Enhanced Total Harmonic Distortion Optimization in Cascaded H-Bridge Multilevel Inverters Using the Dwarf Mongoose Optimization Algorithm

Sinan Q. Salih [1], Basim Ghalib Mejbel [2], B. A. Ahmad [3], Taha A. Taha [4*], Yasin Bektaş [5], Mohammed M Aldabbagh [6], Abadal-Salam T. Hussain [7], Abdulghafor Mohammed Hashim [8], B. S. Veena [9]
[1] Technical College of Engineering, Al-Bayan University, Baghdad 10011, Iraq
[2] Al Hikma University College, Baghdad, Iraq
[3] Department of Medical Instrumentation Techniques Engineering, Al-Ma'moon University College, Al-Washash, Iraq.
[4, 6] Unit of Renewable Energy, Northern Technical University, Kirkuk, Iraq
[5] Department of Electrical and Energy, Technical Sciences Vocational High School, Aksaray University, Aksaray, Turkey
[7] Department of Medical Instrumentation Techniques Engineering, Technical Engineering College, Al-Kitab University, Altun Kupri, Kirkuk, 36001, Iraq
[8] Al-Amarah University College, Engineering of Technical Mechanical Power Department, Maysan, Iraq
[9] Symbiosis Institute of Technology, Pune Campus, Symbiosis International (Deemed University), Pune, India
Email: [1] sinan.salih@albayan.edu.iq, [2] drbasimghalib@gmail.com, [3] belalanwar@almamonuc.edu.iq, [4] t360pi@gmail.com, [5] yasinbektas@aksaray.edu.tr, [6] Mohammedmalgh@gmail.com, [7] asth2@uoalkitab.edu.iq, [8] abd.ghafoor@alamarahuc.edu.iq, [9] veena@sitpune.edu.in
*Corresponding Author

***Abstract*—Total harmonic distortion (THD) is one of the most essential parameters that define the operational efficiency and power quality in electrical systems applied to solutions like cascaded H-bridge multilevel inverters (CHB-MLI). The reduction of THD is crucial due to the fact that improving the system's power quality and minimizing the losses are key for performance improvement. The purpose of this work is to introduce a new DMO-based approach to optimize the THD of the output voltage in a three-phase nine-level CHB-MLI. The proposed DMO algorithm was also subjected to intense comparison with two benchmark optimization techniques, namely Genetic Algorithm and Particle Swarm Optimization with regards to three parameters, namely convergence rate, stability, and optimization accuracy. A series of MATLAB simulations were run to afford the evaluation of each algorithm under a modulation index of between 0.1 and 1.0. The outcome of the experiment amply proves that in comparison with THD minimization for the given OP, the DMO algorithm was significantly superior to both RSA-based GA and PSO algorithms in their ability to yield higher accuracy while requiring lesser computational time. Consequently, this work could expand the application of the DMO algorithm as a reliable and effective means of enhancing THD in CHB-MLIs as well as advancing the overall quality of power systems in different electrical power networks.**

Keywords*—Total Harmonic Distortion (THD) Optimization; Cascaded H-Bridge Multilevel Inverter (CHB-MLI); Dwarf Mongoose Optimization (DMO) Algorithm; Meta-Heuristic Algorithms.

I. INTRODUCTION

Multilevel inverters (MLIs) are indispensable parts of present-day electrical power system to accomplish the vital responsibility of conversion of direct current (DC) to pseudo sinusoidal Alternating Current (AC) [1]-[4]. They are used for many applications notably in renewable energy resources like photovoltaic system used for conversion solar energy to electrical energy that is synchronized to the grid as pointed out in Panigrahi et al., 2020. Over the last few years, MLIs have been widely used in the high power and high voltage applications owing to their increased capability of improving the quality of power while operating at lower frequency of switching. These features make MLIs highly efficient and reliable for use in these key technologies like High Voltage Direct Current (HVDC) transmission and Flexible Alternating Current Transmission Systems (FACTS) devices for the stability and efficiency of large-scale power systems [5]-[7]. In the same way, the incorporation of MLIs into electric vehicles especially in asynchronous and synchronous motor drives has also become standard hence enhancing their use in efficient energy systems in vehicles [8]-[12].

The foremost issue widely related to MLIs is the minimization of THD, which is the evaluation of the harmonics in the voltage or current waveform apart from the fundamental frequency. Minimizing THD is always desirable in power systems because harmonics have adverse impacts on the system such as increased energy loss, elevated operating temperatures, degradation of other components, and system instability. Lower THD also reduces heating and noise and increases the life span of loads electrical components, and electromagnetic interference [13]-[18]. Moreover, decreasing THD improves the functionality of other instruments connected to the power supply and helps to strengthen the stably of power supply networks, and therefore, is a major goal in power quality.

In response, numerous approaches have been proposed to mitigate THD, all of which are applicable to different circuits of power system networks. The Newton-Raphson technique amongst other conventional procedures indicating mathematical probable solving approaches have been used to solve harmonic elimination problems. The most frequent method is Selective Harmonic Elimination (SHE) which was developed to cancel out certain low order dominant harmonics in the waveform [19]-[23]. Nevertheless, for the purpose of implementing SHE, certain complications arise due to certain requirements for switching regime and calculation parameters: the method needs complicated change-over schemes which may be quite challenging in high power applications.

Besides SHE, PWM and sinusoidal PWM and SVM, have been shown to be suitable methods for minimizing the THD. These methods make use of generation of several voltage levels as well as the management of switching states in order to reduce the number of harmonics. However, they also have limitations because they need to switch between the channels at high speeds which may be challenging, and need complex circuitry to set up that physically complicate a system and place hardware restrictions.

From the same perspective of the AI field, other approaches such as fuzzy logic and artificial neural networks (ANN) have also been adopted in THD minimization. These approaches give flexibility and adaptability but they are limited by the modulation index (M) and cannot furnish solutions in all the range of M values [24]-[27]. In addition, it is often observed that numerous AI-related techniques employ simple basic optimization algorithms, such as Genetic Algorithms (GA) [28]-[30] and Particle Swarm Optimization (PSO) [31]-[36], but the problem is that they have limitations in terms of computational efficiency, convergence speed, and parameters tuning [37]-[40].

As the limitations of traditional optimization methods have been identified, the society has a high need towards optimization methods that would provide higher yield with decreased number of parameters and less model complexity [41]-[46]. In this research, a brand new meta-heuristic concept is presented with the DMO algorithm in an attempt to enhance THD in a three-phase nine-level MLI [47]-[53]. In this point, the DMO algorithm can be considered as an advantageous method over conventional optimization approaches because it can solve the multiple objective problems deterministically and decrease the use of stochastic parameters for reducing computational time [54]-[57]. This is especially important for applications involving high power where switching speed, signal distortion and system simplicity are critical [58]-[62].

The proposed DMO algorithm not only handles fundamental issues such as shortcomings of SHE and PWM but also combines well with sophisticated higher AI-oriented methods creating a fair optimized mix [63]-[66]. Because the DMO algorithm reduces THD across multiple conditions, the algorithm improves the efficiency and stability of MLIs primarily used in high voltage power systems and renewable energy. In my opinion, this idea may play a great role in the continuous construction of improved power systems, and MLI in other sectors as well [67]-[69].

II. Dwarf Mangos Optimization Algorithm

Dwarf Mongoose Optimization Algorithm (DMO) is a meta-heuristic optimization algorithm developed by drawing inspiration from natural life. This algorithm is utilized to solve optimization problems in various domains by mimicking the feeding behavior of the dwarf mongoose, a small carnivorous mammal found in Africa [70]-[74].

Dwarf mongooses live in communities and exhibit cooperative feeding strategies to efficiently provide sustenance to the entire group. Drawing inspiration from the adaptive behaviors of dwarf mongooses, such as the selection of prey size, area utilization, group size, and food provision, the DMO algorithm finds optimal solutions to complex optimization problems [75]-[78]. The algorithm is population-based, utilizing social groups consisting of alpha groups and caregivers (babysitters) to perform search and optimization tasks [79]-[81]. The alpha group makes crucial decisions such as initiating feeding, choosing the feeding path, and determining the distance covered. Caregivers take care of young mongooses and are altered during the group's feeding, contributing to the algorithm's exploration and exploitation stages.

DMO has demonstrated positive results in solving various optimization problems and has been compared to other contemporary algorithms, proving its effectiveness and efficiency in finding near-optimal solutions [82]. The optimization procedures of the DMO algorithm are represented in three stages, as shown in Fig. 1. The DMOA model, pseudo-code, and algorithmic structure are presented below.

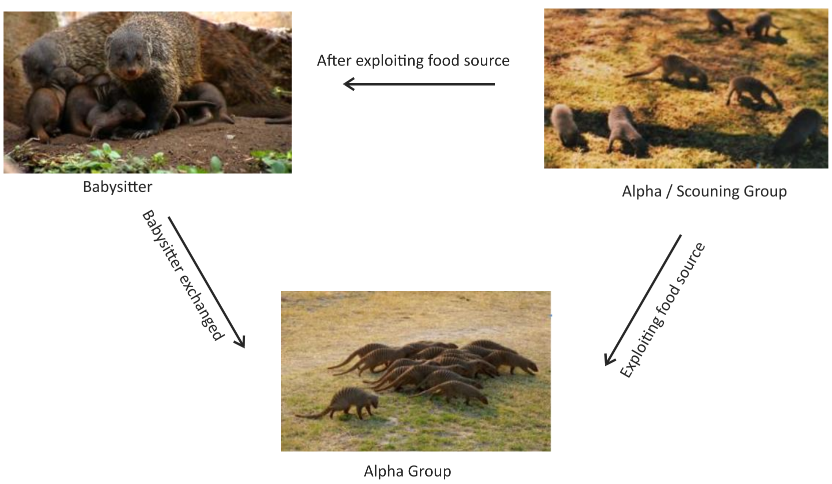

Fig. 1. The optimization procedures of the DMO

A. Initial Population

The DMO method initiates by generating a population of potential solutions in a random manner, as described in Equation (1). The variable Np represents the overall population size, while the variable Q denotes the quantity of decision factors pertaining to the dwarf mongoose. The population is stochastically created through the utilization of Equation (2).

$$S = \begin{bmatrix} s_{1,1} & \cdots & s_{1,Q} \\ \vdots & \ddots & \vdots \\ s_{N_p,1} & \cdots & s_{N_p,Q} \end{bmatrix} \quad (1)$$

$$S_{u,v} = unifrnd(LB, UB, Q) \quad (2)$$

B. The DMO Model

The procedure of the DMO algorithm is divided into three groups. These groups are presented below:

- **Alpha group:** In the first step, the fitness of each solution in the population is calculated using Equation (3) (the value of the fitness function). Based on fitness, the alpha female is selected as specified in Equation (3). The number of dwarf mongooses in the α, the baby-sitter count (bs), and the calling probability of the dominant female (p) in dwarf mongooses are updated using Equation (4). $\emptyset$, is a randomly selected number. For each iteration, the sleeping nest is calculated using Equation (5). The average of ε_j values is calculated using Equation (6). When the criteria for the babysitter are met, the next step is initiated, which involves forming the discovery group.

$$\alpha = \frac{fit_j}{\sum_{j=1}^{N_p} fit_j} \quad (3)$$

$$S_{j+1} = S_j + \emptyset * \rho \quad (4)$$

$$\varepsilon_j = \frac{fit_{j+1} - fit_j}{max\{|fit_{j+1}, fit_j|\}} \quad (5)$$

$$\sigma = \frac{\sum_{j=1}^{N_p} \varepsilon_j}{N_p} \quad (6)$$

- **Scout group:** The discovery group, based on the information that dwarf mongooses do not return to their previous sleeping nests, searches for the next sleeping nest, ensuring the discovery. The logic predicts that the family will discover a new sleeping nest if it continues its food search far enough. This situation is mathematically expressed in Equations (7) and (8). where, the "rand" value is a random number between [0, 1]. DF is a parameter to control the collective movement of the dwarf mongoose group, and $\vec{V}$ is the movement vector. These parameters are calculated using Equations (9) and (10).

$$if \quad \theta_{j+1} > \theta_j : S_{j+1} = S_j - DF * rand * [S_j - \vec{V}] \quad (7)$$

$$else \quad S_{j+1} = S_j + DF * rand * [S_j - \vec{V}] \quad (8)$$

$$DF = \left(1 - \frac{m}{max\_G}\right)^{\left(2 * \frac{m}{max\_G}\right)} \quad (9)$$

$$\vec{\boldsymbol{V}} = \sum_{j=1}^{N_p} \frac{S_j \times \varepsilon_j}{S_j} \quad (10)$$

- **The babysitters:** The babysitter is a supplementary collective that remains in the company of the progeny. Babysitters are frequently rotated to support the dominant female, while additional team members coordinate daily hunting excursions. The pseudo code of DMOA is presented in Table I.

TABLE I. PSEUDO-CODE OF THE DMO ALGORITHM

DMO Algorithms
begin
Set the parameters of DMOA: Np, bb Np = Np - bb Set the value
Set the value of the babysitter change parameter, K.
for m=1 : max_G
Calculate the fitness value of mongooses.
Set the time counter, D.
Calculate **Equation (3).**
Calculate the candidate food location **(Equation 4).**
Evaluate the new fitness value.
Evaluate the sleeping nest **(Equation 5).**
Calculate the average of sleeping nests **(Equation 6).**
Calculate the movement vector **(Equation 10).** If D ≥ K, change the babysitter.
Initialize the bb position using **(Equation 1)** and calculate fitness values.
Update the best solution. **end**
Return the best solution.
end

III. RESULTS AND DISCUSSIONS

The babysitter is a supplementary collective that remains in the company of the progeny. Babysitters are frequently rotated to support the dominant female, while additional team members coordinate daily hunting excursions.

A. Fitness Function for THD Minimization

The purpose of the fitness function is to obtain a fundamental voltage value with a lower THD. The fitness function is given in Equation (11). where, θi represents the switching angles. Since there will be a single switching for each bridge in the nine-level CHB-MLI, a total of four angles, $\theta 1$, $\theta 2$, $\theta 3$, and $\theta 4$, are considered. The inclusion of these angles in the calculation results in the voltage value V1p, and Vref is the desired reference fundamental voltage value. Where, V1p is the peak value of the calculated output voltage, while Vref is the peak value of the desired fundamental voltage. The fundamental voltage modulation index M is controlled. The modulation index is defined as the ratio of the desired peak value of the fundamental voltage to the total DC voltage value, as given in Equation (12).

$$FF = \min_{\theta_i}\{|V_{1p} - V_{ref}| + \sum_{j=5,7,11\ldots}^{49} V_j\} \quad (11)$$

$$M = \frac{V_{1p}}{\sum V_{DC}} \quad (12)$$

B. Optimization of Switching Angles for THD Minimization

THD minimization for a 9-level CHB-MLI inverter using the DMO algorithm has been performed. The results were validated using the FFT analysis tool in MATLAB Simulink. For GA, PSO, and DMO algorithms, 5 independent runs were conducted, each consisting of 50 individuals. Each run comprised 100 iterations.

For modulation index range between 0 and 1, each algorithm was run 5 times, and the best results for GA are presented in Table II, for PSO in Table III, and for DMO in Table IV. Table II shows the switching angles calculated with GA and the simulation results when these angles are applied to the inverter. Table III and Table IV present the switching angles calculated with PSO and DMO algorithms, along with the simulation results. Upon examination of the tables, it is observed that, for the given modulation index range, the algorithm that controls the fundamental voltage with the most minor error and achieves the best THD value is the DMO algorithm. PSO, on the other hand, outperformed the GA algorithm. Fig. 2 shows the convergence curves of the algorithms for a modulation index of 1.0. As seen, the algorithm that finds a solution earliest and with a better fitness value is the DMO algorithm. When compared to other optimization methods like GA and PSO, the DMO algorithm has the following advantages:

- **Higher Divergence:** DMO exhibits higher diversity in the problem space. This characteristic often assists in finding better global solutions.
- **Better Speed and Convergence:** DMO can converge faster and generate solutions more rapidly in certain situations. This has been demonstrated in THD optimization.
- **Parameter Sensitivity:** DMO is an algorithm that, in some cases, shows less sensitivity or is less responsive to parameter settings.
- **Complexity:** DMO is less complex than GA and PSO, requiring fewer adjustments.

However, each optimization algorithm may perform better or worse for different problems and application scenarios. The choice of which algorithm to use should be evaluated based on the specific characteristics and requirements of a given situation (Çelik, 2023). The advantages and disadvantages of each algorithm are different, and the preferred algorithm can vary depending on the application context (Çelik & Kumar, 2021). In conclusion, for THD optimization, DMO proves to be superior to GA and PSO algorithms.

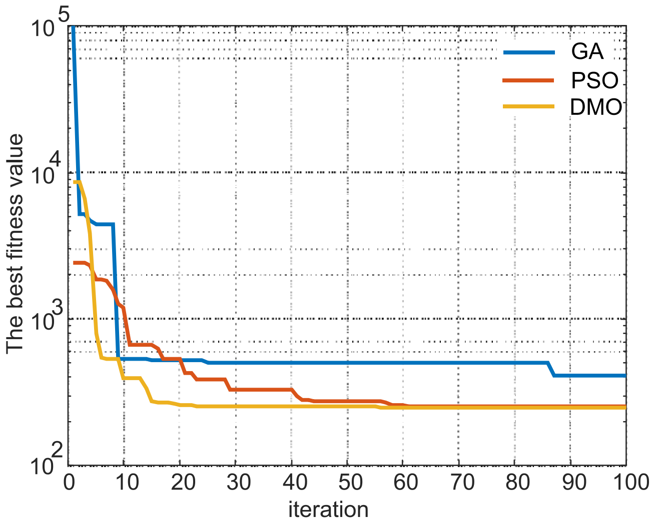

Fig. 2. Convergence curves for GA, PSO, and DMO for M=1.0

C. Consistency Test

The standard deviation is a measure of how much values in a data set deviate from the mean. In other words, it indicates how much the data points are spread out around the mean value. A low standard deviation means that the results obtained are more consistent and show less variability, indicating that the algorithm is more reliable and its performance is more predictable.

For each algorithm, the consistency of results was tested by comparing the best FF (fitness value), worst FF, average FF, and standard deviation (SD). The statistical analysis results for GA, PSO, and DMO are given in Table V, Table VI, and Table VII, respectively. As observed, the algorithm with the lowest standard deviation values is the DMO algorithm. PSO outperformed GA in terms of consistency.

D. Speed Test

An optimization speed test is a method used to evaluate an optimization algorithm's working speed and result generation speed. This test assesses the performance of an algorithm by measuring its solution time and speed.

Each of the three algorithms was run in 5 different trials, and each trial was conducted with 100 repetitions. The results obtained are presented in Table VIII. According to these results, the DMO algorithm is identified as the fastest, while GA is determined as the slowest algorithm.

TABLE II. SWITCHING ANGLES CALCULATED WITH GA

GA-THD										
m		**θ_1**	**θ_2**	**θ_3**	**θ_4**	**Vref(max)**	**Vref(rms)**	**V1p(rms)**	**error(%)**	**THD (%)**
Low	0.1	1.25324	1.56987	1.57080	1.57080	31.1	22	21.88	0.55%	81.98
	0.2	0.91551	1.55388	1.57080	1.57080	62.2	44	43.74	0.59%	31.56
	0.3	0.72382	1.38037	1.56991	1.57080	93.3	66	65.61	0.59%	17.17
Medium	0.4	0.68755	1.08395	1.55905	1.57080	124.4	88	87.46	0.61%	15.24
	0.5	0.70103	0.97232	1.33031	1.57080	155.5	110	109.3	0.64%	12.50
	0.6	0.44427	0.90939	1.20066	1.57080	186.6	132	131.2	0.61%	8.95
High	0.7	0.63771	0.85119	1.05783	1.32974	217.7	154	153	0.65%	8.29
	0.8	0.41486	0.81670	1.03502	1.16486	248.8	176	174.9	0.62%	7.78
	0.9	0.08328	0.27442	0.56629	1.54637	279.9	198	197.3	0.35%	5.25
	1.0	0.19495	0.40987	0.72392	1.05394	311.0	220	219.3	0.32%	5.32

TABLE III. SWITCHING ANGLES CALCULATED WITH PSO

PSO-THD										
m		**θ_1**	**θ_2**	**θ_3**	**θ_4**	**Vref(max)**	**Vref(rms)**	**V1p(rms)**	**error(%)**	**THD (%)**
Low	0.1	1.25227	1.57080	1.57080	1.57080	31.1	22	21.86	0.64%	81.80
	0.2	0.91357	1.55745	1.56867	1.57080	62.2	44	43.75	0.57%	31.51
	0.3	0.83233	1.29807	1.57080	1.57080	93.3	66	65.81	0.29%	18.74
Medium	0.4	0.71650	1.05657	1.56019	1.57080	124.4	88	87.71	0.33%	14.70
	0.5	0.72671	0.93416	1.33979	1.57080	155.5	110	109.7	0.27%	12.28
	0.6	0.62987	0.89079	1.20133	1.48478	186.6	132	131.5	0.38%	8.02
High	0.7	0.66086	0.77720	1.05472	1.36595	217.7	154	153.5	0.32%	8.19
	0.8	0.44211	0.84467	0.96275	1.18738	248.8	176	175.4	0.34%	7.16
	0.9	0.09049	0.56487	0.76939	1.29990	279.9	198	197.2	0.40%	5.89
	1.0	0.16927	0.42080	0.73278	1.04751	311.0	220	219.2	0.36%	5.09

TABLE IV. SWITCHING ANGLES CALCULATED WITH DMO

DMO-THD										
m		**θ_1**	**θ_2**	**θ_3**	**θ_4**	**Vref(max)**	**Vref(rms)**	**V1p(rms)**	**error(%)**	**THD (%)**
Low	0.1	1.25155	1.57080	1.57080	1.57080	31.1	22	22	**0.00%**	**81.53**
	0.2	0.90035	1.56281	1.57080	1.57080	62.2	44	43.96	**0.09%**	**31.15**
	0.3	0.74652	1.35878	1.57079	1.57080	93.3	66	65.98	**0.03%**	**16.59**
Medium	0.4	0.70201	1.06326	1.56251	1.57050	124.4	88	87.9	**0.11%**	**14.56**
	0.5	0.72771	0.95647	1.32300	1.56534	155.5	110	109.9	**0.09%**	**12.08**
	0.6	0.61719	0.91465	1.17107	1.49344	186.6	132	132.1	**-0.08%**	**7.97**
High	0.7	0.64445	0.84405	1.06562	1.31157	217.7	154	153.8	**0.13%**	**7.89**
	0.8	0.43091	0.84920	0.96353	1.18695	248.8	176	175.4	**0.34%**	**7.09**
	0.9	0.09255	0.26872	0.57777	1.54006	279.9	198	197.4	**0.30%**	**5.14**
	1.0	0.17221	0.41732	0.72942	1.04757	311.0	220	219.4	**0.27%**	**5.08**

TABLE V. CONSISTENCY TEST RESULTS FOR THE GA ALGORITHM

	M	**Best FF**	**Worst FF**	**Average FF**	**SD**
Low	0.1	639.1005	681.4048	646.0766	22.08179178
	0.2	402.1548	628.7134	449.9921	99.95809935
	0.3	343.3644	625.0000	428.5866	113.8551927
Medium	0.4	325.0000	760.9142	483.1489	174.5489118
	0.5	411.8874	594.4970	468.6769	75.26091957
	0.6	350.0000	476.1420	398.6683	52.50764789
High	0.7	322.1084	369.4670	340.9151	20.79198513
	0.8	350.0000	527.0231	405.6887	73.8926317
	0.9	350.5010	527.0231	415.7465	67.76408978
	1.0	412.0000	521.0000	443.4694	46.33881392

TABLE VI. CONSISTENCY TEST RESULTS FOR THE PSO ALGORITHM

	M	**Best FF**	**Worst FF**	**Average FF**	**SD**
Low	0.1	639.9195	639.9193	0.000151658	639.9191
	0.2	373.4845	372.5665	0.523020136	372.2170
	0.3	243.4628	241.6354	1.346578969	240.0000
Medium	0.4	335.8261	332.3950	2.173133603	330.0449
	0.5	318.6277	316.2707	2.089369069	313.2210
	0.6	239.7146	233.5729	3.615158234	230.3388
High	0.7	343.5299	336.0832	4.719616123	331.7954
	0.8	239.7378	236.2114	3.355964747	231.7386
	0.9	215.9969	213.5371	2.260840591	210.2884
	1.0	252.4363	249.6602	1.658498588	248.2629

TABLE VII. CONSISTENCY TEST RESULTS FOR THE DMO ALGORITHM

	M	**Best FF**	**Worst FF**	**Average FF**	**SD**
Low	0.1	639.9397	640.0677	639.9709	0.054494
	0.2	372.2047	394.2057	378.9300	8.915979
	0.3	242.5685	309.2399	259.8002	27.90816
Medium	0.4	330.8299	405.0950	349.1023	31.66964
	0.5	350.5683	418.7842	367.8205	28.78559
	0.6	223.0783	229.9863	226.9226	2.723931
High	0.7	321.5113	441.7283	390.5902	62.22153
	0.8	317.7837	326.2569	320.8432	3.273073
	0.9	208.0000	291.3917	245.6687	38.21190
	1.0	253.4175	268.9137	261.7454	6.995747

TABLE VIII. COMPARATIVE TABLE OF CALCULATION TIMES FOR EACH EXPERIMENT OF THE ALGORITHMS

Algorithm	Run Order					Average Time (s)
	1	2	3	4	5	
GA	1.156	1.141	1.146	1.176	1.173	1.1584
PSO	0.620	0.710	0.712	0.669	0.728	0.6878
DMO	**0.450**	**0.452**	**0.408**	**0.441**	**0.468**	**0.4438**

As seen in Table II, Table III, and Table IV, for low, medium, and high modulation index values, GA, PSO, and DMO algorithms found suitable solutions. Multilevel inverters are generally not operated at low modulation indices. The modulation value used in applications exceeds the medium modulation value. As shown in the table, for low, medium, and high modulation indices, the DMO algorithm found more suitable solutions. Switching angles obtained for low, medium, and high modulation indices with GA, PSO, and DMO algorithms were applied to the three-phase 9-level inverter Simulink model. The voltage waveform obtained with GA, PSO, and DMO algorithms is presented in Fig. 3, Fig. 4, and Fig. 5, respectively.

Fig. 3 presents the harmonic analysis of the waveform obtained with GA. For a modulation index of 0.3, the calculated fundamental voltage value has a peak value of 92.79V with a 0.59% error and an rms value of 65.61V. Under this condition (Fig. 6), the THD value is measured as 17.17%. For a modulation index of 0.6, the fundamental voltage value reaches a peak value of 185.5V with a 0.61% error and an rms value of 131.2V. The THD value for this modulation index is calculated as 8.91%. For a modulation index of 1.0, the fundamental voltage value has a peak value of 310.1V with a 0.32% error and an rms value of 219.3V. In this case, the THD value is measured as 5.32%.

Fig. 4 presents the harmonic analysis of the waveform obtained with PSO. For a modulation index of 0.3, the calculated fundamental voltage value has a peak value of 93.06V with a 0.29% error and an rms value of 65.81V. The THD value for a modulation index of 0.3 is measured as 18.74%. For a modulation index of 0.6, the fundamental voltage value reaches a peak value of 186V with a 0.38% error and an rms value of 131.5V. In this case (Fig. 7), the THD value is calculated as 8.02%. For a modulation index of 1.0, the fundamental voltage value has a peak value of 310V with a 0.36% error and an rms value of 219.2V. The THD value for a unit modulation index is measured as 5.09%.

Fig. 5 includes the harmonic analysis of the waveform obtained with DMO. For a modulation index of 0.3, the calculated fundamental voltage value has a peak value of 93.31V with a 0.03% error and an rms value of 65.98V. In this case (Fig. 8), the THD value is measured as 15.59%. For a modulation index of 0.6, the fundamental voltage value reaches a peak value of 186.8V with a 0.08% error and an rms value of 132.1V. The THD value for a modulation index of 0.6 is calculated as 7.97%. For a modulation index of 1.0, the fundamental voltage value has a peak value of 310.3V with a 0.27% error and an rms value of 219.2V. The THD value for a modulation index of 1.0 is measured as 5.08%.

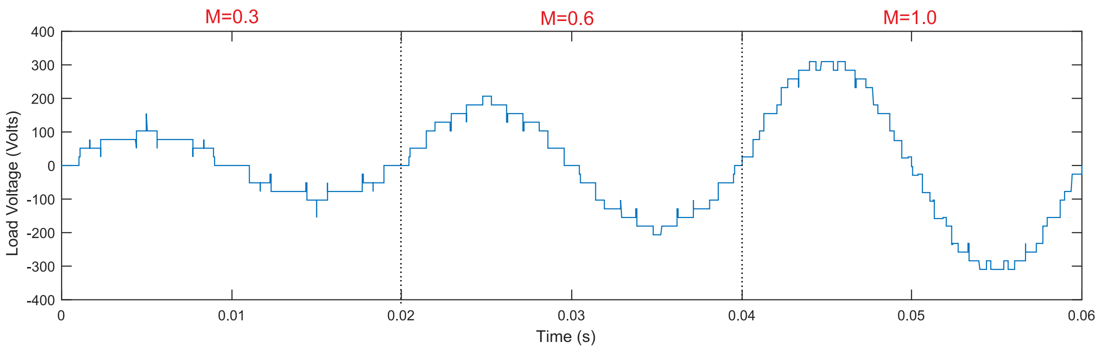

Fig. 3. Inverter output waveforms for modulation indices M=0.3, M=0.6, and M=1.0 (GA)

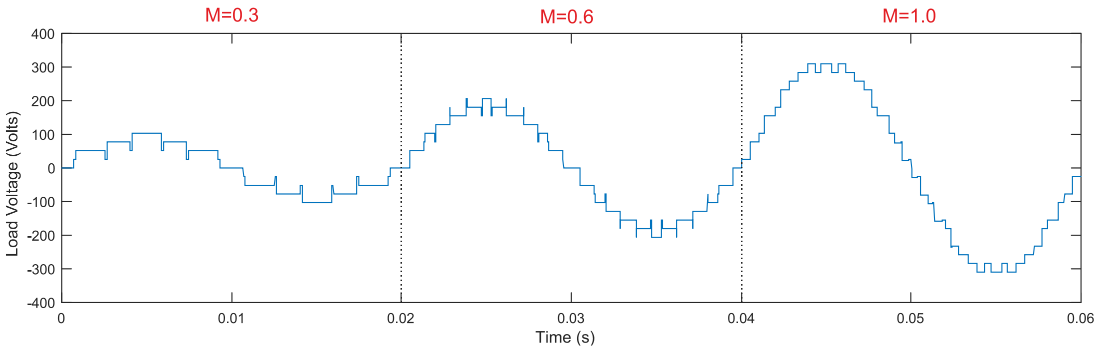

Fig. 4. Inverter output waveforms for modulation indices M=0.3, M=0.6, and M=1.0 (PSO)

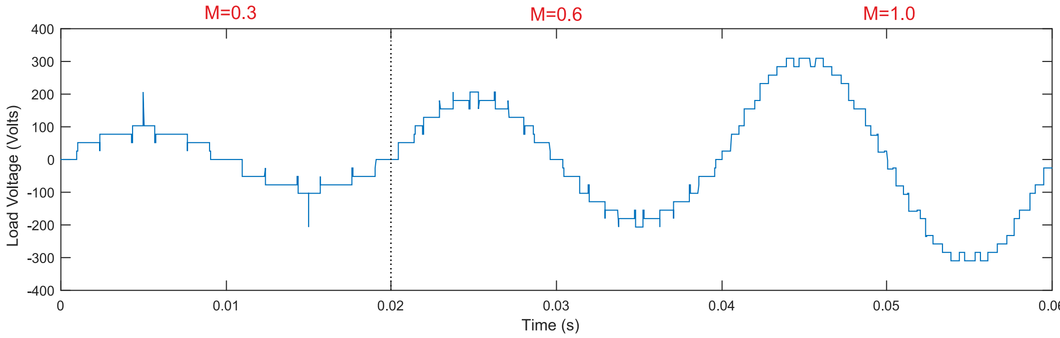

Fig. 5. Inverter output waveforms for modulation indices M=0.3, M=0.6, and M=1.0 (DMO)

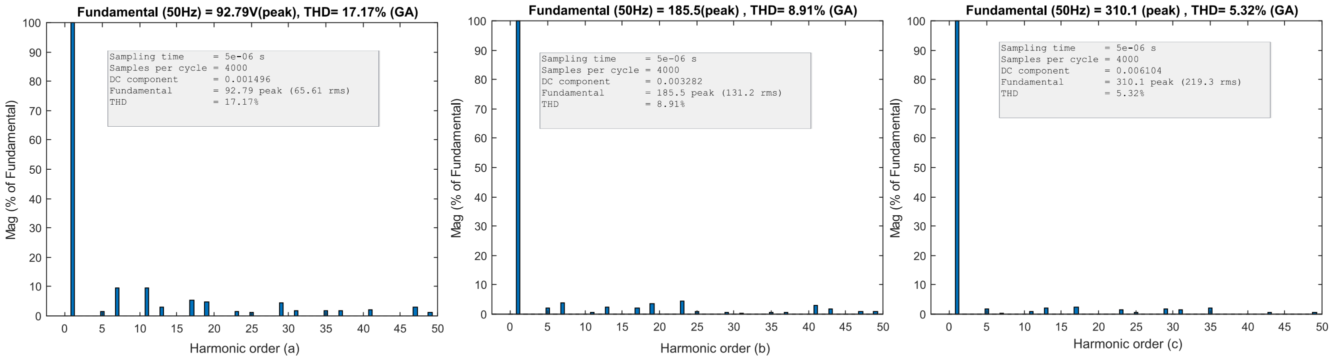

Fig. 6. THD analysis for (a) M=0.3, (b) M=0.6, and (c) M=1.0 (GA)

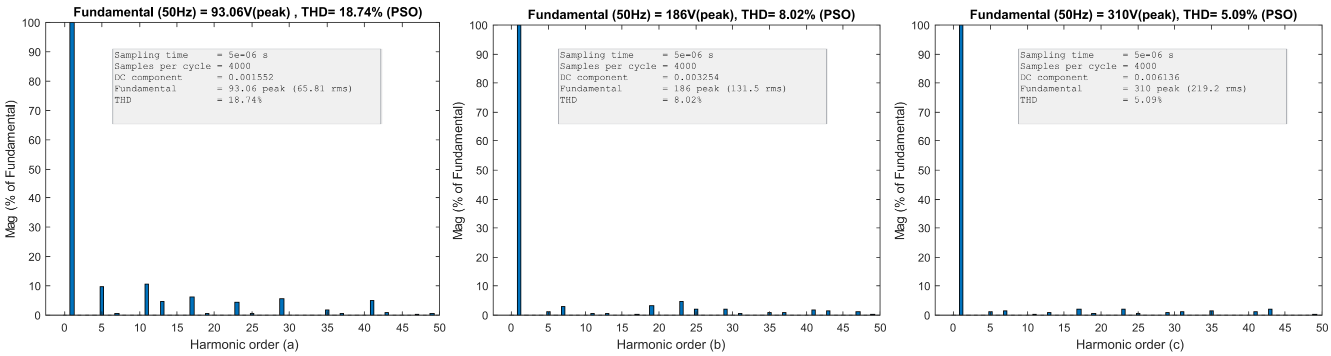

Fig. 7. THD analysis for (a) M=0.3, (b) M=0.6, and (c) M=1.0 (PSO)

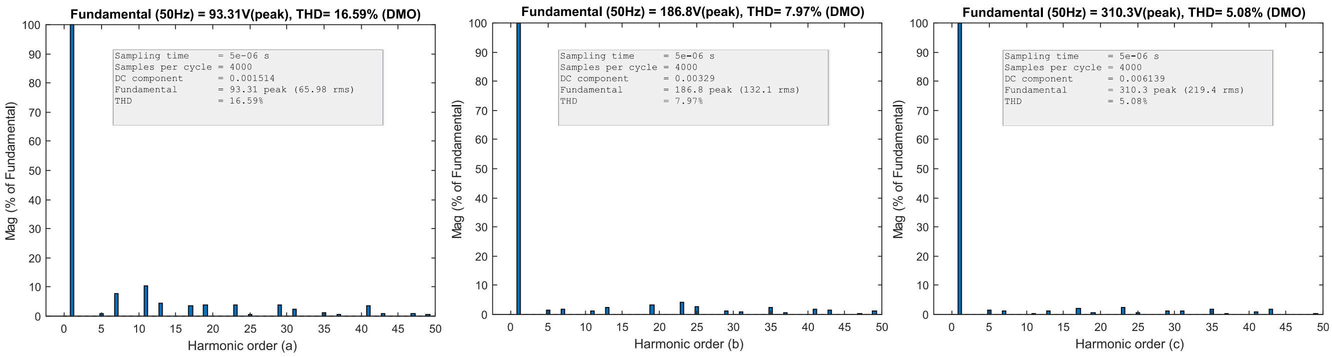

Fig. 8. THD analysis for (a) M=0.3, (b) M=0.6, and (c) M=1.0 (DMO)

IV. CONCLUSION

In this study, we focused on the DMOA, which is a new metaheuristic algorithm that was only used in this current research to solve the THD issue. The primary focus of this research was to evaluate the performance of the DMOA in the context of a three-phase, nine-level cascaded H-bridge multilevel inverter, where it was compared with two established optimization techniques: these two algorithms are the Genetic Algorithm (GA) and Particle Swarm Optimization (PSO).

The performance analysis has of the three algorithms demonstrated that it was possible to get acceptable solutions in the modulation index of between 0.1 and 1.0. Peculiarly, both GA and PSO approximated the THD in the inhibition of which range was between 0.8 to 1.0 only; nonetheless, the DMOA was able to optimize the successful results across a broader modulation index range of between 0.6 to 1.0. This discovery suggests the relative advantage of DMOA finding a better level of flexibility and optimality for THD than other approaches.

By considering critical aspects like sensitivity, speed, and statistical estimates, subsequent assessment of the algorithms pointed to superiority of DMOA in all assessed scenarios. In particular, it was more efficient and accurate than GA and PSO for the specific problem reported. As compared to GA, the PSO algolithm's fundamental voltage control error was higher, though the analysis proves that the DMOA is less likely to experience control error and therefore is more suitable for practical application. However, the errors observed in the fundamental voltage control were considerable lower in the GA algorithm case, showing that this technique is far from optimal in this regard.

To sum up, the DMOA has been described as an effective method for the THD optimization in MLIs without requiring high computational resources for its application contrary to some other methods. Furthermore, flexibility in applying DMOA to derive solutions to other contingencies of optimization problems in different fields extends its application potential in the field of engineering and power system.

ACKNOWLEDGMENT

Sinan Q. Salih expresses his appreciation to Al-Bayan University which has offered the equipment and the opportunities that enable this study. The funding of this research was facilitated by Al-Bayan University, Technical College of Engineering, Baghdad – 10011, Iraq

REFERENCES

[1] J. O. Agushaka, A. E. Ezugwu, and L. Abualigah, "Dwarf mongoose optimization algorithm," *Computer methods in applied mechanics and engineering*, vol. 391, p. 114570, 2022.

[2] J. O. Agushaka, A. E. Ezugwu, O. N. Olaide, O. Akinola, R. A. Zitar, and L. Abualigah, "Improved dwarf mongoose optimization for constrained engineering design problems," *Journal of Bionic Engineering*, vol. 20, no. 3, pp. 1263-1295, 2023.

[3] O. A. Akinola, A. E. Ezugwu, O. N. Oyelade, and J. O. Agushaka, "A hybrid binary dwarf mongoose optimization algorithm with simulated annealing for feature selection on high dimensional multi-class datasets," *Scientific Reports*, vol. 12, no. 1, p. 14945, 2022.

[4] C. W. Sun, T. Z. Huang, H. X. Dou, T. Xu, and L. J. Deng, "A fast Lanczos-based hierarchical algorithm for tensor ring decomposition," *Signal Processing*, p. 109705, 2024.

[5] S. O. Babalola, P. A. Steenkamp, M. O. Daramola, and S. A. Iwarere, "Mechanistic study of cefixime degradation with an atmospheric air dielectric barrier discharge–Influence of radical scavengers and metal ion catalyst," *Separation and Purification Technology*, vol. 353, p. 128376, 2025.

[6] H. J. Guo, X. J. Chen, R. Shu, X. B. Zhong, L. X. Zhang, and Y. X. Song, "Ionic liquid-integrated aqueous electrolyte regulation on solvation chemistry and electrode interface for reversible dendrite-free zinc anodes," *Journal of Colloid and Interface Science*, vol. 678, pp. 627-636, 2025.

[7] P. Gao, Y. Zhang, M. Wang, W. Yu, Z. Yan, and J. Li, "Cost-efficient sunlight-driven thermoelectric electrolysis over Mo-doped Ni5P4 nanosheets for highly efficient alkaline water/seawater splitting," *Journal of Materials Science & Technology*, vol. 211, pp. 134-144, 2025.

[8] F. Aldosari, L. Abualigah, and K. H. Almotairi, "A normal distributed dwarf mongoose optimization algorithm for global optimization and data clustering applications," *Symmetry*, vol. 14, no. 5, p. 1021, 2022.

[9] A. K. Arani, A. Ghasemi, H. Karami, M. Akhbari, and G. B. Gharehpetian, "Optimal switching algorithm for different topologies of 15-level inverter using genetic algorithm," in *2019 5th Conference on Knowledge Based Engineering and Innovation (KBEI)*, pp. 352-358, 2019.

[10] H. Behbahanifard, S. Abazari, and A. Sadoughi, "New scheme of SHE-PWM technique for cascaded multilevel inverters with regulation of DC voltage sources," *ISA transactions*, vol. 97, pp. 44-52, 2020.

[11] N. N. R. Ahmad, R. Nasir, E. Ricci, C. P. Leo, R. Bahru, and S. P. Koh, "Integration of deep eutectic solvent with adsorption and membrane-based processes for CO2 capture: An innovative approach," *Separation and Purification Technology*, p. 129592, 2024.

[12] O. K. Ahmed, S. Algburi, M. A. Jasim, T. A. Taha, A. M. Saleh, and K. F. Yassin, "Experimental assessment of the effect of black dye and water depth on the performance of PV/solar distiller," *Desalination and Water Treatment*, vol. 318, p. 100317, 2024.

[13] J. Bai, Y. Zheng, J. Wang, S. Shi, and S. Liu, "Design, development and multi-scenario application of portable multifunctional test master based on μM-PMU: The case study of Lingang new City Grid, Shanghai," *Measurement*, p. 115750, 2024.

[14] H. Fadheli, S. K. A. Khalid, and L. M. Fadzil, "A Non-GPS Return to Home Algorithm for Drones using Convolutional Neural Network," *Journal of Advanced Research in Applied Sciences and Engineering Technology*, vol. 51, no. 1, pp. 15-27, 2025.

[15] M. Mythreyee and A. Nalini, "Genetic Algorithm Based Smart Grid System for Distributed Renewable Energy Sources," *Computer Systems Science & Engineering*, vol. 45, no. 1, 2023.

[16] K. Dinakaran, F. Kavin, P. Anitha, D. Gurupandi, and K. Pradeepa, "Enhanced Generalization Performance in Deep Learning for Monitoring Driver Distraction: A Systematic Review," *Journal of Advanced Research in Applied Sciences and Engineering Technology*, vol. 48, no. 1, pp. 137-151, 2024.

[17] A. M. Lafta *et al.*, "Brain Inspired Cognitive Architecture of Hierarchical Distributed Model Based on Artificial Intelligence," in *2024 International Conference on Smart Systems for Electrical, Electronics, Communication and Computer Engineering (ICSSEECC)*, pp. 654-659, 2024.

[18] Y. Zhang *et al*, "Metal foams for the interfering energy conversion: Electromagnetic wave absorption, shielding, and sound attenuation," *Journal of Materials Science & Technology*, vol. 215, pp. 258-282, 2024.

[19] X. Wan, L. Zhang, T. Wang, N. Zhang, and H. Li, "Synergistic optimization of multifunctional properties in carbon fiber/phenolic composites by designing array carbon nanotubes structures on the surface of carbon fibers," *Journal of Materials Science & Technology*, vol. 215, pp. 233-243, 2024.

[20] H. Li *et al.*, "Efficient adsorption of waste carbon nanotube by polyacrylamide gel to form wrinkled core-shell particles towards multifunctional composites for EMI shielding and sensing," *Separation and Purification Technology*, vol. 354, p. 128903, 2025.

[21] R. I. H. Hussein *et al*, "Enhanced Transformer Protection Using Fuzzy-Logic-Integrated Differential Relays: A Comparative Study with Rule-based Methods," *Journal of Robotics and Control (JRC)*, vol. 5, no. 5, pp. 1299-1310, 2024.

[22] Q. Cheng, J. He, S. Yang, X. Xiong, Z. Liang, and Y. Luo, "Evolving fatigue damage detection based on multi-component nonlinear modulation mechanism of tuned laser-generated Rayleigh waves," *International Journal of Fatigue*, vol. 184, p. 108328, 2024.

[23] S. R. Ahmed *et al*, "Optimizing Solar Energy Harvesting: A Comprehensive Study on Photovoltaic Tracking Systems and Their Impact on Renewable Energy Efficiency," in *International Conference on Forthcoming Networks and Sustainability in the AIoT Era*, pp. 246-253, 2024.

[24] M. Zhang *et al*, "Harmonic Pollution Zoning Method Based on Improved k-Shape Clustering," *IEEJ Transactions on Electrical and Electronic Engineering*, 2024.

[25] E. Çelik, "IEGQO-AOA: information-exchanged Gaussian arithmetic optimization algorithm with quasi-opposition learning," *Knowledge-Based Systems*, vol. 260, p. 110169, 2023.

[26] E. Çelik, N. Öztürk, and Y. Arya, "Advancement of the search process of salp swarm algorithm for global optimization problems," *Expert Systems with Applications*, vol. 182, p. 115292, 2021.

[27] M. A. Djehaf, S. A. Zidi, Y. D. Kobibi, and S. Hadjeri, "Modeling of a multi-level converter based VSC HVDC supplying a dead load," in *2015 International Conference on Electrical and Information Technologies (ICEIT)*, pp. 218-223, 2015.

[28] W. Pan *et al*, "Development of an automated photolysis rates prediction system based on machine learning," *Journal of Environmental Sciences*, vol. 151, pp. 211-224, 2025.

[29] T. A. Taha, N. I. A. Wahab, M. K. Hassan, and H. I. Zaynal, "Selective Harmonic Elimination in Multilevel Inverters Using the Bonobo Optimization Algorithm," in *International Conference on Forthcoming Networks and Sustainability in the AIoT Era*, pp. 304-321, 2024.

[30] L. Li *et al*., "Source and variability of formaldehyde in the Fenwei Plain: An integrated multi-source satellite and emission inventory study," *Journal of Environmental Sciences*, vol. 150, pp. 254-266, 2025.

[31] M. S. Mauludin, M. Khairudin, R. Asnawi, W. A. Mustafa, and S. F. Toha, "The Advancement of Artificial Intelligence's Application in Hybrid Solar and Wind Power Plant Optimization: A Study of the Literature." *Journal of Advanced Research in Applied Sciences and Engineering Technology*, vol. 50, no. 2, pp. 279-293, 2025.

[32] T. A. Taha *et al*., "Enhancing Multilevel Inverter Performance: A Novel Dung Beetle Optimizer-based Selective Harmonic Elimination Approach," *Journal of Robotics and Control (JRC)*, vol. 5, no. 4, pp. 944-953, 2024.

[33] N. F. Maidin, S. Baharom, and A. B. M. Sultan, "A Comparative Study on Testing Optimization Techniques with Combinatorial Interaction Testing for Optimizing Software Product Line Testing," *Journal of Advanced Research in Applied Sciences and Engineering Technology*, vol. 49, no. 1, pp. 77-94, 2025.

[34] B. K. Dora, S. Bhat, S. Halder, and M. Sahoo, "Solution of Reactive Power Dispatch problems using Enhanced Dwarf Mongoose Optimization Algorithm," in *2023 International Conference for Advancement in Technology (ICONAT)*, pp. 1-6, 2023.

[35] W. Fei, X. Du, and B. Wu, "A generalized half-wave symmetry SHE-PWM formulation for multilevel voltage inverters," *IEEE Transactions on Industrial Electronics*, vol. 57, no. 9, pp. 3030-3038, 2009.

[36] T. A. Taha, N. I. Wahab, M. K. Hassan, H. I. Zaynal, F. H. Taha, and A. M. Hashim, "Real-Time Optimal Switching Angle Scheme for a Cascaded H-Bridge Inverter using Bonobo Optimizer," *Journal of Robotics and Control (JRC)*, vol. 5, no. 4, pp. 918-930, 2024.

[37] Y. Ban *et al*., "Design and multi-objective optimization of hybrid process of membrane separation and electrochemical hydrogen pump for hydrogen production from biogas," *Separation and Purification Technology*, p. 129506, 2024.

[38] L. Li *et al*., "Optimization of the annulus space structure for hydrocyclone separation of rubber particles based on NSGA-II and GMDH," *Separation and Purification Technology*, p. 129341, 2024.

[39] Z. Wang *et al*., "Design and control of liquid-only transfer extractive dividing-wall column," *Separation and Purification Technology*, vol. 354, p. 129267, 2025.

[40] Y. Zeng *et al*., "All-fiber spatial and wavelength gain-flattening of few-mode EDFA via mode selective coupler," *Optics & Laser Technology*, vol. 181, p. 111778, 2025.

[41] C. M. Hutson, G. K. Venayagamoorthy, and K. A. Corzine, "Optimal SVM switching for a multilevel multi-phase machine using modified discrete PSO," in *2008 IEEE swarm intelligence symposium*, pp. 1-6, 2008.

[42] E. Bektaş *et al*., "Enhancing Harmonic Reduction in Multilevel Inverters using the Weevil Damage Optimization Algorithm," *Journal of Robotics and Control (JRC)*, vol. 5, no. 3, pp. 717-722, 2024.

[43] H. Karaca and E. Bektas, "Selective Harmonic Elimination Using Genetic Algorithm for Multilevel Inverter with Reduced Number of Power Switches," *Engineering Letters*, vol. 24, no. 2, 2016.

[44] N. Mittal, B. Singh, S. P. Singh, R. Dixit, and D. Kumar, "Multilevel inverters: A literature survey on topologies and control strategies," in *2012 2nd International Conference on Power, Control and Embedded Systems*, pp. 1-11, 2012.

[45] R. Panigrahi, S. K. Mishra, S. C. Srivastava, A. K. Srivastava, and N. N. Schulz, "Grid integration of small-scale photovoltaic systems in secondary distribution network—A review," *IEEE Transactions on Industry Applications*, vol. 56, no. 3, pp. 3178-3195, 2020.

[46] H. Zhang, S. Wang, and J. Wang, "Automatic optimization design of laser triangulation ranging sensors using an improved genetic algorithm," *Measurement*, p. 115739, 2024.

[47] Y. Bektaş, H. Karaca, T. A. Taha, and H. I. Zaynal, "Red deer algorithm-based selective harmonic elimination technique for multilevel inverters," *Bulletin of Electrical Engineering and Informatics*, vol. 12, no. 5, pp. 2643-2650, 2023.

[48] K. K. Karri, V. Singh, and S. Pattnaik, "A new reduced component multi-level inverter with low total standing voltage for renewable and EV application," *International Journal of System Assurance Engineering and Management*, pp. 1-19, 2024.

[49] P. A. Gray, N. J. B. Hosein, X. Lan, and P. W. Lehn, "A Bidirectional Current-Fed Isolated MMC With Partial Soft-Switching for High Step Ratio DC–DC Applications," in *IEEE Transactions on Power Electronics*, vol. 39, no. 7, pp. 8281-8292, July 2024.

[50] A. S. T. Hussain, D. Z. Ghafoor, S. A. Ahmed, and T. A. Taha, "Smart inverter for low power application based hybrid power system," in *AIP Conference Proceedings*, vol. 2787, no. 1, 2023.

[51] A. Thanabalan *et al*., "Performance Analysis of Deterministic Particle Swarm Optimization MPPT for a Standalone Photovoltaic System," *Journal of Advanced Research in Applied Sciences and Engineering Technology*, vol. 49, no. 1, pp. 108-116, 2025.

[52] S. N. Alali and A. Assalem, "New Methods for Optimal Power Allocation and Joint Resource Scheduling in 5G Network which Use Mobile Edge Computing," *Journal of Advanced Research in Applied Sciences and Engineering Technology*, vol. 47, no. 2, pp. 237-265, 2024.

[53] L. I. Zongyao, X. Huang, L. Wang, Y. Chen, T. Shi, and W. Shen, "Sustainable and efficient separation of ternary multi-azeotropic mixture butanone/ethanol/water based on the intensified reactive extractive distillation: process design, multi-objective optimization, and multi-criteria decision-making," *Separation and Purification Technology*, p. 129694, 2024.

[54] Y. Hao, Z. Wang, J. Fu, X. Bai, C. Li, and Q. Pan, "Combinatorial-restless-bandit-based transmitter-receiver online selection of distributed MIMO radar with non-stationary channels," *Signal Processing*, p. 109707, 2024.

[55] H. Wang, J. Yan, W. Lu, J. Li, L. Song, and C. Han, "A rotating machinery feature enhancement method based on improved symplectic geometry mode component sparsity," *Measurement*, p. 115608, 2024.

[56] Y. Yu, Z. Guo, L. Zhang, J. Zhang, M. Zhu, S. Wu, and J. Xiao, "Compact and fabrication tolerant polarization insensitive mode-order converter for MDM systems," *Optics & Laser Technology*, vol. 181, p. 111780, 2025.

[57] P. Link, L. Penter, U. Rückert, L. Klingel, A. Verl, and S. Ihlenfeldt, "Real-time quality prediction and local adjustment of friction with digital twin in sheet metal forming," *Robotics and Computer-Integrated Manufacturing*, vol. 91, p. 102848, 2025.

[58] L. Miao *et al*., "Continuous stiffness optimization of mobile robot in automated fiber placement," *Robotics and Computer-Integrated Manufacturing*, vol. 91, p. 102833, 2025.

[59] S. Natarajan and G. AjithKumar, "Single Source Self balanced Switched Capacitor based Singe Phase Nine level Inverter," *e-Prime-Advances in Electrical Engineering, Electronics and Energy*, p. 100757, 2024.

[60] M. Y. Lada, M. A. M. Radzi, J. Jasni, H. Hizam, A. Jidin, and S. H. Mohamad, "Evaluation of conventional inverter and nine level multilevel inverter in shunt active power filter," in *AIP Conference Proceedings*, vol. 3128, no. 1, 2024.

[61] U. Gajula, K. Manivannan, and N. M. Reddy, "Performance analysis for induction motor fed by reduced switch symmetrical multilevel inverter topology," *International Journal of Power Electronics and Drive Systems (IJPEDS)*, vol. 15, no. 2, pp. 925-934, 2024.

[62] B. R. Vishwanath and P. S. Puttaswamy, "A Comparative Analysis Of Ga-Based Shepwm In A Three-Phase Cascade H-Bridge And A Reduced Switch Nine-Level Inverter," *International Journal on Technical and Physical Problems of Engineering (IJTPE)*, vol. 16, no. 1, pp. 325-332, 2024.

[63] Z. Gu *et al*., "Tapered photonic crystal fiber based on artificial intelligence-design for pulse compression," *Optics & Laser Technology*, vol. 181, p. 111650, 2025.

[64] M. G. Raj and S. K. Pani, “Intrusion detection system using combination of deep residual fuzzy network and white shark-dwarf mongoose optimization,” *Soft Computing*, pp. 1-17, 2023.

[65] M. Sadoughi, A. Pourdadashnia, M. Farhadi-Kangarlu, and S. Galvani, “PSO-optimized SHE-PWM technique in a cascaded H-bridge multilevel inverter for variable output voltage applications,” *IEEE Transactions on Power Electronics*, vol. 37, no. 7, pp. 8065-8075, 2022.

[66] A. Sayyah, M. Aflaki, and A. Rezazadeh, “Optimization of total harmonic current distortion and torque pulsation reduction in high-power induction motors using genetic algorithms,” *Journal of Zhejiang University-Science A*, vol. 9, pp. 1741-1752, 2008.

[67] J. K. Tandekar, A. Ojha, and S. Jain, “Application of CHB-MLI as a Three-Phase Star-Connected Nine-Level Shunt Active Power Filter,” *Multilevel Converters*, pp. 339-360, 2024.

[68] T. A. Taha, M. K. Hassan, N. I. A. Wahab, and H. I. Zaynal, “Red Deer Algorithm-Based Optimal Total Harmonic Distortion Minimization for Multilevel Inverters,” in *2023 IEEE IAS Global Conference on Renewable Energy and Hydrogen Technologies (GlobConHT)*, pp. 1-8, 2023.

[69] R. Kumar, M. A. Chaudhari, P. Chaturvedi, and S. C. Choube, “A PLL-less grid-tied three-phase multilevel inverter with reduced device count and LCL filter,” *International Journal of Circuit Theory and Applications*, 2024.

[70] S. K. Dalai, K. P. Panda, Y. P. Siwakoti, and G. Panda, "Three-Phase Switched-Capacitor Boost Self-Balanced Multilevel Inverter for Photovoltaic Applications," in *IEEE Transactions on Energy Conversion*, vol. 39, no. 3, pp. 1818-1827, Sept. 2024.

[71] M. A. S. B. Bimazlim, “Selective harmonic elimination pulse width modulation for three-phase nine-level inverter using improved whale optimization algorithm,” in *AIP Conference Proceedings*, vol. 2579, no. 1, 2023.

[72] A. Mourya and M. Gautam, “Modeling and Simulation of Total Harmonic Distortion (THD) in Multilevel H Bridge Inverters for Healthcare,” in *Frontiers of ICT in Healthcare: Proceedings of EAIT 2022*, pp. 53-64, 2023.

[73] M. Khizer, S. Liaquat, M. F. Zia, S. Kanukollu, A. Al-Durra, and S. M. Muyeen, “Selective harmonic elimination in a multilevel inverter using multi-criteria search enhanced firefly algorithm,” *IEEE Access*, vol. 11, pp. 3706-3716, 2023.

[74] M. A. S. Bimazlim, B. Ismail, M. Z. Aihsan, R. Ali, and M. S. M. A. Walter, “Selective Harmonic Elimination Pulse Width Modulation (Shepwm) For Five-Phase Nine-Level Inverter Using Improved Whale Optimization Algorithm,” *Journal of Engineering Science and Technology*, vol. 17, no. 6, pp. 4469-4486, 2022.

[75] J. Wang, X. Wang, and Y. Ye, “Three-Phase Neutral-Point-Clamped Step-up Nine-Level Inverter for Grid-Connected Applications,” in *2022 IEEE 9th International Conference on Power Electronics Systems and Applications (PESA)*, pp. 1-6, 2022.

[76] P. R. Kasari and S. Bhattacharjee, “An improved grid integration technique for SPV-based CHB-MLI in distribution network,” *International Journal of Power Electronics*, vol. 16, no. 3, pp. 315-344, 2022.

[77] G. Vashishtha, R. D. Kulkarni, and L. M. Antony, “Design, Simulation and Comparative Analysis of Novel Nine Level Symmetrical Multilevel Inverter with Improved THD and Reduced Number of Switches for Power Quality Improvement,” in *2022 2nd International Conference on Intelligent Technologies (CONIT)*, pp. 1-7, 2022.

[78] M. N. Rao, N. Karthick, and A. M. Rao, “Energy Balancing Capability of a Three Phase Nine-Level Inverter for Solar Water Pumping Applications,” in *2022 2nd International Conference on Power Electronics & IoT Applications in Renewable Energy and its Control (PARC)*, pp. 1-6, 2022.

[79] A. O. Abdali, A. K. Abdulabbas, and H. J. Nekad, “Non-conventional Cascade Multilevel Inverter with Lower Number of Switches by Using Multilevel PWM,” *Iraqi Journal for Electrical & Electronic Engineering*, vol. 17, no. 1, 2021.

[80] B. P. Shashank, T. Ananya, S. Venkatesh, and N. Srinivas, “Application of Multi Level Inverter Using MMC and FACTS in Distributed Energy Systems,” in *2023 4th International Conference for Emerging Technology (INCET)*, pp. 1-5, 2023.

[81] T. R. Sumithira and A. Nirmal Kumar, “Elimination of harmonics in multilevel inverters connected to solar photovoltaic systems using ANFIS: an experimental case study,” *Journal of applied research and technology*, vol. 11, no. 1, pp. 124-132, 2013.

[82] B. Zhou, B. Li, J. He, Y. Li, and Q. Li, “A novel mitigation strategy of subsequent commutation failures in the hybrid cascaded LCC-MMC HVDC transmission system,” *International Journal of Electrical Power & Energy Systems*, vol. 148, p. 108969, 2023.