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Design and Optimization of a Reduced-Switch 7-Level MLI for Standalone Energy Systems Using Hybrid Metaheuristic Algorithms

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Abstract –
The rapid advancements in the power electronics sector have led to the evolution of multilevel inverters (MLIs) for various applications. Today, MLIs are preferred over conventional two-level inverters due to several advantages, such as lower voltage stress, reduced electromagnetic interference, and smaller filter size requirements. However, traditional MLIs often require a higher number of components to generate more voltage levels. To address this, this paper introduces a novel 7-level MLI with a reduced switch count, designed specifically for standalone energy systems. To efficiently control the system and reduce harmonics, a firefly-assisted Glowworm Swarm Optimization (GSO) algorithm is applied for selective harmonic elimination (SHE). The Moth-Flame Optimization (MFO) algorithm is utilized to eliminate low-order harmonics from the output voltage of the proposed MLI. Additionally, the Firefly Algorithm (FA) and Particle Swarm Optimization (PSO) are implemented to compare their effectiveness with the MFO algorithm. An Incremental Conductance (IC) algorithm is used to maximize power extraction from the energy system. The overall system is simulated in the MATLAB environment, with individual results discussed in detail. Finally, an experimental test setup validates the integrated MLI's performance with the SHE PWM control scheme, and the results are compared with those from traditional PWM control techniques.
Keywords: *Firefly algorithm (FA); multilevel inverter (MLI); selective harmonic elimination (SHE). GSO, MFO and PSO.*

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I.Introduction:

The demand for multilevel inverters (MLIs) continues to rise due to their critical role in high-power applications such as electric vehicles, motor drives, flexible AC transmission systems, laminators, mills, conveyors, and especially in power conversion from renewable energy sources. MLIs are widely adopted because they produce a stepped output waveform, which reduces harmonic distortion and lowers the stress on semiconductor devices [1,2,3]. Despite these advantages, power electronic converters, including MLIs, still face the issue of harmonics. These harmonics can negatively impact various applications, such as reducing efficiency, causing torque pulsations in electrical drives, and shortening the system's lifespan. To address these challenges, researchers have developed numerous control and modulation techniques aimed at reducing harmonics and enhancing the performance of power electronic converters. Among these, the Selective Harmonic Elimination (SHE) technique has gained significant attention due to its precise control over the harmonic spectrum in the output voltage. SHE has emerged as a widely researched alternative to traditional modulation methods, offering several advantages, such as acceptable performance even with low switching-to fundamental frequency ratios and direct control over specific output waveform harmonics [4,5]. These benefits make SHE particularly suitable for applications like variable speed drives and ground power units, where minimizing harmonic distortion is essential for optimal performance. Despite favorable outcomes, conventional Selective Harmonic Elimination (SHE) approaches have struggled to effectively eliminate low-order harmonics across the entire operating range. The mathematical constraints inherent in SHE has led researchers to modify the equation set, making the problem more manageable while still meeting the original objectives. It was later discovered that incorporating unequal DC-link voltages into the equation set offers a more accurate simulation for existing method.

II.Literature Survey:

Recently, many researchers have employed meta-heuristic algorithms for Selective Harmonic Elimination (SHE) in multilevel inverters, focusing on improving their performance and reducing harmonic distortion. These optimization algorithms, such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Firefly Algorithm (FA), have shown great potential in solving the complex, non-linear equations involved in SHE. By adjusting the switching angles of the inverter, these algorithms minimize specific harmonic frequencies, leading to a significant reduction in Total Harmonic Distortion (THD). This enhances the overall output quality, allowing multilevel inverters to produce cleaner voltage and current waveforms. As a result, the integration of meta-heuristic functions in SHE has become a popular research area, offering more precise control over harmonic content and making it easier to meet stringent power quality standards. The improvements in harmonic elimination through meta-heuristic optimization have a direct impact on the performance of devices relying on multilevel inverters, such as electric drives, renewable energy systems, and electric vehicles. These devices benefit from increased efficiency, lower operational noise, and extended equipment lifespan due to the reduction of harmful harmonics. Additionally, meta-heuristic algorithms provide flexibility in dealing with different inverter topologies and configurations, allowing for the optimization of not only standard inverters but also more complex multilevel inverters like 5-level, 7-level, and 11 level systems. Overall, meta-heuristic approaches have enhanced the capability of multilevel inverters, making them more suitable for high-performance applications.In [1], level-shifted and phase-shifted PWM techniques for inverter control are discussed. A hybrid APSO-GA is used to eliminate lower-order harmonics in multilevel inverters, addressing control complexity in high-switch-count gain inverters and the difficulty of solving nonlinear transcendental equations in SHEPWM techniques. In [2], a novel 11-level inverter topology is proposed, exploring various designs to increase output voltage steps without mentioning specific limitations. In [3], a modified FA (Firefly Algorithm) is employed for harmonic elimination in nine-level cascaded H-bridge inverters with optimal switching angles, validated experimentally using an OPAL-RT hardware setup. It notes that existing FA methods lack balance in social-cognitive components due to static tuning, and other hybridized structures in literature also lack this balance. In [4], AI techniques for harmonic elimination in inverters are reviewed, comparing calculus based and AI methods for solving transcendental equations.

The study concludes that AI methods overcome limitations in calculus-based techniques, with a performance review of 13 AI algorithms. In [5], an asymmetric multilevel inverter with fewer switches is developed, introducing a new topology to reduce switch components. Traditional topologies have high component counts, cost, and complexity, while this design addresses issues like power quality under partial shading. In [6], the ASO SHE method is shown to outperform other techniques for SHE in MLIs with PV systems, utilizing numerical methods and optimization techniques, though limitations are not explicitly mentioned. In [7], a fuzzy logic MPPT technique for PV systems and a new inverter topology with reduced device count are described. APSO is used for harmonic minimization in MLIs, though solving nonlinear equations remains complex, and its application is limited to symmetrical and asymmetrical MLIs. In [8], a review of recent MLI topologies, controllers, and PWM techniques provides comparative analysis and discusses future directions. The circuit complexity in topologies with fewer levels is noted, as is the need for more capacitors in ELHMLI for medium-voltage applications. In [9], existing topologies are found to have high switch counts and costs, while a proposed MLI topology has disadvantages in fault tolerance. In [10], reduced peak overshoot, rise time, steady-state error, and THD are reported. Power factor improvement, reactive power adjustment, and harmonic suppression using fuzzy PI and PSO PI controllers are noted, though grid current imbalance remains due to unbalanced power from the CHB inverter. In [11], a Direct Model Predictive Control approach is introduced for grid tied inverters, reducing computational burden through virtual sectors and optimal state identification, but high computational load persists due to numerous switching devices. In [12], improved ANN architecture is utilized for THD reduction, compared with state-of-the-art techniques, but there is a lack of efficiency explanation for THD in output voltage, and input inaccuracies may lead to unreliable output in fuzzy logic. In [13], a hybrid GA-PSO optimization technique is developed for MLI topologies, aiming to reduce the high cost and complexity of traditional designs. RS MLIs are proposed to minimize component count and enhance reliability. In [14], a 3 phase HMLI for 7-, 9-, and 11-level outputs is proposed, incorporating an output filter for THD compliance, with validation in MATLAB/Simulink. Increased complexity with higher-level outputs is noted, and the proposed topology simplifies switch control circuits, reducing switching losses and cost. In [15], a 7-level RSMLI with reduced switches for standalone PV systems is proposed, achieving low THD values compared to conventional MLIs, though NPC MLIs require more switches and diodes for additional voltage levels.

In [16], the AVO algorithm is applied for SHE equations in MLIs, providing precise fundamental voltage control with minimal error across modulation index ranges, though SHE equations remain complex and computationally intensive. In [17], the MFO algorithm is used to reduce THD in inverters and is shown to outperform other meta-heuristic methods for consistent THD reduction, without specific limitations mentioned. In [18], a modified PDPWM method for equal power distribution among inverter cells is proposed, discussing high-frequency cascaded MLI switching methods. Low order harmonics arise from ripples in DC link capacitors, leading to unequal power delivery. In [19], the Taguchi method is used to optimize switching angles for harmonic distortion reduction, with experimental results showing superiority in reducing THD, though GA parameter selection is challenging and the Taguchi method is rarely used in power electronics. In [20], various research aspects, including conceptualization, investigation, and supervision, are described, noting the NR method's sensitivity to initial values and tendency to get stuck at local optima. GA is effective for 9-level MLIs, but GWO experiences sudden THD increases. In [21], a 15-level inverter with reduced switches for renewable energy applications is proposed, using GA for selective harmonic elimination to minimize THD, validated experimentally for harmonic cancellation and fundamental regulation. Existing topologies have reliability issues and high total standing voltage (TSV). In [22], a novel ZVS inverter approach for motor drives is proposed, improving adaptability, EMI, switching losses, and power density.

However, motor winding damage is a concern due to incomplete commutation profiling. In [23], the RDA-based optimization approach is applied to the SHE problem, noting low-order harmonics' impact on efficiency, motor torque, and lifespan. Advanced MLI topologies increase control and modulation complexity. In [24], real-time calculation of switching angles using the Differential Evolution Algorithm is used for harmonic elimination, though application is limited by separate DC sources, and crossover constants require user determination. In [25], SMT-SHE modulation for ACHB-MLI is proposed with industrial validation, addressing harmonic torque generation and efficiency reduction in a textile factory. Capacitor selection for the ACHB-MLI structure faces contradictory constraints. In [26], the THD minimization problem for MLIs is formulated with modulation index constraints, achieving lower THD than previous methods, though results are suboptimal due to MI error. In [27], a 15-level cascaded MLI with 28 power switches is analysed, with a modified topology requiring fewer switches.

Traditional circuits had higher THD, switching loss, and complexity, while the proposed topologies required 10–12 switches. In [28], increasing exploration of MLI topologies is reported, though size, cost, and complexity of switching components hinder commercial adoption. In [29], a 7-level CMLI with fewer switches is proposed, with modified carriers for gate pulse generation and an added third harmonic component to increase fundamental output voltage. In [30], SC-based MLIswith reduced switching stress and modular construction are explored, though uneven conducting paths, high TSV, and increased voltage drop across capacitors are challenges.

III.Proposal Of Innovative Method For Predicting Optimum Wind Generator Detailed Explanation:

This section focuses on seven-level inverters and the application of various meta-heuristic optimization techniques for improving their performance. Seven-level inverters are widely used in power electronics due to their ability to produce higher-quality output waveforms with reduced harmonic distortion. However, achieving optimal performance, particularly in terms of selective harmonic elimination (SHE), is a complex challenge. Meta-heuristic algorithms such as Particle Swarm Optimization (PSO), Glowworm Swarm Optimization (GSO), Firefly Algorithm (FA), and Moth-Flame Optimization (MFO) have been employed to address these complexities. These algorithms are used to optimize switching angles in the inverter, ensuring effective harmonic suppression while maintaining efficiency in power conversion. By using these advanced techniques, researchers aim to minimize Total Harmonic Distortion (THD) and enhance the overall power quality of the inverter system.Each meta-heuristic method offers unique strengths in solving the non-linear and complex problems associated with seven-level inverters. PSO, for example, excels in finding global optima with fewer iterations, making it suitable for reducing low-order harmonics.

GSO and FA are particularly effective in handling multi-dimensional optimization problems, offering better exploration of the solution space to enhance waveform quality. MFO, with its unique exploitation and exploration mechanism, provides a balance between searching for global and local optima, which is essential for high-precision harmonic elimination. These algorithms have been compared and tested in various studies, demonstrating their capability to significantly improve the performance of seven-level inverters across a range of modulation indices. seven-level inverters are considered which has three H bridge cells shown in figure 1. These cells connected in series and also various output voltage levels are produced by every H-bridge cell (+Vdc and -Vdc) and measurement of voltage levels 2x+1 is used. Here x shows the number of bridges in a seven-level inverter which is equal to 3. This type of inverters is also called three level inverters because of its H-bridge count. It has no clamping diodes, absence of voltage balancing capacitors, tight control modular design and easy adjustment of output voltage levels[15]

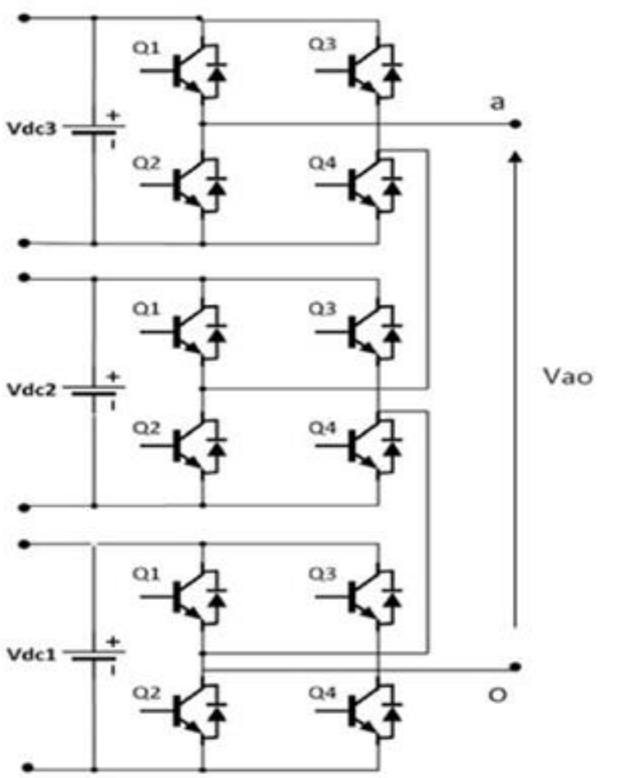

Figure 1 topology of seven level inverters

3.1 Glowworm Swarm Optimization (GSO)

The glow-worms possess a specific idea scope known as the local-decision range and carry their own luciferin values. A brighter glow has a higher attraction to draw this glow toward this traverse as it searches for a neighbour set in the local-decision range, and the flight direction will fluctuate depending on the neighbour's preference. Additionally, the number of neighbours will have an impact on the size of the local decision range; when the neighbour density is low, the policy-making radius of glow will increase in Favor of seeking out more neighbours

The process of algorithms defines following parameters

1. The load of virtual machine encodes i with objective function J(xi(t)) the position of feature data is xi(t) into acceleration α. The value of luciferin li spread with neighbour (Ni(t)) of glow worm. Each iteration of feature set the new factor of decision is updated by equation (4.1).
2. $d\ i\ t$ +1 $=min\ rs$,max 0,$rd\ i\ t$ +$\beta(nt-\ Ni(t))$………… 1
3. After the iteration of VM of new neighbors is 4. $Ni\ t$ = j: $xi\ t\ -xi(t)$
4. $Ni\ t$ = j: $xi\ t\ -xi(t)$ ……………………………………(2)
5. The movement of VM component by local decision is.
6. $p\ ij\ t$ = $k\in Ni(t)\ l\ i\ t\ -l\ i(t)\ lk\ t\ -li(t)$ ……………………………………………….(3)
7. Update the new set of features
8. $x\ i\ t$+1 =$xi\ t$ +$s\ sj\ t\ -xi\ t$ $j\ t\ -xi\ t$ ……………………………………(4)
9. Update the value if luciferin $i\ t$ = 1$-\rho\ li\ t$$-$1 +$\gamma j\ xi\ t$ ………………………………………(5)

3.2 Moth-Flame Optimization (MFO)

The process of selection for the selective harmonic by MFO algorithm. The description of MFO algorithm describe here [20, 21].

Moth-flame optimization algorithm is dynamic population based meta-heuristic function. The processing of algorithm describes here

The set of moths is defined as M, in which Mi is the i-th moth and Mij is the corresponding position of the i-th moth. Now OM define as fitness constraints

The algorithm describes the global optimal solution as FO = I,P,T ………………………..(6)   : $\varphi\ \rightarrow$ $\{M,OM\}$………………………..(7)   :M $\rightarrow M$………………………..(8)   :M

$\rightarrow\{true, false\}$………………………..(9) The processing of algorithm as M=I() While T(M) is equal to false M=P(M);
End Update the position of flames as Mi=S(Mi,Fi)……………………………………………….. (10) □ □ Mi,j $=Diebt$ cos 2∏t $+Fj$……………………….(11) □ □$i = Fj-Mi$ ………………………..(12)
The flame is updated as □ □$lame\ no = round\ N - LN - 1\ T$ …………………………………(13)
Where N is number of initial flames, T is total number of iterations, and L is current number of the iterations.
Processing of MFO algorithm
1. Define value of M according to formula (6) and estimate OM as M
2. The position of M and OM is constant and F and OF can be found by matching sequence of M and OM
3. By formula (8) estimates the numbers of moth and the end moths' flames removed
4. The distance between moths is calculated by formula (12)
5. Update the value of moths according to formula (11)
6. By M estimate OM
7. Decide the end condition is met, otherwise go to step 2

3.3 Firefly Algorithm

Firefly algorithm is meta-heuristic optimization algorithm based on the flashing behaviours of fireflies in environment. Firefly algorithm resolve the problem of NP-hard problem and manage the dynamic behaviours of data. It's a random algorithm, to put it another way, a random search is utilized to locate a collection of solutions. The FA, at its most basic, focuses on producing solutions inside a search area and selecting the greatest surviving option. A random search avoids being stuck in local optimums. Exploration in metaheuristic algorithms refers to discovering multiple solutions inside the search space, whereas exploitation refers to the search process focusing on the best neighbouring solutions. The firefly algorithm has three basic features are (1) the firefly becomes a.The firefly becomes brighter and more attractive when it moves randomly, and all fireflies are of the same sex. (2) The attractiveness of the fireflies is proportional to the brightness of the light and the distance from it. The light absorption coefficient γ calculates the reduction in light intensity. The value of the objective function also determines the luminance of the firefly. (3) the distance between fireflies is obtained form equation (1) so that Xi,k is the kth part of the spatial coordination and ith firefly[24.25.26]
□ □ $i, = (xi - xj)2 + (yi - yj)2$…………….(14)
The movement of firefly and attracted fireflies measured as
□ □$i = Xi + B0erij2\ Xj - Xi + a\ rand - 1\ 2$ ……….(15)
A is a randomizer variable, rand is a random integer between [0, 1], and B is the attractiveness of the light source. The parameter is determined by variations in attraction. The process of switching angle optimization The firefly algorithm (FA) employed in stock data as initial population and set the value of parameters as α,γ,β min$and\ t$ = 0 and Fes=0; the factors of brightness of data is Ii at Xi is measured by f(Xi). Define light absorption coefficient γ; While (not meet the stop conditions) For i=1: N all N fireflies For j=1: N all N fireflies If Ij>Ii Then Move firefly i towards j in all dimensions according to Equation (2); End If Attractiveness varies with distance Evaluate the new solution and update its brightness; Fes=Fes+1; End For End For Rank the fireflies and find the current best; t=t+1; End While Optimized switching angle End

IV.Conclusion And Future Work:

The proposed model has significantly fewer parameters and simpler parameters compared to the comparison model, reducing the risk of over fitting. It has the fastest convergence speed and performs multi-step forecasting directly, outperforming the Seq2Seq+attention method which performs it recursively. The study proposes the ideal model with the finest prediction result and fast speed, using the validation set's prediction effect as a benchmark. The model, which uses the Res-CNN net for the feature fusion, is greater than the TFT technique in multi-step prediction mechanisms and direct prediction mechanisms compared to the Seq2Seq+attention model.

The study proposes a solution to the wind power multi-step prediction issue using a multi-source information fusion and deep learning algorithmic. It suggests that utilizing time-varying information and static variable information for feature selection can increase forecasting model accuracy. Additionally, historical statistical data can be added for better prediction. The method also improves model generalization and feature engineering, making it faster and more accurate than recursive prediction

Res-CNN multi-source data fusion enhances model generalization and enhances forecasting capability. The direct prediction technique and self-attention mechanism exhibit effective multi-step prediction skills. It trains faster and predicts better than recursive prediction.

The study's numerical wind farm power forecasting experiment reveals that a deep learning prediction model outperforms Seq2Seq+attention, but the multi-step problem still has a significant time lag during strong gusts. The study also missed critical aspects like the division of working circumstances, which significantly impact data driven forecasting approaches.

The conclusion shows variables and methodologies. Performance, wind turbines, PV generating power, and randomizing PV energy are employed for intermittent production The models used in these studies are LSTM time series forecasting and wind turbine power curve approximation models. An LSTM forecasting model and awind turbine power curve model were able to predict the 24-hour wind direction and speed in addition to wind generator output power. The large area of wind generators can be anticipated and determined with this tool. Predictions for wind speed, direction, and power was clustered. Forecasts for wind and direction have RMSE (0.35 m/sec, 7.9 rad) and R2 (94%, 71%). Generator power is random. Similar to the wind, wind turbine power swings randomly, but with a minimum beginning speed. Different locations affect wind and PV generator performance and power. After installing a generator, wind speed randomness must be used to estimate output power. This study proves its practicality using artificial intelligence and clustering to find a good location, discover wind power production potential across a vast region, and determine the best production periods. This study predicts wind speed, direction, and output power over 12 h using an LSTM and wind turbine power curve approximation model. The data will help a country to choose wind turbine locations and estimate performance year-round.

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The conclusion outlines the approaches and variables that were used. Intermittent production makes use of performance, wind turbines, photovoltaic power generation, and the randomization of photovoltaic energy. LSTM time series forecasting and wind turbine power curve approximation models were utilized in these studies. These models were able to predict the 24-hour wind direction and speed, as well as the output power of the wind generator. The large area of wind generators can be anticipated and determined with this tool. Predictions for wind speed, direction, and power was clustered. Forecasts for wind and direction have RMSE (0.35 m/sec, 7.9 rad) and R2 (94%, 71%). Generator power is random. Similar to the wind, wind turbine power swings randomly, but with a minimum beginning speed. Different locations affect wind and PV generator performance and power. After installing a generator, wind speed randomness must be used to estimate output power. This study utilized clustering and AI to determine optimal wind power production locations and periods. An LSTM and a wind turbine power curve approximation model were used in this research project to provide forecasts about the wind speed, direction, and output power over a period of 12 hours. Wind turbine impacts must be balanced using a comprehensive, multi-stakeholder strategy. Planning, community interaction, environmental preservation, and renewable energy promotion are needed. To maximize wind energy advantages, minimize the environmental and community consequences. With this information, a nation will be better able to identify places for wind turbines and predict their performance throughout the year

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