{s}$, corresponding to a sampling frequency of 12 kHz. Each EMT case is simulated for 0.25 s, and FFT analysis is performed over the final five fundamental cycles, corresponding to an 83.33-ms window containing 1000 samples over the interval 0.1667–0.2500 s. The integer-cycle steady-state window is retained for all candidate designs and uncertainty realizations to ensure a consistent harmonic comparison.

Probabilistic compliance is evaluated using Monte Carlo sampling. For each candidate $\mathbf{x}$, let N_{MCS} denote the number of sampled uncertainty realizations and $\{\xi_k\}_{k=1}^{N_{MCS}}$ the corresponding scenario set. The empirical satisfaction probability of the TVHD constraint is

$$\hat{P}_T(\mathbf{x}) = \frac{1}{N_{MCS}} \sum_{k=1}^{N_{MCS}} \mathbb{I}(TVHD(\mathbf{x}, \xi_k) \leq TVHD_{\max}), \quad (21)$$

and the per-order DVHD satisfaction probabilities are

$$\hat{P}_D(n; \mathbf{x}) = \frac{1}{N_{MCS}} \sum_{k=1}^{N_{MCS}} \mathbb{I}(DVHD_n(\mathbf{x}, \xi_k) \leq DVHD_{\max}), \quad n \in \mathcal{H}. \quad (22)$$

The chance constraints are enforced as

$$\hat{P}_T(\mathbf{x}) \geq \Psi, \quad \hat{P}_D(n; \mathbf{x}) \geq \Psi, \quad \forall n \in \mathcal{H}, \quad (23)$$

where Ψ denotes the required satisfaction probability. In this study, $\Psi = 95\%$ and $N_{MCS} = 100$ realizations are used for each candidate evaluation within the optimization loop. The adequacy of this sample size is subsequently examined through an independent Monte Carlo convergence analysis using progressively larger scenario sets.

In addition to the chance constraints, the optimization considers the upper-tail harmonic performance of the sampled scenarios. A conditional value-at-risk (CVaR) metric is therefore used to characterize severe distortion realizations within the Monte Carlo set. Using an upper-tail fraction of $\alpha = 5\%$, the harmonic-risk objective is defined as

$$f_1(\mathbf{x}) = CVaR_\alpha \left(\{TVHD(\mathbf{x}, \xi_k)\}_{k=1}^{N_{MCS}} \right) + \max_{n \in \mathcal{H}} CVaR_\alpha \left(\{DVHD_n(\mathbf{x}, \xi_k)\}_{k=1}^{N_{MCS}} \right). \quad (24)$$

The second objective represents the filter lifecycle cost and is defined as

$$f_2(\mathbf{x}) = TC_{\text{filter}}(\mathbf{x}) = IC(\mathbf{x}) + CE(\mathbf{x}), \quad (25)$$

where $IC(\mathbf{x})$ denotes the investment cost and $CE(\mathbf{x})$ represents the operating energy-loss cost. The investment cost is modeled as

$$IC(\mathbf{x}) = k_1 R + k_2 L + k_3 (C_m + C_a), \quad (26)$$

and the operating cost is expressed as

$$CE(\mathbf{x}) = 8760 \left(\frac{(1+T)^y - 1}{T(1+T)^y} \right) k_4 FPL, \quad (27)$$

where k_1 , k_2 , k_3 , and k_4 are the cost coefficients associated with the damping resistor, inductor, capacitor components, and energy losses, respectively. The adopted values are $k_1 = 5 \text{ pu}/\Omega$, $k_2 = 3 \text{ pu}/\text{mH}$, $k_3 = 2 \text{ pu}/\mu\text{F}$, and $k_4 = 0.1 \text{ pu}/\text{kW}$ [33], [46]. The interest rate is $T = 0.05$, and the assumed filter lifetime is $y = 15$ years [47]. The filter power loss FPL is obtained from the EMT steady-state response.

The two objectives are treated using Pareto dominance rather than being combined through fixed weighting coefficients. At each iteration, feasible candidates are compared in the (f_1, f_2) objective space, and the non-dominated solutions are retained in an external Pareto archive. A feasible solution $\mathbf{x}_a$ dominates $\mathbf{x}_b$ if

$$f_j(\mathbf{x}_a) \leq f_j(\mathbf{x}_b), \quad j \in \{1, 2\}, \quad (28)$$

with a strict inequality for at least one objective. To remove the effect of different objective scales, the archived objective values are normalized as

$$\tilde{f}_j(\mathbf{x}) = \frac{f_j(\mathbf{x}) - f_j^{\min}}{f_j^{\max} - f_j^{\min}}, \quad j \in \{1, 2\}, \quad (29)$$

where $f_j^{\min}$ and $f_j^{\max}$ are the minimum and maximum archived values of the j th objective.

The reported compromise design is selected from the Pareto archive using a knee-point criterion. Let $\mathbf{p}^{(1)}$ and $\mathbf{p}^{(2)}$ denote the two extreme normalized Pareto solutions. For each non-dominated solution $\mathbf{p}_i$, its perpendicular distance from the line connecting the two extreme points is calculated as

$$d_i = \frac{|(\mathbf{p}^{(2)} - \mathbf{p}^{(1)}) \times (\mathbf{p}^{(1)} - \mathbf{p}_i)|}{\|\mathbf{p}^{(2)} - \mathbf{p}^{(1)}\|}, \quad (30)$$

and the solution with the maximum d_i is selected as the knee-point compromise. This criterion identifies the design providing the strongest trade-off between harmonic risk and lifecycle cost before further improvement in one objective requires a disproportionate deterioration in the other.

For the population update at iteration t , the search leader $\mathbf{x}_{\text{best}}^{(t)}$ is selected from the current Pareto archive $\mathcal{A}^{(t)}$ using the same normalized maximum-distance criterion. The selected archive member therefore provides the reference position for the exploration and exploitation operators. The DSBOA population is denoted by $\{\mathbf{x}_i\}_{i=1}^{N_{\text{pop}}}$. During exploration, candidate positions are updated according to

$$\mathbf{x}_i^{(t+1)} = \mathbf{x}_i^{(t)} + r_1 (\mathbf{x}_{\text{best}}^{(t)} - \mathbf{x}_i^{(t)}) + r_2 (\mathbf{x}_{\text{rand}}^{(t)} - \mathbf{x}_i^{(t)}), \quad (31)$$

where $\mathbf{x}_{\text{rand}}^{(t)}$ is a randomly selected candidate and $r_1, r_2 \in (0, 1)$ are uniformly distributed random coefficients. During exploitation, the candidate update is expressed as

$$\mathbf{x}_i^{(t+1)} = \mathbf{x}_{\text{best}}^{(t)} + r_3 (\mathbf{x}_{\text{best}}^{(t)} - \mathbf{x}_i^{(t)}), \quad (32)$$

where $r_3 \in (0, 1)$ controls the magnitude of the local update around the selected search leader.

The resulting framework explicitly separates the search and evaluation stages. The SBOA operators generate new candidate filter parameters, while the EMT-Monte Carlo layer determines their harmonic performance, probabilistic feasibility, and objective values. Pareto dominance governs archive retention, the current knee-point solution provides the search leader, and the final reported design is selected from the terminal Pareto archive using the same compromise criterion.

To ensure implementability, each design variable is constrained within practical bounds:

$$\begin{aligned} R &\in [R_{\min}, R_{\max}], & L &\in [L_{\min}, L_{\max}], \\ C_a &\in [C_{a,\min}, C_{a,\max}], & C_m &\in [C_{m,\min}, C_{m,\max}]. \end{aligned} \quad (33)$$

The search bounds are derived from established C-type filter design criteria [38], [45]. The quality factor is restricted to $0.01 \leq Q_f \leq 0.5$, and the tuning order to $3.75 \leq n_t \leq 5.75$. The main-capacitor reactive power is limited to $942.23 \leq Q_c \leq 1429.8$ kVAR, corresponding to displacement power-factor targets between 0.95 and 1.0 from an initial value of $\text{DPF}_{\text{act}} = 0.7165$ [10].

The adopted uncertainty ranges define the scenario space explored during optimization and therefore influence the resulting harmonic-performance distributions and feasible region. Their combined effects are evaluated through Monte

Algorithm 1 DSBOA-Based Reliability-Oriented C-Type Filter Synthesis Through Monte Carlo-Driven EMT Co-Simulation

Require: Harmonic set $\mathcal{H} = \{5, 7, 11, 13\}$; chance level Ψ ; limits $\text{TVHD}_{\max}$ and $\text{DVHD}_{\max}$; DSBOA settings ($N_{\text{pop}} = 20, N_{\text{iter}} = 20$); $N_{\text{MCS}} = 100$; $N_w = 16$; bounds for $\mathbf{x} = [R, L, C_a, C_m]^T$ and ξ ; CVaR tail fraction α ; constraint penalties.

Ensure: Selected compromise design $\mathbf{x}^*$, final Pareto archive, and associated harmonic-risk and cost metrics.

- 1: **Initialization:** Generate $\{\mathbf{x}_i^{(0)}\}_{i=1}^{N_{\text{pop}}}$ within the admissible bounds; compile the PSCAD project once and initialize N_w independent workers.
- 2: Set $t \leftarrow 0$.
- 3: **while** $t < N_{\text{iter}}$ **do**
- 4: **for** $i = 1$ to N_{pop} **do**
- 5: Generate N_{MCS} uncertainty realizations $\{\xi_{i,k}\}_{k=1}^{N_{\text{MCS}}}$ for candidate $\mathbf{x}_i^{(t)}$.
- 6: **end for**
- 7: Form the candidate-scenario job set $\mathcal{J}^{(t)} = \{(i, k) \mid i = 1, \dots, N_{\text{pop}}, k = 1, \dots, N_{\text{MCS}}\}$ and distribute the jobs among the N_w PSCAD workers while retaining indices (i, k) .
- 8: **for** $(i, k) \in \mathcal{J}^{(t)}$ **do**
- 9: Transfer $(\mathbf{x}_i^{(t)}, \xi_{i,k})$ to PSCAD, execute the EMT simulation, and record $v_{\text{PCC}}(t)$.
- 10: Apply FFT to the steady-state window; obtain $V_{\text{PCC},1}$ and $V_{\text{PCC}}(n)$; compute TVHD and DVHD $_n, \forall n \in \mathcal{H}$.
- 11: Return the performance indices and associated (i, k) identifiers to MATLAB.
- 12: **end for**
- 13: Synchronize all returned results and regroup them by candidate.
- 14: **for** $i = 1$ to N_{pop} **do**
- 15: Compute $\hat{P}_T(\mathbf{x}_i^{(t)})$ and $\hat{P}_D(n; \mathbf{x}_i^{(t)})$ from the N_{MCS} scenario results.
- 16: Determine feasibility using the chance constraints; assign penalties to infeasible candidates.
- 17: Compute the CVaR-based harmonic-risk objective $f_1(\mathbf{x}_i^{(t)})$ and lifecycle-cost objective $f_2(\mathbf{x}_i^{(t)})$.
- 18: **end for**
- 19: Update the external Pareto archive $\mathcal{A}^{(t)}$ using feasible non-dominated candidates.
- 20: Normalize the current Pareto objectives and select $\mathbf{x}_{\text{best}}^{(t)}$ using the maximum perpendicular-distance criterion.
- 21: Generate $\mathbf{x}_i^{(t+1)}$ using the DSBOA exploration/exploitation operators and project out-of-bound variables onto the admissible ranges.
- 22: Set $t \leftarrow t + 1$.
- 23: **end while**
- 24: Normalize the final Pareto objectives and select the knee-point compromise $\mathbf{x}^*$ using the maximum perpendicular-distance criterion.
- 25: **Output:** Return $\mathbf{x}^*$, the final Pareto archive, and the associated reliability and cost metrics.

Carlo sampling, while Section IV separately examines the individual influence of the principal EMT-model parameters through a one-at-a-time sensitivity analysis over the same prescribed ranges.

Algorithm 1 summarizes the computational procedure. MATLAB supervises DSBOA population updates, Monte Carlo scenario generation, and objective and constraint

evaluation, while PSCAD executes the EMT simulations. Candidate–scenario evaluations are parallelized using $N_w = 16$ workers, corresponding to the 16 physical cores of the AMD Ryzen 9 7950X processor. The PSCAD project is compiled once, after which each worker operates an independent simulation instance based on the compiled model. At each iteration, $N_{pop} = 20$ candidates and $N_{MCS} = 100$ uncertainty realizations generate 2000 independent EMT jobs distributed among the workers. For each pair $(\mathbf{x}_i, \xi_{i,k})$, the parameters are transferred to PSCAD and the resulting PCC response and harmonic indices are returned to MATLAB with their candidate and scenario identifiers.

After all EMT evaluations of an iteration are completed, the results are synchronized and regrouped by candidate. MATLAB then computes the chance-constraint probabilities, CVaR-based harmonic-risk objective, lifecycle cost, and feasibility status before Pareto archive updating, search-leader selection, and generation of the next population. Thus, the independent EMT evaluations are executed in parallel, whereas the DSBOA iterations remain sequential because the population at iteration $t + 1$ depends on the completed evaluation of iteration t .

With $N_{MCS} = 100$, $N_{pop} = 20$, and $N_{iter} = 20$, one optimization run comprises 40,000 candidate–scenario EMT evaluations. Under the 16-worker configuration, the measured wall-clock time is approximately 5–7 minutes on a workstation equipped with an AMD Ryzen 9 7950X processor and 64 GB of RAM. This runtime excludes the one-time PSCAD compilation and parallel-environment initialization, but includes job dispatch, EMT execution, MATLAB–PSCAD data exchange, harmonic extraction, synchronization, probabilistic assessment, and DSBOA updates. Ten independent optimization runs were performed under the same computational configuration to assess run-to-run repeatability. The reported design is selected using the prescribed Pareto knee-point criterion, while the statistical variation across the ten runs is reported separately in Section IV. The subsequent Monte Carlo convergence analysis further examines the adequacy of $N_{MCS} = 100$.

IV. PERFORMANCE EVALUATION AND COMPARATIVE DISCUSSION

The proposed framework is evaluated using a benchmark medium-voltage, three-phase industrial distribution system adopted in previous harmonic-filter studies [10], [33], [38]. The system supplies dominant inductive loads rated at 5100 kW and 4965 kVAR and operates at a fundamental frequency of 60 Hz with a nominal line-to-neutral voltage of 2.4 kV. Harmonic emissions from the upstream grid and DG units are modeled as time-invariant sources subject to a $\pm 10\%$ uncertainty margin, consistent with the variability ranges considered in [48] and [49].

Closed-loop MATLAB–PSCAD optimization has also been employed in recent EMT-based design studies [36], [37]. Reference [36] directly incorporated PSCAD EMT feedback into multi-objective C-type passive-filter parameter

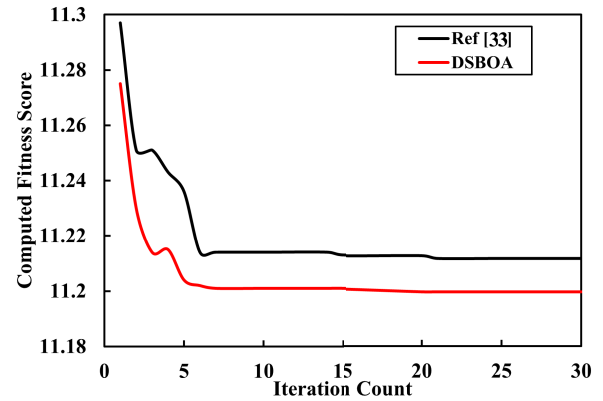


FIGURE 4. Comparative convergence profiles of DSBOA and SBOA [33] over 20 iterations.

TABLE 1. Optimized C-type filter parameters obtained by different methods.

Method	R (Ω)	C_m (μF)	C_a (μF)	L (mH)
Ref. [25]	1.7	859.3	6668.2	1.06
Ref. [26]	6.2	504.1	2087.2	3.4
Ref. [38]	13.0	967.1	16273.5	0.4
Ref. [45]	8.3	507.5	8024.3	0.9
Ref. [33]	47.3	753.9	18303.3	0.4
DSBOA	54.6	812.1	20415.6	0.2

optimization, while [37] applied the same EMT-in-the-loop design principle to optimized shunt-compensation parameters. Although the physical applications differ, both studies demonstrate the methodological role of EMT simulation as an internal candidate evaluator rather than solely as a post-design validation tool. In the present comparative assessment, all benchmark filter designs are evaluated using the same system model, harmonic limits, and performance indices to provide a consistent basis for comparison.

Figure 4 compares the convergence profiles of DSBOA and the SBOA implementation reported in [33]. DSBOA exhibits a faster reduction in the fitness value during the initial iterations and reaches a near-stationary value of approximately 11.20 within the first six iterations. Only negligible changes are observed thereafter, supporting the adopted maximum iteration number of $N_{iter} = 20$.

For a balanced comparison, all benchmark methods are evaluated using identical system data, harmonic limits, and performance indices.

Table 1 lists the C-type filter parameters obtained using the different design methods. The resulting component values vary considerably among the methods, reflecting differences in their optimization formulations and design criteria. Their electrical performance is compared in Table 4, while the corresponding lifecycle-cost components are summarized in Table 3.

To evaluate the repeatability of the stochastic optimization process, ten independent DSBOA runs were performed using identical population size, iteration limit, uncertainty

TABLE 2. Statistical performance over ten independent DSBOA runs.

Metric	Best	Mean	Std.	Worst
TVHD (%)	2.50	2.54	0.06	2.64
Max. DVHD (%)	2.35	2.39	0.05	2.48
Cost (p.u.)	48047.9	48610.4	782.6	50018.7

TABLE 3. Lifecycle-cost decomposition of the compared filter designs.

Method	Investment cost <i>IC</i> (p.u.)	Operating cost <i>CE</i> (p.u.)	Total cost (p.u.)
Ref. [25]	15066.7	86078.3	101145.0
Ref. [26]	5223.8	35328.3	40552.1
Ref. [38]	34547.4	23693.1	58240.5
Ref. [45]	17107.8	39872.3	56980.1
Ref. [33]	38352.1	17101.0	55453.1
DSBOA	42729.0	5318.9	48047.9

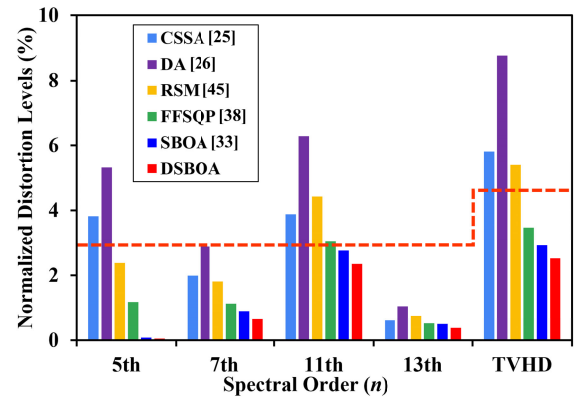
TABLE 4. Performance comparison of the proposed DSBOA with reference methods.

Method	PF (%)	TVHD (%)	PL (kW)	FPL (kW)
Ref. [25]	98.9	5.8	11.0	9.5
Ref. [26]	94.1	8.8	11.5	3.9
Ref. [38]	96.4	4.2	12.9	2.1
Ref. [45]	97.1	3.8	12.0	2.0
Ref. [33]	98.5	2.9	11.0	1.9
DSBOA	99.34	2.5	9.0	1.2

model, and computational settings but independent initial populations. Table 2 summarizes the resulting feasible run-level solutions. The final TVHD values exhibit a mean of 2.54% and a standard deviation of 0.06%, while the maximum DVHD has a mean of 2.39% with a standard deviation of 0.05%. The corresponding lifecycle cost varies around a mean of 48610.4 p.u. with a standard deviation of 782.6 p.u. All ten selected run-level solutions satisfy the adopted harmonic constraints, indicating limited run-to-run dispersion. The selected knee-point design from the retained optimization result is used for the detailed comparative and sensitivity analyses presented subsequently.

Table 3 decomposes the lifecycle cost using the common formulation in Eqs. (25)–(27). The DSBOA design does not minimize the investment component alone; its *IC* is higher than that of several benchmark designs because of the selected physical component combination. However, its substantially lower filter power loss reduces the operating-cost contribution to 5318.9 p.u., compared with 17101.0 p.u. for SBOA. Consequently, the total lifecycle cost decreases from 55453.1 p.u. for SBOA to 48047.9 p.u. for DSBOA. This decomposition clarifies that the economic advantage of the selected design is primarily associated with the long-term loss reduction rather than with minimum initial investment.

Ref. [33] represents the closest methodological benchmark because it combines SBOA with Monte Carlo uncertainty evaluation and probabilistic passive-filter constraints. The principal distinction is therefore not the underlying SBOA

**FIGURE 5.** Spectral analysis of voltage harmonics and TVHD compared against established grid standards (red dashed line).

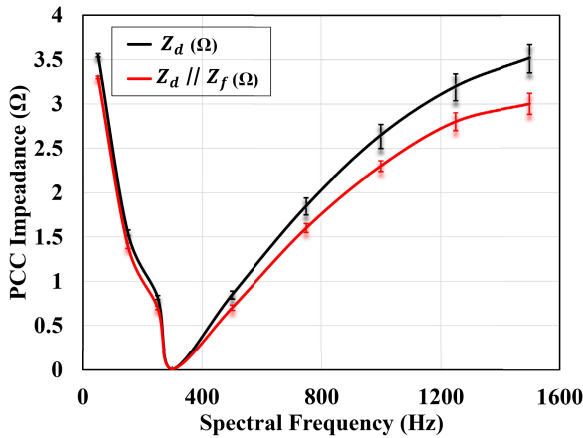
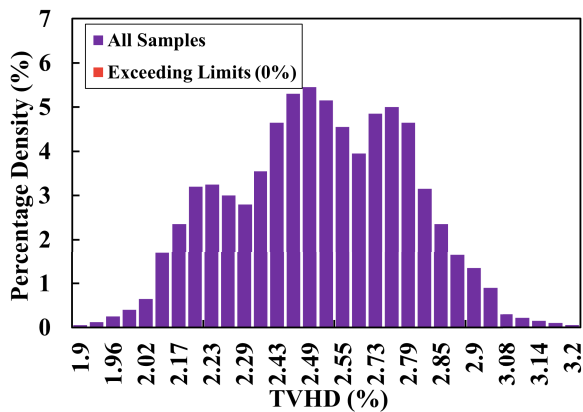
search mechanism, but the candidate-evaluation environment. In Ref. [33], candidate performance is obtained from the harmonic-domain system formulation, whereas the proposed DSBOA evaluates each candidate–scenario pair directly through the PSCAD EMT model. The resulting cost difference should consequently be interpreted together with the optimized component selection and associated operating losses. As shown in Table 3, the DSBOA design does not minimize initial investment alone; instead, its lower filter losses substantially reduce the lifecycle operating-cost component, yielding a lower total lifecycle cost than the SBOA benchmark.

Table 4 compares the displacement power factor (PF), TVHD, transmission-line power loss (PL), and filter power loss (FPL) obtained using the crow spiral-based search algorithm (CSSA) [25], Dragonfly Algorithm (DA) [26], feasible sequential quadratic programming (FFSQP) [38], response surface methodology (RSM) [45], Secretary Bird Optimization Algorithm (SBOA) [33], and the proposed DSBOA. The DSBOA design achieves a PF of 99.34%, TVHD of 2.5%, PL of 9.0 kW, and FPL of 1.2 kW. Among the evaluated designs, it therefore provides the highest PF and the lowest TVHD, PL, and FPL. Its TVHD also remains below the adopted limit in [10], whereas the CSSA and DA designs exceed this limit. The cost is lower than those obtained using CSSA, FFSQP, RSM, and SBOA, although DA yields a lower cost with higher harmonic distortion and losses.

Table 5 further compares the optimization characteristics of the benchmark methods. The approaches in [25], [26], [38] determine candidate performance from deterministic harmonic-domain models, while [45] employs response-surface approximations to reduce the repeated solution of the underlying network equations. Reference [33] extends passive-filter optimization to probabilistic uncertainty assessment using SBOA and Monte Carlo sampling, although candidate evaluation remains based on the harmonic-domain system representation. In the proposed framework, the SBOA search mechanism is retained, but each candidate–scenario pair is evaluated directly through the closed-loop MATLAB–PSCAD EMT model. Consequently,

TABLE 5. Comparison of passive-filter optimization frameworks.

Criterion	Ref. [25]	Ref. [26]	Ref. [38]	Ref. [45]	Ref. [33]	This work
Optimization method	CSSA	DA	FFSQP	RSM	SBOA	DSBOA
Candidate evaluation	Harmonic domain	Harmonic domain	Harmonic domain	Response surface	Harmonic domain	EMT time domain
Uncertainty treatment	Deterministic	Deterministic	Deterministic	Deterministic	Probabilistic	Probabilistic
Optimization coupling	Static	Static	Static	Surrogate based	Static	Closed-loop EMT
Design objective	Single	Single	Single	Multi-criteria	Multi-criteria	Multi-objective
Risk-aware evaluation	No	No	No	No	Probabilistic constraints	CVaR + chance constraints

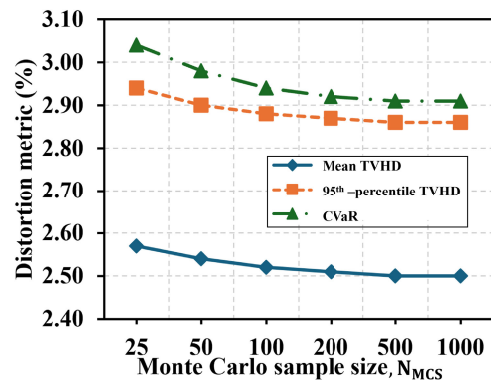

FIGURE 6. Impedance-frequency scan at PCC.

FIGURE 7. Empirical probability distribution of TVHD under Monte Carlo uncertainty evaluation.

candidate feasibility and ranking are determined from the resulting time-domain responses through chance constraints and CVaR-based harmonic-risk assessment. Together with the quantitative comparisons in Tables 1–4, this distinction explains the different optimization outcomes obtained by the investigated methods.

Figure 5 compares the PCC voltage distortion obtained using DSBOA with the benchmark designs CSSA [25], DA [26], FFSQP [38], RSM [45], and SBOA [33]. The comparison includes DVHD at the 5th, 7th, 11th,

TABLE 6. Monte Carlo sample-size convergence for the selected DSBOA filter.

N_{MCS}	Mean TVHD (%)	95th-percentile TVHD (%)	CVaR (%)	$\hat{P}_T$ (%)	$\min \hat{P}_D$ (%)
25	2.57	2.94	3.04	100	100
50	2.54	2.90	2.98	100	100
100	2.52	2.88	2.94	100	100
200	2.51	2.87	2.92	100	100
500	2.50	2.86	2.91	100	100
1000	2.50	2.86	2.91	100	100


FIGURE 8. Convergence of the Monte Carlo statistical estimates with increasing sample size for the selected DSBOA filter.

and 13th harmonic orders together with TVHD. The DSBOA design limits the 5th harmonic to 0.05%, compared with 3.82%, 5.31%, 2.38%, 1.18%, and 0.08% for CSSA, DA, RSM, FFSQP, and SBOA, respectively. The corresponding 7th, 11th, and 13th harmonic components are 0.65%, 2.35%, and 0.38%, while TVHD is reduced to 2.5%. Relative to SBOA [33], the resulting TVHD reduction is approximately 13.7%.

Figure 6 shows the PCC impedance-frequency characteristics before and after filter connection. Before compensation, the equivalent impedance Z_d increases with frequency over the investigated range. After connecting the filter, the equivalent impedance $Z_d \parallel Z_f$ exhibits a pronounced minimum near 300 Hz, corresponding to the 5th harmonic of the 60-Hz system. The compensated impedance also remains below the uncompensated characteristic over much of the

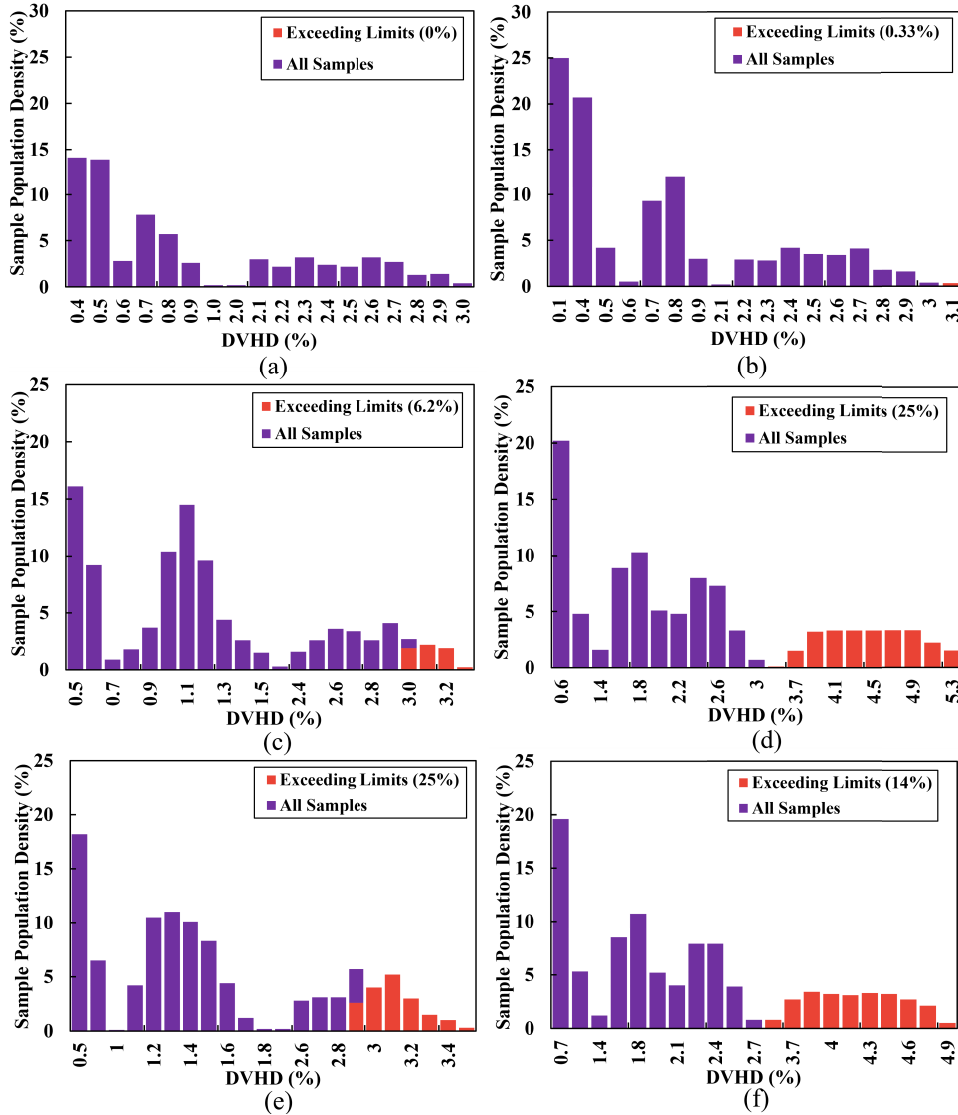


FIGURE 9. Empirical probability distributions of DVHD under Monte Carlo uncertainty evaluation for (a) the proposed DSBOA-based synthesis, (b) SBOA [33], (c) FFSQP [38], (d) RSM [45], (e) CSSA [25], and (f) DA [26].

higher-frequency range, indicating that the filter modifies the PCC impedance profile beyond its principal tuning region.

Figure 7 presents the empirical TVHD distribution obtained from the Monte Carlo evaluation. The samples are concentrated around 2.5%, with most realizations lying between approximately 2.2% and 2.9%. No sample exceeds the adopted IEEE 519–2022 TVHD limit within the considered Monte Carlo set.

To examine the sensitivity of the probabilistic assessment to the Monte Carlo sample size, the selected DSBOA filter is additionally evaluated using an independent set of 1000 uncertainty realizations generated from the same uncertainty model adopted during optimization. The statistical indices are computed cumulatively for $N_{MCS} \in \{25, 50, 100, 200, 500, 1000\}$. The assessment considers the mean TVHD, 95th-percentile TVHD, upper-tail CVaR, empirical TVHD satisfaction probability $\hat{P}_T$, and minimum

per-order DVHD satisfaction probability $\min_{n \in \mathcal{H}} \hat{P}_D(n)$. These quantities characterize the central, upper-tail, and probabilistic-feasibility properties that directly influence the proposed reliability-oriented formulation.

As shown in Table 6 and Figure 8, the Monte Carlo estimates progressively stabilize as the sample size increases. The differences are more pronounced for the smaller sets of 25 and 50 realizations, whereas only minor changes are observed from $N_{MCS} = 100$ onward. The mean TVHD changes from 2.52% at $N_{MCS} = 100$ to 2.50% at $N_{MCS} = 1000$, while the 95th-percentile TVHD changes from 2.88% to 2.86% and the upper-tail CVaR from 2.94% to 2.91%. Relative to the 1000-sample reference, these deviations are approximately 0.80%, 0.70%, and 1.03%, respectively. The maximum relative deviation among the considered distortion-based statistical indices at $N_{MCS} = 100$ is therefore approximately 1.03%. Moreover, both $\hat{P}_T$ and $\min_{n \in \mathcal{H}} \hat{P}_D(n)$

remain unchanged, preserving the feasibility classification of the selected filter across the investigated sample sizes.

These results support the use of $N_{MCS} = 100$ for repeated candidate evaluation within the optimization loop. With $N_{pop} = 20$ and $N_{iter} = 20$, this setting requires 40,000 EMT evaluations per optimization run, whereas increasing N_{MCS} to 500 or 1000 would increase this requirement to 200,000 or 400,000 evaluations, respectively. The adopted sample size therefore provides a balance between the observed statistical convergence and the computational burden of EMT-in-the-loop optimization, while the independent 1000-sample evaluation provides additional verification of the selected design.

Figure 9 compares the empirical DVHD distributions obtained using DSBOA and the benchmark designs CSSA [25], DA [26], FFSQP [38], RSM [45], and SBOA [33]. No DVHD exceedance is observed for the DSBOA design within the considered samples. In contrast, the benchmark methods exhibit different exceedance levels, with the SBOA design [33] showing the smallest nonzero exceedance among them and larger exceedances observed for FFSQP [38], RSM [45], CSSA [25], and DA [26].

To complement the joint uncertainty assessment provided by the Monte Carlo analysis, an additional one-at-a-time EMT parameter sensitivity study is performed for the selected DSBOA filter. The transmission-line impedance Z_{tl} , demand-side impedance Z_d , background harmonic voltage V_g , DG harmonic-current injection I_{dg} , and filter parameters R , L , C_a , and C_m are independently varied over the same uncertainty bounds adopted in the optimization. For each parameter, five normalized perturbation levels $\lambda \in \{-1, -0.5, 0, 0.5, 1\}$ are considered, where $\lambda = -1$ and $\lambda = 1$ represent the lower and upper prescribed bounds, respectively, while all remaining parameters are maintained at their nominal values. For Z_{tl} and Z_d , the resistive and reactive components are varied proportionally to preserve the corresponding impedance angle. The background and DG harmonic components are similarly varied within their prescribed amplitude ranges. Since the nominal operating point is common to all parameters, the complete analysis requires 33 independent EMT simulations.

Figure 10 and Table 7 show that the EMT response exhibits different sensitivities to the investigated parameters. The filter inductance L and main capacitance C_m produce the largest variations because they directly affect the filter tuning characteristic, followed by the background harmonic voltage V_g . In contrast, the damping resistance R has the smallest influence over its prescribed variation range. Relative to the nominal TVHD of 2.50% and maximum DVHD of 2.35%, the largest observed relative variations are approximately 11.6% and 14.0%, respectively.

Across all investigated parameter variations, the maximum TVHD and maximum DVHD are 2.79% and 2.68%, respectively, both remaining below the adopted limits of 5% and 3%. The closest approach to the individual harmonic limit therefore retains a margin of approximately 0.32 percentage points, and no individual parameter variation changes

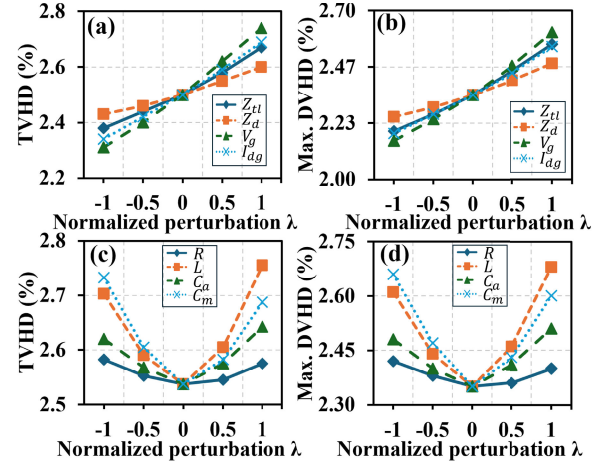


FIGURE 10. EMT-based parameter sensitivity of the selected DSBOA filter: (a) TVHD under network and harmonic-source variations; (b) maximum DVHD under network and harmonic-source variations; (c) TVHD under filter-component variations; and (d) maximum DVHD under filter-component variations.

TABLE 7. EMT-based sensitivity of the selected DSBOA filter.

Parameter	Max. TVHD (%)	Max. DVHD (%)	Max. Δ TVHD (%)	Max. Δ DVHD (%)
Z_{tl}	2.67	2.56	6.8	8.9
Z_d	2.60	2.48	4.0	5.5
V_g	2.74	2.61	9.6	11.1
I_{dg}	2.69	2.55	7.6	8.5
R	2.56	2.42	2.4	3.0
L	2.79	2.68	11.6	14.0
C_a	2.64	2.51	5.6	6.8
C_m	2.76	2.66	10.4	13.2

the compliance classification of the selected filter. This parameter-wise EMT analysis complements the Monte Carlo results in Figs. 7 and 9: the former isolates the influence of individual physical parameters, whereas the latter evaluates their simultaneous stochastic variation.

Figure 11 shows the final non-dominated trade-off between the harmonic-risk objective f_1 and lifecycle-cost objective f_2 . Each point represents a Pareto-feasible design retained by the optimization. The selected design corresponds to the knee point identified using the normalized maximum-distance criterion in Eq. (30). This solution provides the strongest compromise between the two objectives before further reduction in harmonic risk requires a disproportionately larger increase in lifecycle cost.

To examine the influence of the cost coefficients, Figure 12 presents a local sensitivity analysis around the nominal values of k_1 , k_2 , k_3 , and k_4 adopted from [33] and [46]. The resulting changes in TVHD and total cost remain limited over the investigated coefficient ranges, and the selected solution remains close to the trade-off region identified in Figure 11.

The present validation is limited to offline EMT co-simulation and therefore should not be interpreted as experimental verification. The use of a common PSCAD model for all benchmark designs, together with

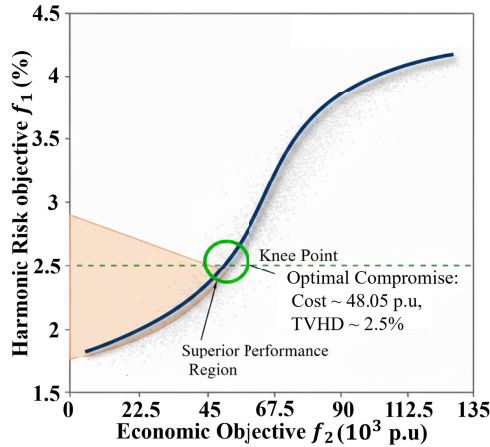


FIGURE 11. Pareto trade-off between harmonic-risk objective f_1 and lifecycle-cost objective f_2 , with the selected knee-point compromise identified using the normalized maximum-distance criterion.

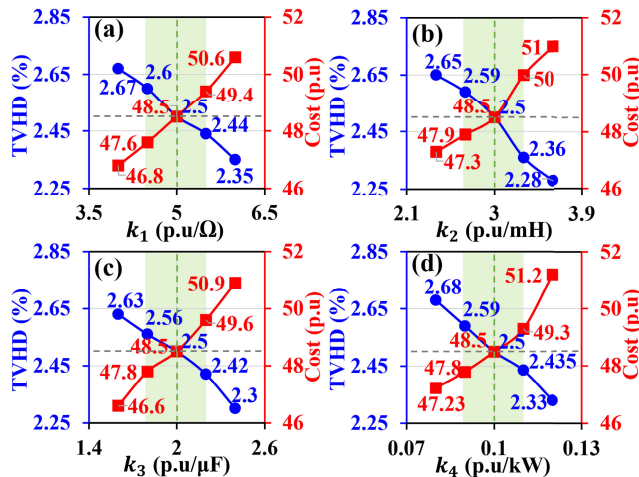


FIGURE 12. Local sensitivity of the selected DSBOA solution to the adopted cost-weighting factors: (a) k_1 , (b) k_2 , (c) k_3 , and (d) k_4 .

the Monte Carlo convergence, repeated-run optimization statistics, and EMT parameter-sensitivity analyses, provides numerical verification within the scope of the proposed computational framework. Nevertheless, laboratory-scale or real-time hardware-in-the-loop validation would provide an additional assessment of implementation effects associated with measurement, controller execution, and physical component nonidealities. Such validation is therefore identified as the next stage of this work, consistent with the use of real-time platforms for passive-filter assessment reported in [41].

V. CONCLUSION

This work developed an EMT-in-the-loop, reliability-oriented synthesis framework for C-type passive harmonic filters in DG-integrated distribution systems. The proposed DSBOA implementation retains the underlying SBOA search mechanism while evaluating candidate feasibility and objective values directly from PSCAD time-domain responses under sampled network, harmonic-source, and component uncertainties. The final design is selected from the

resulting Pareto set using a defined knee-point compromise criterion.

For the investigated system, the selected filter reduces PCC TVHD to 2.5%, approximately 13.7% below the SBOA benchmark, while no TVHD or DVHD limit exceedance is observed within the considered Monte Carlo samples. The design also achieves a PF of 99.34%, transmission-line and filter losses of 9.0 kW and 1.2 kW, respectively, and a lifecycle cost of 48047.9 p.u. The Monte Carlo sample-size study shows that the principal statistical indices change by no more than approximately 1.03% between $N_{MCS} = 100$ and the 1000-sample reference, while the EMT parameter-sensitivity analysis confirms that the adopted harmonic limits remain satisfied over the investigated uncertainty ranges. Repeated optimization runs further indicate limited run-to-run dispersion.

These results indicate that embedding scenario-dependent EMT evaluation within passive-filter optimization can improve the robustness of candidate assessment when harmonic performance is evaluated under compounded uncertainty. The present validation remains computational and does not replace experimental verification; future work will therefore extend the framework to laboratory-scale or hardware-in-the-loop implementation.

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DATA ACCESS STATEMENT

The data underpinning this study were generated through computational modeling and simulation. The data are available from the corresponding author upon reasonable request, subject to any applicable restrictions.

REFERENCES

- [1] M. Mahdavi, A. Bagheri, A. Soleimani, A. Pinnarelli, F. Jurado, and A. Awafo, "Effects of changing consumer demand on distributed generation and grid optimization," *IEEE Access*, vol. 13, pp. 93798–93817, 2025.
- [2] G. A. Landbrug, G. G. Dranka, and R. V. De Oliveira, "Voltage control approach with dynamic voltage reference for PV distributed generation operating under cloud-induced shading conditions," *IEEE Access*, vol. 13, pp. 49092–49106, 2025.
- [3] V. Porobic, I. Todorovic, I. Isakov, K. Kyslan, and D. Jerkan, "Integrated framework for development, emulation, and testing of high-level converter control functions for distributed generation sources," *IEEE Access*, vol. 9, pp. 145852–145865, 2021.
- [4] J. Li, X. Zhou, Y. Zhou, and A. Han, "Optimal configuration of distributed generation based on an improved Beluga whale optimization," *IEEE Access*, vol. 12, pp. 31000–31013, 2024.
- [5] J. Cheng, L. Wang, and T. Pan, "Optimized configuration of distributed power generation based on multi-stakeholder and energy storage synergy," *IEEE Access*, vol. 11, pp. 129773–129787, 2023.
- [6] A. T. Mohamed, A. El-Morshedy, E. Tag-Eldin, A. Emam, and M. M. Samy, "Increasing transmitted power with cost mitigation via modified EHV power lines in Egyptian grid," *IEEE Access*, vol. 11, pp. 21554–21561, 2023.
- [7] M. Vukobratović, P. Marić, S. Nikolovski, and H. Glavaš, "Distributed generation harmonic interaction in the active distribution network," *Tehnički vjesnik*, vol. 25, no. 6, pp. 1720–1730, 2018.

- [8] M. Bajaj, N. K. Sharma, M. Pushkarna, H. Malik, M. A. Alotaibi, and A. Almutairi, "Optimal design of passive power filter using multi-objective Pareto-based firefly algorithm and analysis under background and load-side's nonlinearity," *IEEE Access*, vol. 9, pp. 22724–22744, 2021.
- [9] *IEEE Standard for Interconnection and Interoperability of Distributed Energy Resources With Associated Electric Power Systems Interfaces*, IEEE Standard 1547-2018, Apr. 2018, pp. 1–138.
- [10] *IEEE Standard for Harmonic Control in Electric Power Systems*, IEEE Standard 519-2022, Aug. 2022, pp. 1–31.
- [11] J. C. Das, "Passive filters—Potentialities and limitations," *IEEE Trans. Ind. Appl.*, vol. 40, no. 1, pp. 232–241, Jan. 2004.
- [12] G. W. Chang, H.-L. Wang, and S.-Y. Chu, "A probabilistic approach for optimal passive harmonic filter planning," *IEEE Trans. Power Del.*, vol. 22, no. 3, pp. 1790–1798, Jul. 2007.
- [13] A. Knezevic, "Real-time power system impedance estimation for DG applications using PV-inverter based harmonic injection method," M.S. thesis, Dept. Elect. Eng., Univ. of Cape Town, Cape Town, South Africa, 2017. [Online]. Available: <http://hdl.handle.net/11427/25325>
- [14] G. W. Chang, H.-L. Wang, G.-S. Chuang, and S.-Y. Chu, "Passive harmonic filter planning in a power system with considering probabilistic constraints," *IEEE Trans. Power Del.*, vol. 24, no. 1, pp. 208–218, Jan. 2009.
- [15] A. Kalair, N. Abas, A. R. Kalair, Z. Saleem, and N. Khan, "Review of harmonic analysis, modeling and mitigation techniques," *Renew. Sustain. Energy Rev.*, vol. 78, pp. 1152–1187, Oct. 2017.
- [16] R. N. Beres, X. Wang, M. Liserre, F. Blaabjerg, and C. L. Bak, "A review of passive power filters for three-phase grid-connected voltage-source converters," *IEEE J. Emerg. Sel. Topics Power Electron.*, vol. 4, no. 1, pp. 54–69, Mar. 2016.
- [17] C. Boonseng, N. Nilnimitr, and K. Kularbphetpong, "An investigation on the selection of filter topologies for passive filter applications by neural network," in *Proc. Int. Conf. Power, Energy Innov. (ICPEI)*, Oct. 2019, pp. 48–51.
- [18] A. Argüello, R. Torquato, and W. Freitas, "Passive filter tuning for harmonic resonance mitigation in wind parks," *IEEE Trans. Power Del.*, vol. 38, no. 6, pp. 3834–3846, Dec. 2023.
- [19] *Electromagnetic Compatibility (EMC)—Part 3-6: Limits—Assessment of Emission Limits for the Connection of Distorting Installations to MV, HV and EHV Power Systems*, Standard IEC TR 61000-3-6:2008, 2008. [Online]. Available: <https://webstore.iec.ch/publication/4155>
- [20] N. Cho, S. Lee, H. Lee, and I. Seo, "Comparisons of IEC/TR 61000-3-6 and IEEE STD 519 in the MV systems," in *Proc. 25th Int. Conf. Electr. Distrib.*, Jun. 2019, pp. 1–5. [Online]. Available: <https://www.cired-repository.org/server/api/core/bitstreams/600391f6-f2f5-4f80-8877-ae9e5be1145/content>
- [21] J. C. Churio-Barboza and J. M. Maza-Ortega, "Comprehensive design methodology of tuned passive filters based on a probabilistic approach," *IET Gener., Transmiss. Distrib.*, vol. 8, no. 1, pp. 170–177, Jan. 2014.
- [22] Y.-Y. Hong and W.-J. Liao, "Optimal passive filter planning considering probabilistic parameters using cumulant and adaptive dynamic clone selection algorithm," *Int. J. Electr. Power Energy Syst.*, vol. 45, no. 1, pp. 159–166, Feb. 2013.
- [23] T. A. H. Alghamdi, F. Anayi, and M. Packianather, "Optimal design of passive power filters using the MRFO algorithm and a practical harmonic analysis approach including uncertainties in distribution networks," *Energies*, vol. 15, no. 7, p. 2566, Apr. 2022.
- [24] X.-M. Li and Y. Xu, "Non-fragile passive filtering for networked systems with sensor failures," in *Proc. Int. Conf. Adv. Mech. Syst. (ICAMEchS)*, Dec. 2017, pp. 178–183.
- [25] N. M. Khattab, S. H. E. Abdel Aleem, A. El'Gharably, T. A. Boghdady, R. A. Turkey, Z. M. Ali, and M. M. Sayed, "A novel design of fourth-order harmonic passive filters for total demand distortion minimization using crow spiral-based search algorithm," *Ain Shams Eng. J.*, vol. 13, no. 3, May 2022, Art. no. 101632.
- [26] S. Ismael, S. H. E. Abdel Aleem, A. Abdelaziz, and F. Bendary, "Optimal harmonic passive filters for power factor correction, harmonic mitigation and electricity bill reduction using dragonfly algorithm," in *Proc. 25th Int. Conf. Electr. Distrib.*, 2019, pp. 1–5.
- [27] W. Elsayed, "Enhanced honey badger algorithm with Lévy flights for solving economic load dispatch problems," *Eng. Res. J. - Fac. Eng. (Shoubra)*, vol. 51, no. 4, pp. 19–29, Oct. 2022.
- [28] Y. Fu, D. Liu, J. Chen, and L. He, "Secretary bird optimization algorithm: A new metaheuristic for solving global optimization problems," *Artif. Intell. Rev.*, vol. 57, no. 5, Apr. 2024, Art. no. 123.
- [29] N.-C. Yang, D. Mehmood, and K.-Y. Lai, "Multi-objective artificial bee colony algorithm with minimum Manhattan distance for passive power filter optimization problems," *Mathematics*, vol. 9, no. 24, p. 3187, Dec. 2021.
- [30] N.-C. Yang and S.-W. Liu, "Multi-objective teaching–learning-based optimization with Pareto front for optimal design of passive power filters," *Energies*, vol. 14, no. 19, p. 6408, Oct. 2021.
- [31] H. H. Abbas, Q. Shafiee, and H. Bevrani, "Optimal passive LCL filter design for grid-connected converters in weak grids," *Electric Power Syst. Res.*, vol. 235, Oct. 2024, Art. no. 110896.
- [32] Y.-T. Hsiao, S.-M. Lin, S.-M. Chen, and C.-J. Chou, "Multi-objective optimization of planning single-tuned harmonic filter utilizing interactive forest algorithm," *Inf. Sci.*, vol. 661, Mar. 2024, Art. no. 120141.
- [33] M. Elsis, J.-T. Yu, and C.-L. Su, "New design of reliable passive filter for harmonic mitigation using secretary bird optimization considering power system uncertainty," *IEEE Trans. Rel.*, vol. 74, no. 4, pp. 4650–4663, Dec. 2025.
- [34] F. Plumier, "Co-simulation of electromagnetic transients and phasor models of electric power systems," Ph.D. dissertation, Dept. Electr., Electron. Comput. Sci., Univ. Liège, Liège, Belgium, Nov. 2015.
- [35] G. V. Iswaran, V. Vittal, and M. Khorsand, "Analysis of the efficacy of RMS-EMT co-simulation in capturing the response of IBR-rich grids," *Electric Power Syst. Res.*, vol. 262, Jan. 2027, Art. no. 113607, doi: 10.1016/j.epsr.2026.113607.
- [36] A. T. Mohamed, H. Cong, M. C. Tavares, Q. Li, L. Xie, H. Zheng, and M. M. Samy, "Auto-reclosing promotion via optimized secondary arc harmonics suppression in hybrid AC/DC systems," *IEEE Trans. Power Del.*, vol. 41, no. 1, pp. 470–482, Feb. 2026.
- [37] A. T. Mohamed, H. Cong, M. C. Tavares, K. Zhang, and Q. Li, "Optimized secondary arc mitigation in hybrid AC/DC transmission lines," *IEEE Trans. Power Del.*, vol. 40, no. 6, pp. 3323–3333, Dec. 2025.
- [38] S. H. E. Abdel Aleem, A. F. Zobaa, and M. M. Abdel Aziz, "Optimal C-type passive filter based on minimization of the voltage harmonic distortion for nonlinear loads," *IEEE Trans. Ind. Electron.*, vol. 59, no. 1, pp. 281–289, Jan. 2012.
- [39] L. Luo, Y. Li, J. Xu, J. Li, B. Hu, and F. Liu, "A new converter transformer and a corresponding inductive filtering method for HVDC transmission system," *IEEE Trans. Power Del.*, vol. 23, no. 3, pp. 1426–1431, Jul. 2008.
- [40] A. B. Nassif, W. Xu, and W. Freitas, "An investigation on the selection of filter topologies for passive filter applications," *IEEE Trans. Power Del.*, vol. 24, no. 3, pp. 1710–1718, Jul. 2009.
- [41] M. A. Ismeil, A. Alfouly, H. S. Hussein, and I. Hamdan, "Hardware in the loop real-time simulation of improving hosting capacity in photovoltaic systems distribution grid with passive filtering using OPAL-RT," *IEEE Access*, vol. 11, pp. 78119–78134, 2023.
- [42] A. F. Zobaa, "Mixed-integer distributed ant colony multi-objective optimization of single-tuned passive harmonic filter parameters," *IEEE Access*, vol. 7, pp. 44862–44870, 2019.
- [43] N.-C. Yang and Y.-W. Hsu, "OpenDSS-based harmonic power flow analysis for distribution systems with passive power filters," *IEEE Access*, vol. 11, pp. 69190–69203, 2023.
- [44] H. Wu, L. Zeng, Q. Ren, and L. Ai, "Robust design scheme of C-type filter considering harmonic dynamic characteristics of traction power supply system," *IEEE Access*, vol. 10, pp. 47782–47791, 2022.
- [45] M. E. Balci and A. D. Karaoglan, "Optimal design of C-type passive filters based on response surface methodology for typical industrial power systems," *Electric Power Compon. Syst.*, vol. 41, no. 7, pp. 653–668, May 2013.
- [46] C.-J. Chou, C.-W. Liu, J.-Y. Lee, and K.-D. Lee, "Optimal planning of large passive-harmonic-filters set at high voltage level," *IEEE Trans. Power Syst.*, vol. 15, no. 1, pp. 433–441, Feb. 2000.
- [47] K. Z. Heetun, S. H. E. Abdel Aleem, and A. F. Zobaa, "Voltage stability analysis of grid-connected wind farms with FACTS: Static and dynamic analysis," *Energy Policy Res.*, vol. 3, no. 1, pp. 1–12, Jan. 2016.
- [48] A. F. Zobaa and M. M. A. Aziz, "Loss minimization for nonlinear loads based on transmission loss minimization," *IEEE Trans. Power Del.*, vol. 19, no. 4, pp. 1740–1745, Apr. 2004.
- [49] M. Bajaj and A. K. Singh, "Optimal design of passive power filter for enhancing the harmonic-constrained hosting capacity of renewable DG systems," *Comput. Electr. Eng.*, vol. 97, Jan. 2022, Art. no. 107646.



AHMED TALEB MOHAMED received the B.Sc. (Hons.) and M.Sc. degrees in electrical engineering from Cairo University, Giza, Egypt, in 2017 and 2022, respectively. He is currently pursuing the Ph.D. degree with the State Key Laboratory of Alternate Electrical Power System with Renewable Energy Sources, North China Electric Power University (NCEPU), Beijing, China.

He is currently an Assistant Lecturer with the Faculty of Engineering, Cairo University. His research interests include power systems analysis, electromagnetic transient (EMT) studies, hybrid AC/DC transmission systems, and protection-oriented techniques in modern power networks.



AHMED F. ZOBAA (Senior Member, IEEE) received the B.Sc. (Hons.), M.Sc., and Ph.D. degrees in electrical power and machines from Cairo University, Egypt, in 1992, 1997, and 2002, respectively, and the Doctor of Science degree from the Brunel University of London, U.K., in 2017. He was an Instructor, from 1992 to 1997, a Teaching Assistant, from 1997 to 2002, and an Assistant Professor, from 2002 to 2007, at Cairo University. From 2007 to 2010, he was

a Senior Lecturer of renewable energy with the University of Exeter. From 2010 to 2019, he was also a Senior Lecturer of power systems with the Brunel University of London, where he is currently a Reader of electrical and power engineering and a member of the Brunel Interdisciplinary Power Systems Research Centre. His research interests include power quality, (marine) renewable energy, smart grids, energy efficiency, and lighting applications. He is also a registered Chartered Engineer, a Chartered Energy Engineer, an European Engineer, and an International Professional Engineer. He is also a Registered Member of the Engineering Council, U.K., Egypt Syndicate of Engineers, and Egyptian Society of Engineers. He is a Principal Fellow of the Higher Education Academy, U.K., a fellow of the Institution of Engineering and Technology, Energy Institute, U.K., the Chartered Institution of Building Services Engineers, U.K., the Institution of Mechanical Engineers, U.K., the Royal Society of Arts, U.K., and African Academy of Sciences. He received his Postgraduate Certificate in academic practice from the University of Exeter, U.K., in 2010. He is also the Managing Editor of *Journal of Engineering and Applied Science*. He is also an editorial board member, an editor, an associate editor, and an editorial advisory board member of many international journals.



AHMED TELBA (Senior Member, IEEE) received the B.Sc. degree in electrical engineering from the Faculty of Engineering, Menofia University, Egypt, in 1979, and the M.Phil. and Ph.D. degrees in electronics and telecommunications from the University of Bradford, U.K., in 2004 and 2007, respectively, where he is currently pursuing the master's degree with the School of Engineering, Design and Technology.

Currently, he is a Senior Researcher/Lecturer at the Department of Electrical Engineering, College of Engineering, King Saud University (KSU), Riyadh, Saudi Arabia. At KSU, he has taught a wide range of courses, including Analog Circuit Design, Digital Circuit Laboratories, FPGA Design, Microprocessor Applications in Power Systems, and Electronics Troubleshooting. He has published extensively in these areas, with several journal articles, conference papers, and book chapters to his credit. His research interests include analog circuit design, phase-locked loops, jitter in digital telecommunication networks, RFID circuit design, FPGA-based systems, solar cells, piezoelectric actuators, nano-actuators, and energy harvesting devices. He is a Life Member of the International Association of Engineers (IAENG), Hong Kong.



MOHAMED MAHMOUD SAMY received the B.Sc. degree in electrical engineering from Banha University, in 1995, the M.Sc. degree from Zagazig University, in 2007, and the Ph.D. from Cairo University, Egypt, in 2011.

He is currently a Full Professor and the Head of the Electrical Engineering Department, Faculty of Engineering, Beni-Suef University, Beni-Suef, Egypt. From 2016 to 2021, he worked as a Visiting Professor at the Faculty of Engineering, Al-Baha University, Al Bahah, Saudi Arabia. His research interests include electromagnetic fields, high-voltage engineering, and power systems studies. He serves as the Co-Editor-in-Chief for the *Journal of Engineering Science and Sustainable Industrial Technology* and the Associate Editor-in-Chief for the *Journal of Basic and Applied Sciences*.

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