World Journal of Advanced Research and Reviews
eISSN: 2581-9615 CODEN (USA): WJARAI
Cross Ref DOI: 10.30574/wjarr
Journal homepage: https://wjarr.com/

WJARR
World Journal of Advanced Research and Reviews

(Review Article)

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Meta-heuristic optimization of PWM techniques for advanced multilevel inverter applications: A review of Selective Harmonic Elimination (SHE) Strategies

Vishwas S [1, 2, *] and Girish S K [3]

[1] *Department of Electrical and Electronics Engineering, Sri Siddhartha Academy of Higher Education, Tumakuru-572105, Karnataka, India.*
[2] *Department of Electrical and Electronics Engineering, Rajeev Institute of Engineering and Technology, Hassan-573201, Karnataka, India.*
[3] *Department of Electrical and Electronics Engineering, Sri Siddhartha Institute of Technology, Sri Siddhartha Academy of Higher Education, Tumakuru-572105, Karnataka, India.*

World Journal of Advanced Research and Reviews, 2026, 31(02), 344–356

Publication history: Received on 26 June 2026; revised on 02 August 2026; accepted on 04 August 2026

Article DOI: https://doi.org/10.30574/wjarr.2026.31.2.2049

Abstract

Multilevel inverters (MLIs) are the converter topology of choice for medium- and high-power applications, including renewable energy integration, motor drives, and flexible AC transmission systems, owing to their ability to synthesize near-sinusoidal output voltage with lower switching losses and reduced electromagnetic interference compared with two-level converters. Among the modulation strategies used to control MLIs, Selective Harmonic Elimination Pulse Width Modulation (SHE-PWM) remains the preferred low-switching-frequency technique because it offers direct, deterministic control over specific low-order harmonics while maximizing the fundamental output voltage. However, the SHE-PWM problem reduces to a system of nonlinear transcendental equations that becomes increasingly difficult to solve as the number of inverter levels and therefore the number of switching angles — increases. Classical iterative solvers such as the Newton-Raphson method and algebraic approaches based on resultant theory are highly sensitive to initial guesses and become computationally prohibitive at higher levels. This has motivated an extensive body of research applying meta-heuristic optimization algorithms including Genetic Algorithms, Particle Swarm Optimization, Differential Evolution, Ant Colony Optimization, Artificial Bee Colony, Cuckoo Search, Bat Algorithm, Grey Wolf Optimizer, Whale Optimization Algorithm, Salp Swarm Algorithm, Teaching-Learning-Based Optimization, and numerous hybrid variants to solve the SHE-PWM angle-computation problem without requiring an analytical or near-optimal initial guess. This review consolidates and critically examines this literature: it presents the mathematical formulation of the SHE-PWM problem with explicit governing equations, illustrates the underlying staircase waveform and the generic meta-heuristic solution workflow through diagrams, offers a comparative discussion of algorithm families and their reported performance in terms of total harmonic distortion (THD), convergence behaviour, and computational burden, and consolidates this comparison into descriptive and attribute-based tables. Persistent research gaps — including limited real-time embedded implementation, inconsistent benchmarking practices, and insufficient treatment of asymmetric and reduced-switch-count topologies are identified, and future research directions are proposed.

Keywords: Multilevel Inverter; Selective Harmonic Elimination (SHE); Pulse Width Modulation (PWM); Meta-Heuristic Optimization; Particle Swarm Optimization; Genetic Algorithm; Grey Wolf Optimizer; Total Harmonic Distortion (THD).

1 Introduction

Multilevel inverters synthesize a stepped output voltage waveform from multiple discrete DC voltage levels, producing an output that more closely approximates a sinusoid than a conventional two-level inverter. This reduces total harmonic

*Corresponding author: Vishwas S

distortion (THD), device voltage stress (dv/dt), and electromagnetic interference, which is why MLIs are widely deployed in medium-voltage industrial drives, grid-connected photovoltaic systems, static synchronous compensators (STATCOMs), and electric traction systems. The three classical MLI topologies neutral-point-clamped (NPC), flying capacitor, and cascaded H-bridge (CHB) and their more recent reduced-switch-count and modular variants all rely on a modulation strategy to determine the switching instants of the power devices.

Modulation strategies for MLIs are broadly categorized as high-switching-frequency methods (e.g., sinusoidal PWM, space-vector PWM) and fundamental (low) switching-frequency methods, of which Selective Harmonic Elimination PWM is the most established. SHE-PWM computes a fixed set of switching angles per fundamental cycle such that a desired fundamental voltage magnitude is achieved while a specified set of low-order harmonics (typically the 5th, 7th, 11th, 13th, and so on for three-phase systems) is analytically eliminated from the Fourier series representation of the output waveform. Because switching occurs only a few times per cycle, SHE-PWM is particularly attractive for high-power applications where switching losses must be minimized.

The principal difficulty of SHE-PWM lies in solving the resulting system of nonlinear transcendental equations for the switching angles. Two broad solution families have historically been used: (i) algebraic/analytical methods, such as resultant theory and Groebner bases, which can guarantee a complete solution set but scale poorly in computational complexity as the number of levels increases; and (ii) iterative numerical methods, such as Newton-Raphson, which are computationally efficient but highly sensitive to the initial guess and prone to convergence failure or entrapment in local optima, especially at low modulation indices or high inverter levels. These limitations have motivated the adoption of meta-heuristic, nature-inspired optimization algorithms, which reformulate SHE-PWM as an unconstrained or penalty-constrained optimization problem typically minimizing a weighted objective function composed of fundamental voltage error and selected harmonic magnitudes or THD solvable without requiring gradient information or a close initial guess.

This review synthesizes the growing body of literature applying meta-heuristic optimization to SHE-PWM for advanced multilevel inverter applications. Section 2 outlines the SHE-PWM mathematical formulation, governing equations, and conventional solution methods. Section 3 reviews the major families of meta-heuristic algorithms applied to this problem, illustrated with a taxonomy diagram and a generic solution flowchart. Section 4 presents a comparative discussion of reported performance, supported by descriptive and attribute-based comparison tables and a qualitative comparative chart. Section 5 identifies open challenges and research gaps, and Section 6 concludes the review.

2 SHE-PWM Problem Formulation and Conventional Solution Methods

2.1 Multilevel Staircase Output Waveform

Figure 1 illustrates the stepped output voltage waveform characteristic of a cascaded H-bridge multilevel inverter operating under SHE-PWM. Each quarter cycle contains s independently controllable switching angles ($\theta 1$ through θs), which — by exploiting quarter-wave and half-wave symmetry — fully define the output waveform over a complete fundamental cycle. Increasing the number of levels increases s, which increases the number of harmonics that can be simultaneously eliminated but also increases the dimensionality of the equation set that must be solved.

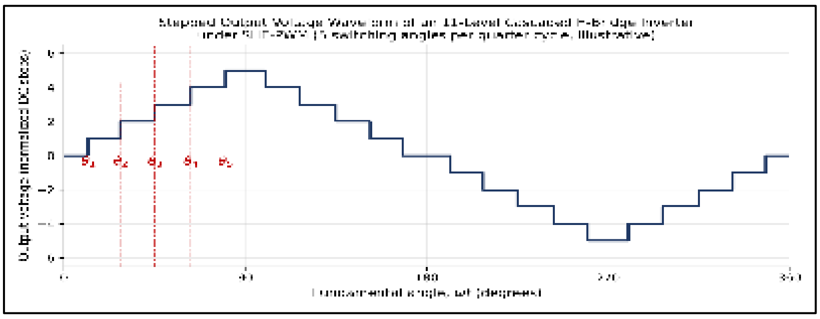

Figure 1 Stepped output voltage waveform of an 11-level cascaded H-bridge inverter

2.2 Mathematical Formulation

For a multilevel inverter with quarter-wave symmetric output voltage and s independently controllable switching angles per quarter cycle, the Fourier series expansion of the stepped output waveform contains only odd harmonics and is given by Equation (1):

$$v(\omega t) = \frac{4V_{dc}}{\pi} \sum_{n=1,3,5,\ldots}^{\infty} \frac{1}{n} \left[\sum_{k=1}^{s} \cos(n\theta_k) \right] \sin(n\omega t) \tag{1}$$

where Vdc is the per-cell DC voltage, s is the number of switching angles per quarter cycle, and θk are the switching angles to be determined. The fundamental (n = 1) component is required to equal a desired value set by the modulation index M, as given in Equation (2):

$$V_1 = \frac{4V_{dc}}{\pi} \sum_{k=1}^{s} \cos(\theta_k) = M \cdot V_{1,max} \tag{2}$$

Each targeted low-order harmonic (typically n = 5, 7, 11, 13, ... for three-phase systems, since triplen harmonics cancel naturally in line-to-line voltages) must be driven to zero, as expressed in Equation (3):

$$V_n = \frac{4V_{dc}}{\pi} \sum_{k=1}^{s} \cos(n\theta_k) = 0, \qquad n = 5, 7, 11, 13, \ldots \tag{3}$$

The switching angles must additionally satisfy the physical ordering constraint given in Equation (4), which ensures a valid, monotonically increasing sequence of switching instants within the first quarter cycle:

$$0 < \theta_1 < \theta_2 < \cdots < \theta_s < \frac{\pi}{2} \tag{4}$$

Equations (2) through (4) together constitute a system of s simultaneous nonlinear transcendental equations in s unknowns — the classical SHE-PWM problem — which must be re-solved for every operating modulation index M across the required control range.

2.3 Reformulation as a Meta-Heuristic Optimization Problem

Rather than solving Equations (2)–(4) directly as a root-finding problem, meta-heuristic approaches recast SHE-PWM as minimization of a scalar objective (fitness) function, typically a weighted combination of the fundamental voltage tracking error and the residual magnitudes of the targeted harmonics, as shown in Equation (5):

$$F(\boldsymbol{\theta}) = w_1 \left| V_1 - M \cdot V_{1,max} \right| + w_2 \sqrt{\sum_{n \in \mathcal{H}} V_n^2} \tag{5}$$

The overall waveform quality achieved by a given angle solution is subsequently evaluated using the total harmonic distortion (THD) metric, defined in Equation (6):

$$THD = \frac{\sqrt{\sum_{n=2}^{\infty} V_n^2}}{V_1} \times 100\% \tag{6}$$

This reformulation removes the need for an analytically derived or near-optimal initial guess, since meta-heuristic algorithms search the angle space using population-based, derivative-free update rules rather than local gradient information.

2.4 Limitations of Conventional Solution Approaches

The Newton-Raphson (NR) iterative method was among the earliest techniques applied to SHE-PWM and remains attractive due to its fast local convergence. However, NR requires a sufficiently accurate initial guess; a poor starting point can cause divergence or convergence to a non-physical solution (angles outside the valid range or unsorted), and a full angle trajectory over the entire modulation index range typically must be traced by sequential continuation, which is computationally expensive to repeat for every topology and level count.

Algebraic techniques recast the transcendental SHE equations as polynomial systems using resultant theory or Groebner bases, in principle yielding the complete solution set without an initial guess. However, the polynomial degree grows rapidly with the number of angles, and symbolic elimination becomes numerically ill-conditioned and computationally intractable beyond a modest number of levels, limiting practical use to lower-level inverters. These shortcomings motivated the shift toward meta-heuristic optimization, which treats SHE-PWM as a global optimization problem solvable through population-based, derivative-free search.

3 Meta-Heuristic Optimization Algorithms Applied to SHE-PWM

Meta-heuristic algorithms applied to SHE-PWM are broadly classifiable into evolutionary algorithms, swarm-intelligence algorithms, human/physics-inspired algorithms, and hybrid/enhanced algorithms that combine two or more paradigms. Figure 2 presents a taxonomy of the principal algorithms reported in the reviewed literature, organized by family.

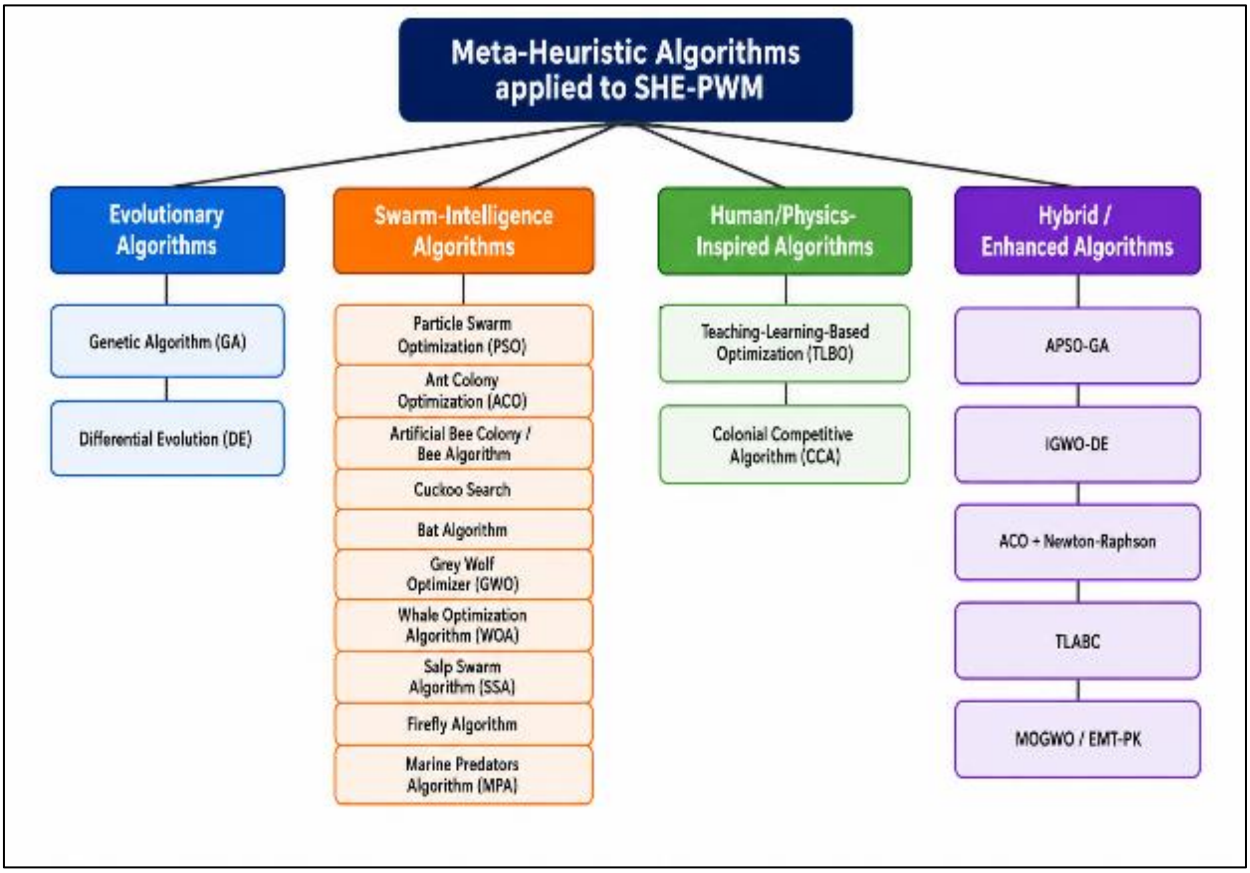

Figure 2 Taxonomy of meta-heuristic optimization algorithms applied to SHE-PWM .

Irrespective of family, nearly all reported approaches follow a common generic solution workflow, illustrated in Figure 3: the SHE-PWM problem is first formulated as an objective function (Equation 5); a population of candidate switching-angle sets is randomly initialized subject to the ordering constraint (Equation 4); candidate fitness is evaluated; and the population is iteratively updated using the algorithm-specific search rule until a convergence criterion is met, after which the optimal angle set is used to generate gating pulses or stored in a look-up table across the modulation-index range.

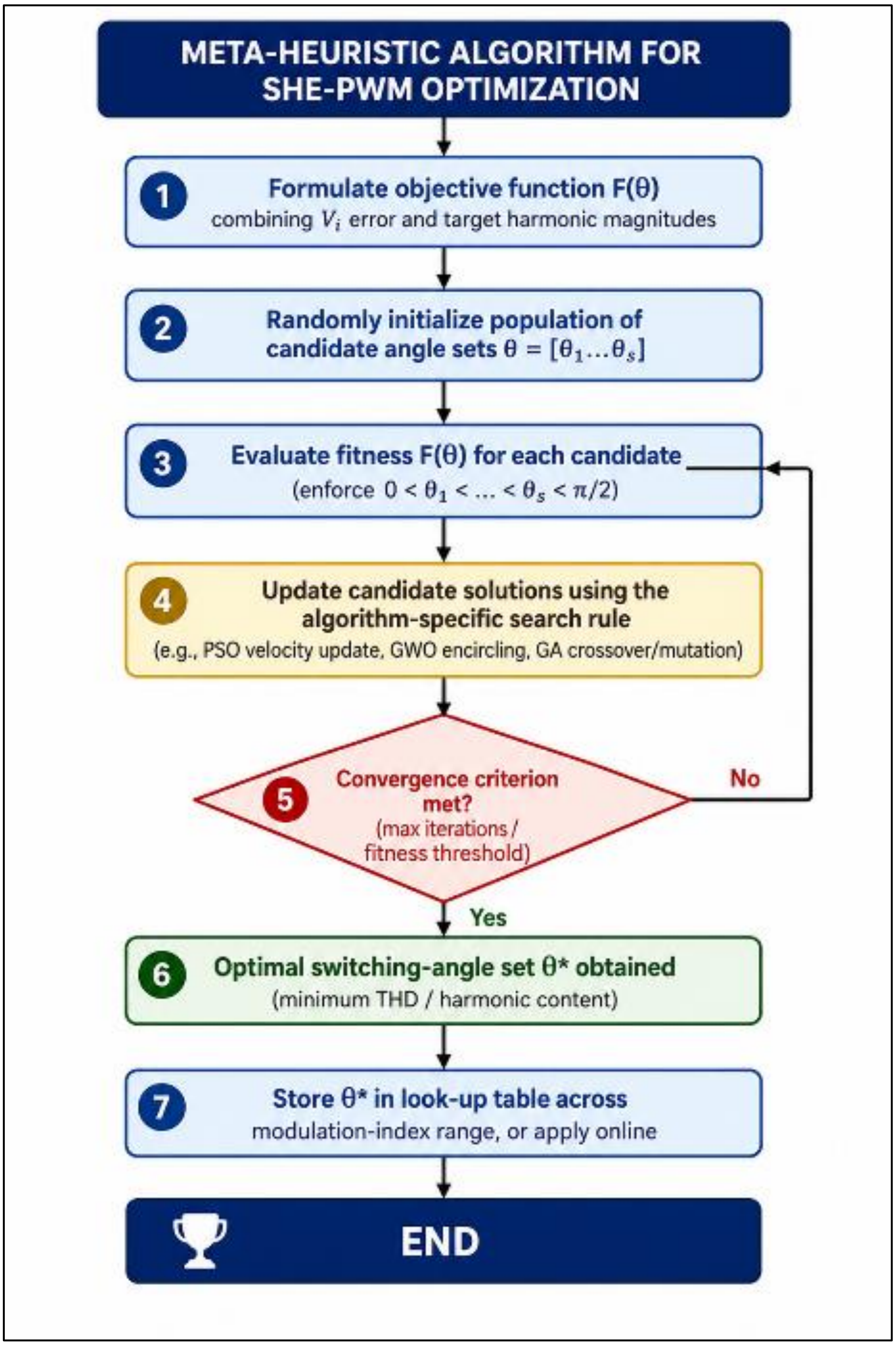

Figure 3 Generic meta-heuristic solution workflow for the SHE-PWM switching-angle optimization problem.

3.1 Evolutionary Algorithms

The Genetic Algorithm (GA) was one of the first meta-heuristics applied to multilevel harmonic optimization. Ozpineci, Tolbert, and Chiasson demonstrated harmonic optimization of multilevel converters using genetic algorithms, showing that GA could find valid switching-angle solutions across the modulation index range without requiring the equation-continuation procedures needed by Newton-Raphson-based methods. Building on this foundation, Urgun and Yigit applied GA to SHE-PWM in single-phase multilevel inverters, reporting effective harmonic suppression across various level counts. Differential Evolution (DE), which uses vector-difference-based mutation as shown conceptually in the update mechanism family, has more often appeared as a component of hybrid algorithms — for example, combined with an improved Grey Wolf Optimizer to counteract premature convergence — than as a standalone SHE solver, reflecting DE's comparative strength in escaping local optima rather than fine local exploitation.

3.2 Swarm-Intelligence Algorithms

Particle Swarm Optimization (PSO) is among the most extensively applied meta-heuristics for SHE-PWM because of its simple velocity-position update rule, given in Equation (7), and fast convergence:

$$v_i^{t-1} = w\,v_i^t + c_1 r_1 \left(p_i^{best} - \theta_i^t\right) + c_2 r_2 \left(g^{best} - \theta_i^t\right), \qquad \theta_i^{t+1} = \theta_i^t + v_i^{t+1} \tag{7}$$

Sadoughi et al. proposed a PSO-optimized SHE-PWM technique for cascaded H-bridge multilevel inverters targeting variable output voltage applications, while Qin et al. developed an improved PSO-based modulation method for modular multilevel converters. PSO's main reported drawback in SHE contexts is susceptibility to premature convergence and stagnation in higher-dimensional angle spaces, which has motivated numerous hybrid and modified variants.

Ant Colony Optimization (ACO), inspired by pheromone-trail foraging behavior, has been applied both in its discretized form and in continuous-domain variants such as Variable Sampling ACO (SamACO). Adeyemo, Fakolujo, and Adepoju applied ACO directly to SHE in multilevel inverters, and a hybrid ACO–Newton-Raphson scheme has also been proposed, in which ACO supplies a robust initial estimate that is then refined by Newton-Raphson to obtain a precisely converged solution, combining ACO's global search capability with NR's fast local convergence.

The Artificial Bee Colony algorithm and its closely related Bee Algorithm (BA), which model the foraging division of labor among scout, employed, and onlooker bees, were applied to SHE strategy design by Kavousi et al. in a widely cited IEEE Transactions on Power Electronics study and have since served as a standard benchmark against which newer algorithms are compared. Cuckoo Search / the Cuckoo Optimization Algorithm, which incorporates Lévy-flight step sizes for enhanced global exploration, was shown by Ravi Eswar et al. to reduce THD in a seven-level cascaded inverter, and a related comparative study reported that a cuckoo-based approach outperformed both the Bee Algorithm and GA for an eleven-level inverter. The Bat Algorithm, which models the frequency-tuning behavior of echolocating bats, was applied by Ganesan et al. to cascaded multilevel inverter harmonic elimination with competitive convergence characteristics.

The Grey Wolf Optimizer (GWO), modeling the leadership hierarchy and cooperative hunting behavior of grey wolves through the encircling and attacking mechanism of Equation (8), has become one of the most widely applied algorithms in recent SHE-PWM literature because of its small number of tunable parameters and strong convergence behavior:

$$\vec{D} = \left|\vec{C} \cdot \vec{\theta}_p(t) - \vec{\theta}(t)\right|, \qquad \vec{\theta}(t+1) = \vec{\theta}_p(t) - \vec{A} \cdot \vec{D} \tag{8}$$

GWO has been applied to eleven- and fifteen-level cascaded inverters, to hybrid cascaded topologies via a Modified GWO with improved exploration-exploitation balance, to reduced-switch-count topologies for renewable energy applications, and — in multi-objective form — to simultaneously minimize several harmonic-related objectives in odd-nary multilevel structures. The Whale Optimization Algorithm (WOA), based on the bubble-net hunting strategy of humpback whales, has similarly been applied in multi-objective form for asymmetrical half-cascaded multilevel inverter harmonic mitigation. The Salp Swarm Algorithm (SSA), modeling the chain-forming swarming behavior of salps, has been applied to cascaded full-bridge and reduced-switch multilevel inverters, and comparative studies have paired SSA with the Multi-Verse Optimization algorithm for multilevel inverter harmonic optimization. The Firefly Algorithm, based on bioluminescent attraction proportional to brightness, has been enhanced with multi-criteria search mechanisms by Khizer et al. to improve global search performance relative to standalone PSO and firefly implementations, and the Marine Predators Algorithm, which alternates Lévy and Brownian motion phases inspired by ocean-predator foraging strategy, has been applied to three-phase multilevel inverter SHE by Riad et al.

3.3 Human-Behavior and Physics/Socially Inspired Algorithms

Teaching-Learning-Based Optimization (TLBO), which models the knowledge-transfer dynamic between a teacher and learners in a classroom, has the practical advantage of requiring no algorithm-specific control parameters beyond population size and iteration count. Haghdar applied TLBO to determine the optimal DC source configuration for SHE in multilevel inverters, demonstrating strong THD reduction while avoiding the parameter-tuning burden associated with PSO or GA. The Colonial Competitive Algorithm (CCA), inspired by socio-political imperialistic competition among colonizing empires, was applied by Etesami, Farokhnia, and Fathi to harmonic minimization in multilevel inverters, using assimilation and competition operators to iteratively strengthen candidate solutions.

3.4 Hybrid and Enhanced Meta-Heuristics

Because individual meta-heuristics exhibit characteristic trade-offs — for example, PSO's fast but sometimes premature convergence versus GWO's or DE's stronger global exploration — a substantial and growing portion of the recent literature proposes hybrid algorithms that combine two or more paradigms. Sifat et al. proposed a hybrid Improved Grey Wolf Optimization–Differential Evolution (IGWO-DE) algorithm for SHE in a PUC-5 multilevel inverter, in which a DE-based donor vector helps the GWO population escape local minima associated with third-harmonic elimination. Etesami et al. subsequently proposed enhanced meta-heuristic methods for the SHE technique, benchmarking a proposed algorithm against DE, ACO, TLBO, BA, GA, PSO, generalized pattern search, and an asynchronous PSO-GA hybrid (APSO-GA) across seven-, nine-, and eleven-level modular multilevel converters, reporting superior performance for the proposed hybrid relative to all eight comparators. A related evolutionary many-tasking approach with prior knowledge (EMT-PK) was later shown to outperform eight widely used metaheuristics/evolutionary algorithms — including DE, ACO, TLBO, BA, GA, PSO, GPS, and APSO-GA — on 7-, 9-, and 11-level modular multilevel converters by sharing optimization experience across similar sub-problems in a single run. Patil, Kadwane, and Gawande combined ACO with Newton-Raphson refinement for a reduced-switch seven-level inverter, and a hybrid Teaching-Learning Artificial Bee Colony (TLABC) approach — combining TLBO's exploitation strength with ABC's exploration strength — has likewise been proposed for general function optimization problems of the type underlying SHE. More recently, the Runge-Kutta optimization algorithm was applied by Sajid et al. to five-, seven-, and nine-level modified H-bridge and cascaded H-bridge topologies, again motivated by the tendency of Newton-Raphson-type solvers to become trapped at local optima.

3.5 Descriptive Comparative Summary of Algorithm Families

Table 1 summarizes the principal meta-heuristic algorithm families reported in the SHE-PWM literature, their biological or behavioral inspiration, their characteristic strengths and weaknesses when applied to switching-angle computation, and representative studies.

4 Comparative Discussion of Reported Performance

A recurring theme across the reviewed literature is that no single meta-heuristic dominates across all performance criteria simultaneously; algorithm suitability depends on the inverter level count, the number of angles to be optimized, the targeted harmonic set, and whether the application demands offline pre-computed angle look-up tables or online/real-time angle generation. A systematic comparative study evaluated a broad set of contemporary meta-heuristics — including Ant Lion Optimization, the Artificial Hummingbird Algorithm, the Dragonfly Algorithm, Harris Hawks Optimization, the Moth-Flame Optimizer, the Sine Cosine Algorithm, the Flow Direction Algorithm, the Equilibrium Optimizer, Atom Search Optimization, the Artificial Electric Field Algorithm, and the Arithmetic Optimization Algorithm — alongside GA, GWO, PSO, SSA, TLBO, and WOA on the SHE problem for an 11-level multilevel inverter, finding that a majority of these algorithms satisfy the 8% THD requirement of the IEEE 519 standard over a modulation-index range of roughly 0.4 to 0.9, but with meaningful differences in convergence consistency and the width of the modulation-index range over which valid, harmonic-free solutions are obtainable.

Table 2 consolidates these descriptive findings into an attribute-based comparison across representative algorithms, rated qualitatively (Low/Moderate/High) based on the consistent characterizations reported across the reviewed studies rather than a single controlled numerical benchmark, since test conditions (inverter level, DC-source configuration, targeted harmonic set, and modulation-index sweep range) vary considerably between the underlying papers.

Table 1 Descriptive comparison of meta-heuristic algorithm families applied to SHE-PWM.

Algorithm	Inspiration Source	Key Characteristics for SHE-PWM	Representative Study
Genetic Algorithm (GA)	Darwinian evolution / natural selection	Population-based search using selection, crossover, mutation; robust to non-convex SHE objective but slower convergence for higher-level inverters	Ozpineci et al. (2005); Urgun & Yigit (2021)
Particle Swarm Optimization (PSO)	Bird flocking / fish schooling behaviour	Simple velocity-position update rule; fast convergence; sensitive to premature stagnation in high-dimensional angle spaces	Sadoughi et al. (2022); Qin et al. (2023)
Differential Evolution (DE)	Vector-difference mutation of evolutionary computation	Strong exploration via donor vectors; effective at escaping local optima when hybridized with other methods	Sifat et al. (2024, hybrid IGWO-DE)
Ant Colony Optimization (ACO)	Pheromone-trail foraging of ants	Well suited to discretized angle search space; variable-sampling variants improve continuous-domain performance	Adeyemo et al. (2015); Hu et al. (2010, SamACO)
Artificial Bee Colony / Bee Algorithm (ABC/BA)	Foraging behaviour of honeybee colonies	Balances exploration (scout bees) and exploitation (employed/onlooker bees); benchmark algorithm in SHE literature	Kavousi et al. (2012)
Cuckoo Search / Cuckoo Optimization Algorithm (COA)	Brood parasitism of cuckoo species; Lévy flight	Lévy-flight steps improve global exploration; reported to outperform GA and BA in THD minimization	Ravi Eswar et al. (2015)
Bat Algorithm (BA)	Echolocation behaviour of microbats	Frequency-tuning mechanism adjusts exploration/exploitation balance; competitive convergence speed	Ganesan et al. (2015)
Grey Wolf Optimizer (GWO)	Leadership hierarchy and hunting behaviour of grey wolves	Few control parameters; strong convergence for 11- to 15-level inverters; widely hybridized (e.g., IGWO-DE)	Dzung et al. (2015); Routray et al. (2020); Sifat et al. (2024)
Whale Optimization Algorithm (WOA)	Bubble-net hunting strategy of humpback whales	Spiral-updating mechanism aids exploitation; effective in multi-objective SHE formulations	Falehi (2020, multi-objective WOA)
Salp Swarm Algorithm (SSA)	Salp chain swarming behaviour in oceans	Leader-follower chain structure aids convergence stability for high step-count inverters	Ceylan (2021)
Teaching-Learning-Based Optimization (TLBO)	Teacher-learner knowledge transfer in a classroom	Parameter-free (no algorithm-specific tuning); shown effective for optimal DC-source selection in SHE	Haghdar (2020)
Colonial Competitive Algorithm (CCA)	Imperialistic competition among colonizing empires	Assimilation and competition operators aid harmonic minimization across inverter levels	Etesami et al. (2015)

Table 2 Attribute-based qualitative comparison of representative meta-heuristics for SHE-PWM, synthesized from descriptive findings across the reviewed literature.

Attribute	**GA**	**PSO**	**ACO**	**GWO**	**WOA**	**TLBO**	**Hybrid (e.g., IGWO-DE)**
Typical convergence speed	Moderate	Fast	Moderate	Fast	Fast	Moderate	Fast
Robustness to local optima	Moderate	Moderate	Moderate–High	High	High	High	Very High
Number of tunable parameters	3–5	3–4	3–4	2–3	2–3	0–1	4–6
Reported suitability for high-level MLI (11+ levels)	Moderate	Moderate	Moderate	High	High	Moderate–High	High
Implementation complexity	Low–Moderate	Low	Moderate	Low–Moderate	Low–Moderate	Low	Moderate–High

Figure 4 visualizes this qualitative synthesis as a comparative chart. It is important to emphasize that the chart summarizes descriptive trends reported across independent studies with differing test conditions rather than results from a single controlled experiment, and should be interpreted as a guide to the general consensus in the literature rather than as precise benchmark data.

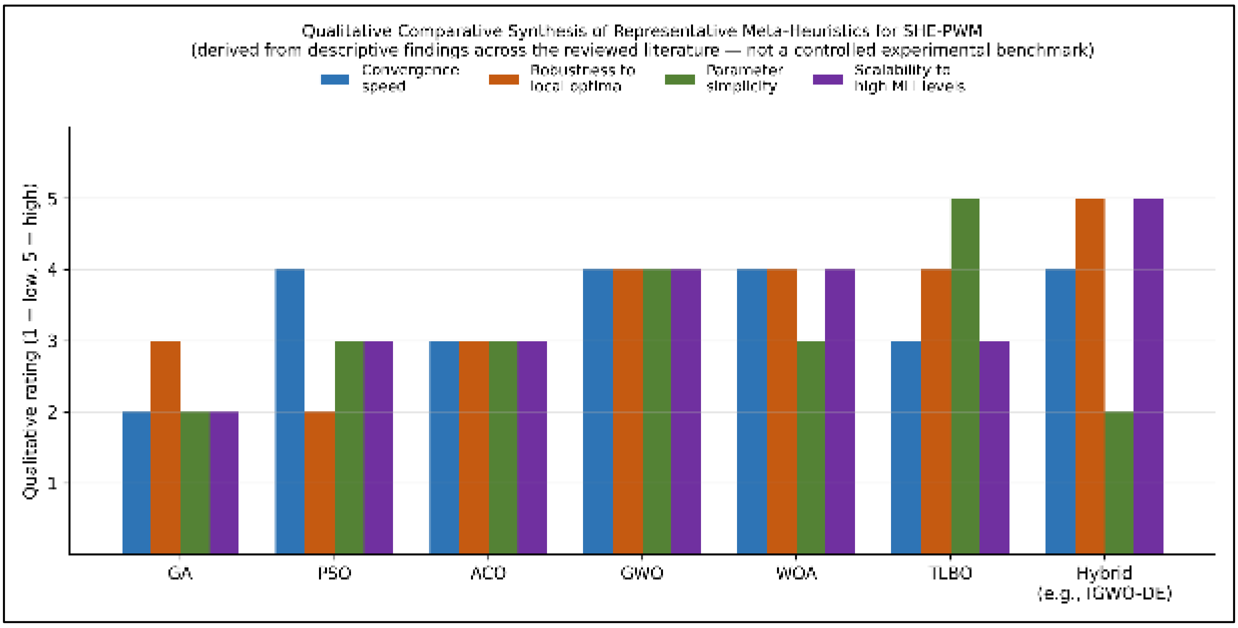

Figure 4 Qualitative comparative synthesis of representative meta-heuristics for SHE-PWM across four attributes, derived from descriptive findings in the reviewed literature.

Several general trends emerge across the reviewed studies. First, swarm-intelligence algorithms with adaptive or self-tuning exploration-exploitation balance — notably GWO, WOA, and SSA — tend to be reported as achieving lower THD and more consistent convergence than earlier-generation algorithms such as basic GA or PSO, particularly as the level count (and hence angle-space dimensionality) increases. Second, algorithms benchmarked against the Bee Algorithm and GA as baselines (e.g., Cuckoo Search, enhanced Firefly) consistently report improvements in convergence speed and THD, though the margin of improvement narrows as problem dimensionality grows. Third, hybrid algorithms that explicitly combine a strong global-exploration mechanism (e.g., DE's donor-vector mutation, ACO's stochastic trail update) with a strong local-exploitation mechanism (e.g., GWO's encircling behavior, Newton-Raphson refinement) are consistently reported to outperform their constituent standalone algorithms, at the cost of increased implementation complexity and additional tunable parameters. Finally, parameter-free algorithms such as TLBO offer a practical advantage in avoiding algorithm-specific tuning, which is otherwise a nontrivial engineering burden when SHE-PWM must be solved repeatedly across the full modulation-index operating range and for multiple inverter topologies.

Challenges and Research Gaps

Benchmarking inconsistency: studies frequently differ in inverter level, targeted harmonic set, DC source configuration (equal vs. unequal), and modulation-index test range, which complicates direct cross-study comparison of reported THD and convergence performance, as reflected in the qualitative rather than strictly numerical nature of Table 2.

Real-time/embedded implementation: the majority of reported meta-heuristic SHE solutions are computed offline and stored in look-up tables; genuinely online, real-time angle generation on embedded digital signal processors or FPGAs remains comparatively underexplored, particularly for higher-level and reduced-switch-count topologies.

Scalability to high-level and asymmetric topologies: as reduced-switch-count and asymmetric multilevel topologies proliferate to reduce component count and cost, the corresponding SHE angle-space grows more irregular, and comparatively few studies have systematically evaluated meta-heuristic robustness across this expanding topology space.

Hybrid algorithm complexity versus benefit: while hybrid meta-heuristics generally report performance gains over standalone algorithms, the added computational and implementation complexity, and the introduction of additional tunable parameters, is not always weighed against the marginal improvement achieved, particularly for lower-level inverters where standalone algorithms already perform adequately.

Dynamic and unbalanced operating conditions: most SHE-PWM meta-heuristic studies assume steady-state, balanced three-phase operation; performance under dynamic modulation-index transients, DC-source voltage fluctuation (e.g., in photovoltaic-fed inverters), or unbalanced loading is comparatively less studied.

Standardized reporting of computational cost: convergence speed is often reported in iteration count rather than wall-clock time or floating-point operations, making it difficult to compare the true computational burden of algorithms with different per-iteration costs (e.g., GA versus GWO versus a hybrid IGWO-DE).

Future Research Directions

Building on the identified gaps, several directions appear promising for future work. Development of lightweight, parameter-light hybrid algorithms optimized specifically for embedded real-time implementation (e.g., on low-cost DSPs or FPGAs) would help close the gap between offline research demonstrations and practical industrial deployment. Standardized benchmarking protocols specifying a common set of test topologies (symmetric and asymmetric), harmonic targets, and modulation-index sweep ranges would substantially improve the comparability of newly proposed algorithms against the substantial existing baseline of GA, PSO, GWO, WOA, and TLBO results. Extension of meta-heuristic SHE-PWM formulations to explicitly incorporate dynamic DC-source variation, as encountered in photovoltaic- and battery-fed multilevel inverters, and to multi-objective formulations that simultaneously optimize THD, switching losses, and device thermal stress, represents a further natural extension of the largely single-objective formulations reviewed here. Finally, continued exploration of hybridization and knowledge-transfer strategies that pair a strong global-search meta-heuristic with a fast local refinement step (in the spirit of ACO-Newton-Raphson, IGWO-DE, or EMT-PK) is likely to remain a productive research direction, provided that the added complexity is systematically justified against standalone algorithm performance.

5 Conclusion

Selective Harmonic Elimination PWM remains a preferred fundamental-frequency modulation strategy for multilevel inverters in medium- and high-power applications because of its direct, deterministic control over specific low-order harmonics and its low switching losses. The nonlinear transcendental nature of the underlying SHE equations, formalized in Equations (1)–(4) of this review, renders classical solution methods increasingly impractical as inverter level count grows, motivating an extensive and still-expanding body of research applying meta-heuristic optimization algorithms — spanning evolutionary algorithms (GA, DE), swarm-intelligence algorithms (PSO, ACO, ABC, Cuckoo Search, Bat Algorithm, GWO, WOA, SSA, Firefly, Marine Predators Algorithm), human/physics-inspired algorithms (TLBO, CCA), and an increasingly prominent set of hybrid variants to the reformulated objective-function minimization problem of Equation (5). This review has consolidated the major algorithm families, illustrated the governing mathematics and generic solution workflow through equations and diagrams, presented descriptive and attribute-based comparison tables and a qualitative comparative chart of reported performance, and identified persistent research gaps around benchmarking standardization, real-time implementation, and scalability to asymmetric and reduced-switch-count topologies. Continued progress in this area is likely to come less from proposing yet another individually named nature-inspired algorithm and more from rigorous, standardized benchmarking, real-time embedded validation, and principled hybridization strategies that are demonstrably justified against strong existing baselines.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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