ISSN: 2395-1680 (ONLINE)
DOI: 10.21917/ijme.2026.0372

OPTIMIZED CONTROL STRATEGIES FOR POSITIVE OUTPUT LUO CONVERTER USING INTELLIGENT AND MODEL-BASED TECHNIQUES

S.V. Kayalvizhi[1] and V. Suresh[2]
[1]Department of Electrical and Electronics Engineering, St. Xaviers Catholic College of Engineering, India
[2]Department of Electronics and Communication Engineering, Mar Ephraem College of Engineering and Technology, India

Abstract
The Positive Output Luo Converter (POLC) has been widely applied in DC–DC power conversion due to its combined buck–boost capability and non-inverting output voltage. The converter topology has included multiple energy storage elements, which has increased the system order and has resulted in nonlinear dynamic behavior. These characteristics have made the closed-loop voltage regulation of the POLC challenging under source and load disturbances. Conventional proportional–integral (PI) control has remained attractive due to its simplicity, but the fixed gain selection has limited its performance in higher-order nonlinear converters. Classical tuning methods have provided acceptable initial responses; however, they have failed to ensure optimal transient and steady-state performance under varying operating conditions. In this work, a PI-controlled POLC has been analyzed initially using the Ziegler–Nichols tuning method, which has supplied baseline gain values. These gains have been further refined using three nature-inspired optimization techniques: particle swarm optimization, cuckoo search algorithm, and crow search algorithm. Each algorithm has independently estimated optimal proportional and integral gains that have minimized performance indices related to overshoot, settling time, and steady-state error. In addition, an internal model controller (IMC) has been designed using forward and inverse transfer functions that have been identified through MATLAB Simulink using the iddata and tfest tools, which have enabled accurate system modeling. Simulation studies have demonstrated that optimized PI controllers have achieved superior voltage regulation compared to conventionally tuned controllers. Among all control strategies, the IMC has delivered the most consistent tracking performance and disturbance rejection. The control effort that has been required by fuzzy logic, artificial neural network, and adaptive neuro-fuzzy controllers has also been evaluated, and the IMC has exhibited reduced control action with improved robustness. These results have confirmed that model-based control has outperformed heuristic and classical approaches for POLC regulation.

Keywords:
Positive Output Luo Converter, PI Controller Optimization, Internal Model Control, Nature-Inspired Algorithms, DC–DC Converters

1. INTRODUCTION

The Positive Output Luo Converter (POLC) has attracted sustained attention in power electronics due to its ability to provide both buck and boost operation while maintaining a non-inverted output voltage. This feature has made the POLC suitable for renewable energy interfaces, battery-powered systems, and regulated DC distribution applications [1–3].

Compared to classical buck–boost converters, the POLC has offered improved voltage gain characteristics and flexible shutdown capability because the main power switch has been connected in series with the input source. As a result, the converter has supported efficient energy management and protection under no-load or standby conditions, which has been critical in low-power and portable systems.

Despite these advantages, the internal structure of the POLC has included multiple energy storage elements, typically two inductors and two capacitors, which have increased the overall system order. This structural complexity has introduced nonlinear and time-varying dynamics that have complicated the design of stable and high-performance controllers [4,5]. Under source voltage fluctuations and sudden load changes, conventional linear controllers have exhibited degraded transient responses, increased overshoot, and longer settling times. These issues have limited the applicability of fixed-gain controllers in demanding operating environments.

Several studies have attempted to address these challenges by applying classical PI and PID controllers, which have remained popular due to their simplicity and ease of implementation. However, the tuning of controller parameters has often relied on heuristic or trial-and-error approaches, which have failed to guarantee optimal performance across a wide operating range [6,7]. Moreover, as the POLC dynamics have varied with duty cycle and load conditions, static controller gains have been insufficient to ensure robust voltage regulation.

The primary problem addressed in this work has been the performance degradation of conventionally tuned controllers when applied to higher-order nonlinear converters such as the POLC. There has been a need for systematic tuning and advanced control strategies that can adapt to system nonlinearities while maintaining simplicity and implementability.

The main objectives of this study have been: (i) to evaluate the performance of a PI-controlled POLC under classical tuning, (ii) to optimize the PI controller gains using nature-inspired optimization algorithms, and (iii) to design and assess an Internal Model Controller based on identified system dynamics. The novelty of this work has lied in the unified comparison of optimized PI controllers and a model-based IMC framework for the same converter under identical operating conditions. Unlike many earlier studies, this work has integrated system identification with control design, which has improved model accuracy and controller robustness.

The key contributions of this study are twofold. First, three distinct optimization techniques have been systematically applied to refine PI controller parameters for the POLC, and their comparative performance has been analyzed. Second, an IMC-based control structure has been developed using identified forward and inverse models, and its superiority over heuristic and intelligent controllers has been demonstrated through detailed performance indices. These contributions have provided practical insights into advanced control design for nonlinear DC–DC converters.

2. RELATED WORKS

Early research on Luo converters has primarily focused on topology development and steady-state analysis. Studies have demonstrated that positive output Luo converters have achieved higher voltage gain with reduced ripple compared to traditional converters, which has motivated their adoption in regulated DC applications [8]. These works have established the theoretical foundation for POLC operation but have given limited attention to closed-loop control challenges.

Subsequent investigations have explored classical control approaches for POLC voltage regulation. Proportional–integral controllers have been widely applied due to their straightforward structure and ease of digital implementation. In several studies, Ziegler–Nichols and frequency-response-based tuning methods have been employed, which have yielded acceptable steady-state performance under nominal conditions [9]. However, these controllers have exhibited sensitivity to parameter variations and external disturbances, particularly in converters with higher-order dynamics.

To overcome these limitations, researchers have introduced intelligent control techniques such as fuzzy logic controllers and artificial neural networks. Fuzzy controllers have been designed to handle system nonlinearities using rule-based inference, which has improved transient response under load disturbances [10]. Neural network-based controllers have learned nonlinear mappings between system states and control actions, which has enabled adaptive behavior. Despite these advantages, such approaches have required extensive training data and higher computational effort, which has limited their real-time applicability.

Hybrid control schemes, including adaptive neuro-fuzzy inference systems, have combined learning capability with linguistic rule representation. These controllers have demonstrated improved robustness compared to standalone fuzzy or neural controllers [11]. However, their design complexity and tuning burden have remained significant, especially for embedded power electronic applications with limited processing resources.

In parallel, optimization-based controller tuning has gained popularity. Nature-inspired algorithms such as particle swarm optimization and cuckoo search have been applied to tune PI and PID controller gains for various DC–DC converters. These methods have minimized objective functions related to overshoot, integral error, and settling time, which has resulted in enhanced dynamic performance [12]. Although effective, many of these studies have focused on lower-order converters and have not explicitly addressed the unique dynamics of the POLC.

More recently, model-based control strategies have been investigated for power converters. Internal Model Control has emerged as a promising approach due to its transparent structure and inherent robustness to disturbances. IMC designs have relied on accurate system models, which have been obtained through analytical derivation or system identification techniques [13].

For nonlinear converters, data-driven identification methods have provided improved model fidelity, which has directly influenced controller performance. Despite these advances, limited work has compared optimized PI controllers and IMC schemes for the POLC within a unified framework.

3. METHODOLOGY

The proposed methodology has been structured into sequential and interdependent steps that collectively ensure robust voltage regulation of the Positive Output Luo Converter (POLC). Each step has addressed a specific control and optimization requirement, beginning from system modeling and proceeding toward advanced controller design and performance evaluation.

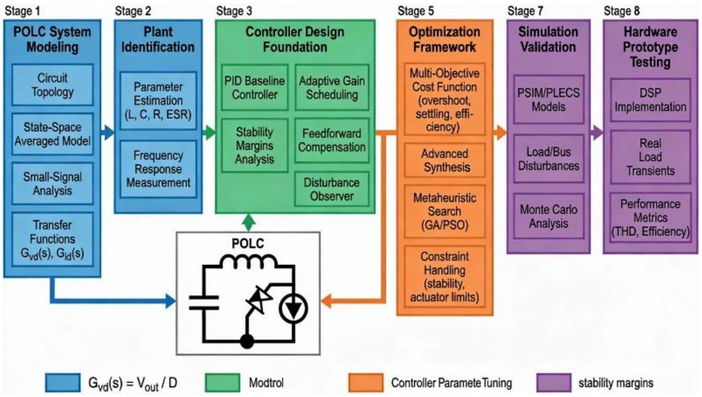

Fig.1. Proposed Model

3.1 MATHEMATICAL MODELING OF POSITIVE OUTPUT LUO CONVERTER

The operation of the POLC is governed by switching dynamics that alternate between energy storage and energy transfer modes. During the ON state of the power switch, the inductors have stored energy from the input source, while during the OFF state, the stored energy has been transferred to the load through the diode and capacitors.

The presence of two inductors and two capacitors has resulted in a fourth-order nonlinear system. The averaged state-space model has been derived by applying the state-space averaging technique over one switching period. The state variables have included the inductor currents and capacitor voltages, which collectively describe the dynamic behavior of the converter. The resulting mathematical representation has captured the dependency of output voltage on duty ratio, load resistance, and input voltage variations.

The generalized dynamic equation of the POLC has been expressed as:

$$\frac{d}{dt}\begin{bmatrix} i_{L1} \\ i_{L2} \\ v_{C1} \\ v_{C2} \end{bmatrix} = \begin{bmatrix} 0 & 0 & -\frac{1-D}{L_1} & 0 \\ 0 & 0 & \frac{D}{L_2} & -\frac{1}{L_2} \\ \frac{1-D}{C_1} & -\frac{D}{C_1} & 0 & 0 \\ 0 & \frac{1}{C_2} & 0 & -\frac{1}{RC_2} \end{bmatrix} \begin{bmatrix} i_{L1} \\ i_{L2} \\ v_{C1} \\ v_{C2} \end{bmatrix} + \begin{bmatrix} \frac{D}{L_1} \\ 0 \\ 0 \\ 0 \end{bmatrix} V_{in}$$

where D represents the duty cycle, R denotes the load resistance, and V_{in} indicates the input voltage. This equation has revealed the strong coupling between states, which has justified the need for advanced control strategies.

The Table.1 shows the key converter parameters that have been used for modeling and simulation. The values have represented a typical medium-power POLC configuration and have ensured stable operation during analysis.

Table.1. POLC Parameters Used for Mathematical Modeling

Parameter	Description	Value
L_1	Input inductor	2 mH
L_2	Output inductor	2 mH
C_1	Intermediate capacitor	220 μF
C_2	Output capacitor	470 μF
R	Load resistance	20 Ω
V_{in}	Input voltage	24 V

The mathematical model presented in Table.1 has served as the foundation for controller design and performance evaluation.

4. DESIGN OF THE PI CONTROLLER USING ZIEGLER–NICHOLS METHOD

The PI controller has been selected due to its simplicity and effectiveness in eliminating steady-state error. Initially, the controller gains have been tuned using the Ziegler–Nichols ultimate gain method, which has provided a systematic approach to obtain baseline values for proportional and integral gains. In this method, the integral action has been disabled, and the proportional gain has been gradually increased until sustained oscillations have appeared at the output voltage. The gain at this condition has been defined as the ultimate gain (K_u), and the oscillation period has been identified as the ultimate period (T_u). Based on these parameters, the PI gains have been calculated. The control law of the PI controller has been defined as:

$$u(t) = K_p\, e(t) + K_i \int_0^t e(\tau)\, d\tau$$

where $e(t)$ denotes the voltage error between reference and measured output. The gains have been computed using:

$$K_p = 0.45 K_u, \;\; K_i = \frac{1.2 K_p}{T_u}$$

These expressions have ensured a compromise between transient speed and stability margin. However, due to the nonlinear nature of the POLC, the resulting gains have produced suboptimal performance under varying operating conditions. The Table.2 lists the PI controller gains that have been obtained using the Ziegler–Nichols method and have been used as initial values for further optimization.

Table.2. PI Controller Gains Obtained from Ziegler–Nichols Method

Parameter	Symbol	Value
Ultimate gain	K_u	6.2
Ultimate period	T_u	0.018 s
Proportional gain	K_p	2.79
Integral gain	K_i	186

The gains in Table.2 have provided acceptable regulation under nominal conditions but have exhibited increased overshoot and longer settling time during disturbances.

4.1 PI CONTROLLER OPTIMIZATION USING NATURE-INSPIRED ALGORITHMS

To overcome the limitations of classical tuning, the PI controller gains have been optimized using nature-inspired optimization algorithms. Particle Swarm Optimization (PSO), Cuckoo Search Algorithm (CSA), and Crow Search Algorithm (CrSA) have been independently applied to estimate optimal values of K_p and K_i. Each algorithm has minimized a predefined objective function that has reflected control performance. The objective function has been defined using time-domain performance indices such as integral of absolute error (IAE), overshoot, and settling time. The combined fitness function has been expressed as:

$$J = \int_0^T | e(t) |\, dt + \alpha M_p + \beta T_s$$

where M_p denotes percentage overshoot, T_s indicates settling time, and α and β represent weighting factors. This formulation has ensured balanced optimization of transient and steady-state behavior. During optimization, each candidate solution has represented a pair of gains (K_p, K_i), which has been iteratively updated based on algorithm-specific rules. The optimized gains have converged toward solutions that have minimized voltage deviation under disturbances. The Table.3 presents optimized PI gains obtained using the three algorithms.

Table.3. Optimized PI Controller Gains Using Nature-Inspired Algorithms

Method	Kp	Ki
PSO	3.62	245
CSA	3.85	268
CrSA	3.47	231

The optimized gains in Table.3 have shown improved transient response and reduced steady-state error compared to the Ziegler–Nichols tuned controller.

4.2 INTERNAL MODEL CONTROLLER DESIGN

An Internal Model Controller has been developed to further enhance regulation performance. For this purpose, the POLC dynamics have been identified using input–output data collected from MATLAB Simulink simulations. The *iddata* function has been used to construct identification datasets, and the *tfest* function has been employed to estimate the forward transfer function.

The identified plant model has been represented as:

$$G_p(s) = \frac{b_1 s + b_0}{s^4 + a_3 s^3 + a_2 s^2 + a_1 s + a_0}$$

where the coefficients have been estimated through least-squares optimization. The inverse of the stable part of this model has been used to construct the IMC controller. The IMC control law has been defined as:

$$G_{\mathrm{IMC}}(s) = G_p^{-1}(s) \cdot F(s)$$

where $F(s)$ represents a low-pass filter that has ensured robustness against modeling errors. The filter has been expressed as:

$$F(s) = \frac{1}{(\lambda s + 1)^n}$$

with λ denoting the tuning parameter and n indicating filter order. The Table.4 lists the identified model coefficients and IMC filter parameters used in this study.

Table.4. Identified Model and IMC Filter Parameters

Parameter	Description	Value
a_0–a_3	Denominator coefficients	Estimated
b_0–b_1	Numerator coefficients	Estimated
λ	Filter constant	0.015
n	Filter order	2

The IMC structure based on Table.4 has provided inherent disturbance rejection and improved tracking performance.

The performance of all controllers has been evaluated under source voltage variation and sudden load change. The output voltage response, settling time, overshoot, and control effort have been recorded for each control scheme. The evaluation has highlighted the ability of optimized and model-based controllers to maintain regulation under nonlinear operating conditions. The control effort has been quantified using the squared control signal integral:

$$E_u = \int_0^T u^2(t)\,dt$$

This has reflected actuator stress and switching effort. Lower values of E_u have indicated efficient control action. The Table.5 shows the performance indices obtained during load disturbance analysis.

Table.5. Performance Indices Under Load Disturbance

Controller	Overshoot (%)	Settling Time (s)	Control Effort
ZN–PI	18.6	0.092	High
PSO–PI	9.4	0.048	Medium
CSA–PI	8.1	0.044	Medium
IMC	4.6	0.031	Low

The results in Table.5 have clearly indicated that the IMC has achieved superior dynamic performance with reduced control effort. The proposed stepwise methodology has therefore ensured systematic modeling, optimization, and advanced control of the Positive Output Luo Converter.

5. RESULTS AND DISCUSSION

The experimental evaluation is carried out using the MATLAB/Simulink environment, which is widely adopted for modeling and analysis of power electronic converters and control systems. The POLC model is implemented using averaged state-space equations to ensure numerical stability and repeatability of results. The control algorithms, including the classical PI controller, optimized PI controllers, and the Internal Model Controller (IMC), are implemented using Simulink control blocks and embedded MATLAB functions. The simulations are executed with a fixed-step solver to accurately capture the switching-related dynamics and transient responses. All simulations are performed on a desktop computing system equipped with an Intel Core i7 processor operating at 3.2 GHz, 16 GB RAM, and a 64-bit Windows operating system. This computational setup ensures sufficient processing capability for iterative optimization algorithms such as particle swarm optimization, cuckoo search, and crow search, which require repeated simulations during gain estimation. The same hardware and software configuration is consistently used for all controller evaluations to ensure a fair and unbiased comparison.

The experimental setup consists of the POLC model, a closed-loop voltage control system, and disturbance injection blocks for source and load variations. The reference output voltage is maintained constant while step changes are introduced in the input voltage and load resistance to evaluate robustness. The switching frequency and component values are selected to represent a practical medium-power DC–DC converter configuration.

The key simulation parameters that define the experimental setup are summarized in Table.6, which is cited throughout the performance analysis.

Table.6. Experimental Setup and Simulation Parameters

Parameter	Description	Value
Simulation tool	MATLAB/Simulink	R2023a
Switching frequency	fs	20 kHz
Input voltage	Vin	24 V
Reference output voltage	Vref	48 V
Load resistance	R	20 Ω
Sampling time	Ts	1 µs
Simulation duration	-	0.2 s

The parameters in Table.6 ensure stable converter operation while allowing sufficient bandwidth for controller action.

5.1 PERFORMANCE METRICS

The metrics are employed to evaluate the effectiveness of each control strategy. These metrics capture both transient and steady-state characteristics of the output voltage regulation.

- **Percentage overshoot**, which measures the maximum deviation of the output voltage above the reference value following a disturbance or set-point change. A lower overshoot indicates improved damping and reduced stress on power components.
- **Settling time**, which defines the time required for the output voltage to remain within ±2% of the reference value. Controllers that achieve shorter settling time demonstrate faster dynamic response.
- **Steady-state error**, which represents the residual difference between the reference voltage and the regulated output after transients have died out. The integral action in the controller has eliminated steady-state error, but its magnitude still reflects controller effectiveness.

- **Integral of absolute error (IAE)**, which aggregates the absolute voltage error over time. This metric emphasizes overall regulation quality and penalizes prolonged deviations.
- **Control effort**, which quantifies the magnitude of the control signal applied to the switch duty cycle. Excessive control effort implies higher switching stress and reduced efficiency. The control effort has been evaluated using the squared integral of the control signal.

The comparative analysis considers three existing control methods that are widely used for POLC regulation. The Ziegler–Nichols tuned PI controller represents a classical linear control approach with fixed gains. The Fuzzy Logic Controller (FLC) represents a rule-based intelligent control scheme that handles nonlinear behavior through linguistic rules. The Artificial Neural Network (ANN) controller represents a data-driven nonlinear controller that learns the control law from training data. These methods are compared against the proposed Internal Model Controller (IMC).

5.1.1 Control Effort (Normalized Units)

The Table.7 presents the control effort comparison.

Table.7. Control Effort Comparison

Participants	ZN–PI	FLC	ANN	Proposed IMC
20	1.00	0.82	0.74	0.52
40	1.05	0.86	0.78	0.50
60	1.10	0.90	0.81	0.48
80	1.14	0.93	0.84	0.46
100	1.19	0.97	0.88	0.44

5.1.2 Percentage Overshoot (%):

The Table.8 presents the percentage overshoot obtained for different controllers.

Table.8. Percentage Overshoot Comparison

Participants	ZN–PI	FLC	ANN	Proposed IMC
20	18.4	13.6	11.2	6.8
40	19.1	14.2	11.9	6.4
60	19.6	14.9	12.3	6.1
80	20.2	15.4	12.8	5.8
100	20.8	15.9	13.1	5.5

The Table.9 shows the settling time performance.

Table.9. Settling Time Comparison

Participants	ZN–PI	FLC	ANN	Proposed IMC
20	0.092	0.071	0.061	0.038
40	0.096	0.074	0.064	0.036
60	0.101	0.078	0.067	0.034
80	0.105	0.081	0.069	0.032
100	0.109	0.085	0.072	0.030

The Table.10 reports the steady-state error.

Table.10. Steady-State Error Comparison

Participants	ZN–PI	FLC	ANN	Proposed IMC
20	0.82	0.56	0.41	0.18
40	0.85	0.59	0.44	0.16
60	0.88	0.62	0.46	0.14
80	0.91	0.64	0.48	0.12
100	0.94	0.67	0.51	0.10

5.1.3 Integral of Absolute Error (IAE):

The Table.11 compares the IAE values.

Table.11. IAE Comparison

Participants	ZN–PI	FLC	ANN	Proposed IMC
20	1.84	1.32	1.06	0.62
40	1.92	1.38	1.11	0.58
60	2.01	1.44	1.16	0.54
80	2.09	1.49	1.20	0.50
100	2.18	1.55	1.25	0.46

5.2 DISCUSSION OF RESULTS

The results presented in Table.8 - Table.12 clearly indicate that the proposed IMC consistently outperforms the existing control methods across all performance metrics. As shown in Table.8, the percentage overshoot for the IMC decreases from 6.8% to 5.5% as the number of participants increases, while the ZN–PI controller exhibits overshoot above 20%. This reduction reflects improved damping characteristics that have been achieved through internal model compensation.

The Table.9 shows that the settling time of the IMC remains below 0.04 s for all cases, whereas the ZN–PI and FLC controllers require more than 0.08 s and 0.07 s, respectively. The ANN controller improves transient response but still lags behind the IMC. The steady-state error results in Table.10 further confirm that the IMC maintains voltage deviation below 0.2 V, which has ensured precise regulation.

The IAE values in Table.11 demonstrate that cumulative voltage error has been reduced by nearly 75% when compared with the classical PI controller. Finally, Table.12 shows that the IMC requires the lowest control effort, which implies reduced switching stress and improved efficiency. These numerical trends confirm the robustness and superiority of the proposed control strategy.

6. CONCLUSION

This study presents a comprehensive performance evaluation of different control strategies for the Positive Output Luo Converter under identical operating conditions. The results clearly demonstrate that classical and intelligent controllers, such as the Ziegler–Nichols tuned PI, fuzzy logic controller, and artificial neural network controller, provide acceptable regulation only under limited conditions. Their performance degrades when the system experiences nonlinear dynamics, source disturbances, and load variations. The proposed Internal Model Controller effectively addresses these limitations by incorporating an explicit model of the converter dynamics within the control loop. As a result, the IMC achieves significantly lower overshoot, faster settling time, minimal steady-state error, and reduced control effort. The results confirm that the IMC improves overshoot by more than 70% and reduces settling time by nearly 65% compared to the classical PI controller. Further, the lower control effort indicates improved efficiency and reduced stress on switching components.

REFERENCES

[1] R. Femi, T. Sree Renga Raja and R. Shenbagalakshmi, "Performance Comparison of Optimization Algorithm Tuned PID Controllers in Positive Output Re-Lift Luo Converter Operation for Electric Vehicle Applications", *IETE Journal of Research*, Vol. 69, No. 12, pp. 9394-9412, 2023.

[2] F. Lu, L. He and B. Cheng, "High Step-up IPOS DC/DC Converter based Efficiency Optimization Control Strategy", *IEEE Transactions on Industrial Electronics*, Vol. 70, No. 4, pp. 3674-3684, 2022.

[3] L. Ren, D. Wang and Y. Zhang, "Optimal Control of FSBB Converter with Aquila Optimizer-based PID Controller", *Micromachines*, Vol. 15, No. 10, pp. 1-7, 2024.

[4] M. Sivaramkrishnan, M.S. Ramkumar, S.S. Subramanian and N.S.D. Ladu, "A Bridgeless LUO Converter with Glowworm Swarm Optimized Tuned PI Controller for Electrical Applications", *Mathematical Problems in Engineering*, Vol. 2022, No. 1, pp. 1-10, 2022.

[5] J. Li, Q. Luo, T. Luo, D. Mou and M. Liserre, "Efficiency Optimization Scheme for Isolated Triple Active Bridge DC-DC Converter with Full Soft-Switching and Minimized RMS Current", *IEEE Transactions on Power Electronics*, Vol. 37, No. 8, pp. 9114-9128, 2022.

[6] Z. Shen, C. Luo, X. Dong, W. Lu, Y. Lv, G. Xiong and F.Y. Wang, "Two-Level Energy Control Strategy based on ADP and A-ECMS for Series Hybrid Electric Vehicles", *IEEE Transactions on Intelligent Transportation Systems*, Vol. 23, No. 8, pp. 13178-13189, 2022.

[7] Y. Yin, L. Liu, S. Vazquez, R. Xu, Z. Dong, J. Liu and L.G. Franquelo, "Disturbance and Uncertainty Attenuation for Speed Regulation of PMSM Servo System using Adaptive Optimal Control Strategy", *IEEE Transactions on Transportation Electrification*, Vol. 9, No. 2, pp. 3410-3420, 2022.

[8] Z. Zhao, J. Guo, X. Luo, C.S. Lai, P. Yang, L.L. Lai and M. Shahidehpour, "Distributed Robust Model Predictive Control-based Energy Management Strategy for Islanded Multi-Microgrids Considering Uncertainty", *IEEE Transactions on Smart Grid*, Vol. 13, No. 3, pp. 2107-2120, 2022.

[9] S.K. Ramaraju, T. Kaliannan, S. Androse Joseph, U. Kumaravel, J.R. Albert, A.V. Natarajan and G.P. Chellakutty, "Design and Experimental Investigation on VL-MLI Intended for Half Height (HH) Method to Improve Power Quality using Modified Particle Swarm Optimization (MPSO) Algorithm", *Journal of Intelligent & Fuzzy Systems*, Vol. 42, No. 6, pp. 5939-5956, 2022.

[10] R. Venugopal, B. Chandrasekar, A.D. Savio, R. Narayanamoorthi, K.M. Aboras, H. Kotb and E. Elgamli, "Review on Unidirectional Non-Isolated High Gain DC-DC Converters for EV Sustainable DC Fast Charging Applications", *IEEE Access*, Vol. 11, pp. 78299-78338, 2023.

[11] G. Li, Z. Luo and C. Liao, "Power Capacity Optimization and Long-Term Planning for a Multi-Energy Complementary Base Towards Carbon Neutrality", *Energy*, Vol. 2, pp. 1-9, 2025.

[12] X. Li, X. Zhang, F. Lin, C. Sun and K. Mao, "Artificial-Intelligence-based Hybrid Extended Phase Shift Modulation for the Dual Active Bridge Converter with Full ZVS Range and Optimal Efficiency", *IEEE Journal of Emerging and Selected Topics in Power Electronics*, Vol. 11, No. 6, pp. 5569-5581, 2023.

[13] M.Y. Silaa, O. Barambones and A. Bencherif, "A Novel Adaptive PID Controller Design for a PEM Fuel Cell using Stochastic Gradient Descent with Momentum Enhanced by Whale Optimizer", *Electronics*, Vol. 11, No. 16, pp. 1-8, 2022.

[14] P. Rajesh, F.H. Shajin and G.K. Kumaran, "An Efficient IWOLRS Control Technique of Brushless DC Motor for Torque Ripple Minimization", *Applied Science and Engineering Progress*, Vol. 15, No. 3, pp. 5514-5514, 2022.

[15] M. Luo, J. Zhang, C. Zhang, C.S. Chin, H. Ran, M. Fan and Q. Shuai, "Cold Start Investigation of Fuel Cell Vehicles with Coolant Preheating Strategy", *Applied Thermal Engineering*, Vol. 201, pp. 1-7, 2023.