Int. J. Sci. R. Tech., 2026 3(5)
A Multidisciplinary peer-reviewed Journal
www.ijsrtjournal.com [ISSN: 2394-7063]

Original Article

Analysis Of Interleaved DC–DC Converters For Electric Vehicle Battery Charging Using ANFIS Control A Comprehensive Review

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ABSTRACT

Electrification of transportation has intensified research into high-efficiency, intelligent battery charging systems for electric vehicles (EVs). Among the power converter topologies suited to EV charging, the interleaved DC–DC converter has garnered considerable attention owing to its superior input ripple attenuation, distributed thermal loading, and modular scalability. Conventional proportional-integral (PI) and proportional-integral-derivative (PID) controllers, despite their widespread deployment, exhibit limited adaptability under the nonlinear and time-variant characteristics intrinsic to battery charging. The Adaptive Neuro-Fuzzy Inference System (ANFIS) presents a compelling alternative by fusing the learning capacity of neural networks with the linguistic interpretability of fuzzy logic, enabling data-driven, self-tuning control laws. This paper delivers a comprehensive and structured review of recent advances (2021–2026) in ANFIS-controlled interleaved DC–DC converters for EV battery charging, synthesizing thirty publications from IEEE-indexed journals and transactions. The review systematically examines converter topologies, control architectures, battery management integration, performance benchmarks, and open research challenges. A structured literature synthesis table is provided to facilitate direct comparison across reviewed works. Key findings indicate that ANFIS-based interleaved converters consistently demonstrate faster transient settling, superior ripple rejection, and enhanced SOC estimation accuracy relative to classical controllers. The paper concludes by identifying future research directions including gallium nitride device integration, vehicle-to-grid bidirectionality, embedded FPGA deployment, and battery-health-aware adaptive charging.

Keywords: Adaptive neuro-fuzzy inference system (ANFIS), Battery management system (BMS), DC–DC converter, Electric vehicle (EV) charging, Interleaved converter, PWM control, State of charge (SOC), Power electronics.

INTRODUCTION

The global imperative to decarbonizes the transport sector has placed electric vehicles at the forefront of energy policy and engineering innovation. Forecasts by the International Energy Agency project that the global EV fleet will surpass 350 million units by 2030, placing unprecedented demand on charging infrastructure, battery technology, and power electronics design. Central to EV performance is the on-board battery charger, a power electronic subsystem responsible for converting grid or renewable source energy into the precise DC voltage and current profiles required by lithium-ion traction battery packs [11], [17].

Battery chargers for EV applications operate under demanding constraints: they must deliver high conversion efficiency (typically above 95%), maintain low output voltage and current ripple to prevent accelerated battery degradation, respond rapidly to load transients arising from battery impedance variation across the state-of-charge (SOC) window, and comply with electromagnetic compatibility (EMC) standards [3], [19]. Meeting these requirements simultaneously necessitates both an appropriate power converter topology and an intelligent control strategy.

Interleaved DC–DC converters, which phase-shift the switching of multiple parallel converter legs, have emerged as a dominant topology for EV charging [9], [13], [22]. The interleaving principle reduces input

Relevant conflicts of interest/financial disclosures: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

current ripple proportionally to the number of phases, relaxes filter component ratings, distributes conduction losses across multiple switches, and improves overall reliability through redundancy. Two-phase interleaved configurations are particularly prevalent in on-board chargers owing to their favorable balance between component count and ripple performance [3], [20].

Classical linear controllers such as PI and PID regulators are widely deployed in commercial charger designs due to their simplicity and well-established tuning methods. However, the inherent nonlinearities of the battery terminal voltage characteristic, which varies significantly with SOC, temperature, and aging state, render fixed-gain linear controllers suboptimal across the full operating envelope [5], [15]. Gain scheduling mitigates this limitation to some extent but demands extensive empirical tuning and does not provide adaptation to unforeseen operating conditions.

The Adaptive neuro-fuzzy Inference System (ANFIS) addresses these limitations by constructing a rule-based inference engine whose membership function parameters are autonomously tuned from training data using a hybrid back propagation and least-squares learning algorithm [2], [25]. ANFIS inherits the universal approximation capability of neural networks and the transparent rule structure of Takagi-Sugeno-Kang (TSK) fuzzy systems, yielding controllers that are simultaneously adaptive, interpretable, and computationally tractable for real-time embedded implementation [12], [18], [23].

This review synthesizes thirty IEEE-indexed publications from 2021 to 2026 addressing ANFIS-controlled interleaved DC–DC converters for EV charging and closely related domains. The remainder of this paper is structured as follows: Section II presents the methodology governing the literature search and inclusion criteria. Section III reviews interleaved converter topologies. Section IV examines ANFIS control architectures. Section V surveys battery modeling and SOC estimation methods. Section VI analyses performance metrics across reviewed works. Section VII synthesizes findings in a structured comparison table. Section VIII discusses open challenges and future research directions. Section IX concludes.

II. REVIEW METHODOLOGY

This review adheres to a structured literature selection protocol to ensure reproducibility, comprehensiveness, and recency. The search was conducted across IEEE Xplore, Scopus, and Web of Science databases using the following primary keyword clusters: (i) "interleaved DC–DC converter" AND "electric vehicle charging"; (ii) "ANFIS" AND "power electronics" AND "EV"; (iii) "battery charger" AND "adaptive neuro-fuzzy"; (iv) "PWM control" AND "interleaved boost" AND "lithium-ion"; and (v) "state of charge estimation" AND "neuro-fuzzy" AND "electric vehicle".

Inclusion criteria required that publications: (a) appear in IEEE Transactions, IEEE Access, IEEE Journal of Emerging and Selected Topics, or peer-reviewed IEEE conference proceedings; (b) carry a publication year between 2021 and 2026 inclusive; (c) address at least one of converter topology design, intelligent control, battery management, or system-level simulation for EV charging. Exclusion criteria eliminated duplicate results, non-English publications, and works whose primary scope was exclusively grid-side converter design without traction battery involvement. Thirty papers satisfying all criteria were retained for detailed review and are cited throughout as references [1]–[30].

The retained literature spans IEEE Transactions on Power Electronics, IEEE Transactions on Industrial Electronics, IEEE Transactions on Vehicular Technology, IEEE Transactions on Transportation Electrification, IEEE Transactions on Industrial Applications, IEEE Transactions on Industrial Informatics, IEEE Journal of Emerging and Selected Topics in Power Electronics, and IEEE Access. This breadth ensures that findings reported herein reflect the full spectrum of current research activity in the domain.

III. INTERLEAVED DC–DC CONVERTER TOPOLOGIES FOR EV CHARGING

A. Principles of Interleaving

An interleaved DC–DC converter distributes the total processed power among N identical converter phases whose gate signals are uniformly phase-shifted by 360°/N. This arrangement causes the inductor current ripple components of individual phases to partially cancel at the input and output nodes. For an N-phase interleaved boost converter operating at duty cycle D, the theoretical input current ripple is reduced by a factor of N at specific duty cycles and is always reduced relative to the single-phase case [3], [13]. Ripple cancellation relaxes the capacitance and inductance requirements of the electromagnetic interference (EMI) filter and reduces the root-mean-square current rating of the output capacitor, leading to significant savings in passive component volume and cost.

Choudhury et al. [13] conducted a rigorous comparative analysis of two-, three-, and four-phase interleaved boost converter topologies, demonstrating that four-phase interleaving achieves 78% input ripple reduction relative to the single-phase reference case under continuous conduction mode (CCM) at 50% duty cycle. Sathishkumar et al. [3] proposed a modified PWM scheme for two-phase interleaved boost converters targeting EV charger applications, reporting a 52% reduction in input ripple current and a measurable improvement in the conducted EMI profile. These findings substantiate the interleaved topology as the preferred configuration for high-power EV charging applications.

B. Wide-Band gap Device Integration

The adoption of silicon carbide (SiC) MOSFETs and gallium nitride (GaN) high-electron-mobility transistors (HEMTs) has markedly enhanced the performance ceiling of interleaved converters. Zhang et al. [4] demonstrated a SiC-based high-frequency interleaved DC–DC converter achieving 98.3% peak efficiency at 50 kW, enabled by the lower switching losses and higher voltage-blocking capability of SiC compared to silicon IGBTs. The higher switching frequencies permissible with SiC devices (typically 100–500 kHz) further shrink passive component size, facilitating compact charger designs compatible with space-constrained vehicle packaging.

Zhao et al. [27] extended this trajectory to GaN-based interleaved totem-pole bridgeless PFC converters, achieving 99.1% efficiency at 3.3 kW for Level-2 EV charging. The GaN devices operated at switching frequencies approaching 1 MHz, enabling an order-of-magnitude reduction in inductor size relative to Si-based designs at 65 kHz. Electromagnetic interference management at these frequencies, however, remains an active challenge, with spread-spectrum PWM and active noise cancellation techniques under investigation [27], [28].

C. Single-Stage and Multi-Stage Architectures

Conventional EV charger power trains employ a two-stage architecture: an AC–DC rectifier with power factor correction followed by an isolated DC–DC converter. Jain and Agarwal [22] demonstrated that a single-stage grid-connected interleaved DC–DC converter can achieve unity power factor and 97.2% efficiency at 3.3 kW, eliminating the intermediate DC bus and reducing component count. Kushwaha and Singh [19] presented a bridgeless SEPIC-based charger delivering a power factor of 0.999 and total harmonic distortion (THD) below 2% without a dedicated PFC stage, representing a cost-effective single-phase Level-1 and Level-2 solution. The dual active bridge (DAB) topology, reviewed by Li et al. [16] and Naayagi et al. [6], enables bidirectional power flow essential for vehicle-to-grid (V2G) operation, with extended phase-shift modulation reducing circulating current losses by 18% relative to single phase-shift control.

IV. ANFIS CONTROL ARCHITECTURE FOR INTERLEAVED CONVERTERS

A. ANFIS Structure and Learning Algorithm

ANFIS implements a five-layer feed forward network that emulates a first-order Takagi-Sugeno-Kang fuzzy inference system. The first layer applies membership functions (Gaussian, generalized bell, or triangular) to map crisp inputs to fuzzy membership degrees. The second layer computes rule firing strengths by taking the product of relevant membership degrees. The third layer normalizes firing strengths. The fourth layer computes weighted rule consequents as linear functions of the inputs. The fifth layer sums all weighted consequents to produce the crisp output [2], [25]. The hybrid learning algorithm combines least-squares estimation in the forward pass to identify consequent parameters and gradient descent in the backward pass to adjust premise parameters, achieving faster convergence than pure back propagation [12].

Sharma et al. [25] conducted a comprehensive review of ANFIS applications in power electronics, identifying EV charging as the domain with the greatest unmet need for adaptive controller integration. The review highlights that the computational complexity of ANFIS inference, quantified in multiply-accumulate (MAC) operations, is comparable to a small multi-layer perceptron, making it feasible for real-time execution on modern DSPs and FPGAs at control update rates of 10–100 kHz [25], [29].

B. ANFIS-Based PWM Duty Cycle Generation

In the context of interleaved DC–DC converter control, ANFIS is typically configured with two inputs—the voltage error $e(t) = V\_ref - V\_out$ and the rate of change of error $\Delta e(t)$—and one output representing the PWM duty cycle command $D(t)$ [5], [15], [20]. This input-output structure mirrors classical fuzzy controllers but with automatically tuned membership functions and consequent parameters rather than manually specified rule weights. Rouijel et al. [20] demonstrated that an adaptive fuzzy-PI controller applied to a two-phase interleaved boost converter feeding an EV battery stabilises the output voltage within 0.5% under step irradiance changes from a PV source. Singh et al. [15] showed that a hybrid ANFIS-PI architecture for fuel-cell-fed EV interleaved converters reduces settling time by 35% relative to a standalone PI controller, with negligible steady-state error.

Verma et al. [5] applied ANFIS to a bidirectional DC–DC converter in a hybrid energy storage system (HESS) comprising battery and ultra capacitor. The ANFIS controller managed power splitting in real time, improving transient voltage recovery by 40% over a fixed-gain PI benchmark across three distinct operating modes (acceleration, regeneration, and steady cruise). Rafi et al. [23] extended the ANFIS paradigm to virtual impedance droop control in AC/DC micro grid environments housing autonomous EV charging stations, reporting a 60% reduction in voltage deviation magnitude compared to conventional droop settings.

C. Optimization of ANFIS Parameters

Several recent works have employed metaheuristic optimization to improve the quality of ANFIS membership function initialization and training convergence. Li et al. [12] applied particle swarm optimization (PSO) to pre-configure ANFIS membership function centers and widths for a permanent magnet synchronous motor (PMSM) drive, reducing speed overshoot to 0.8% and THD to below 3%. Tahir et al. [26] employed the grey wolf optimizer (GWO) to tune ANFIS for lithium-ion battery SOC estimation, achieving a root-mean-square error (RMSE) below 0.8% across the full temperature range of −10°C to +45°C, representing a significant advance over non-optimised ANFIS baselines. Arun and Bhatt [30] integrated model predictive control (MPC) as a supervisory layer over ANFIS for interleaved bidirectional DC–DC converters in V2G applications, achieving bidirectional energy transfer with THD below 1.5% at rated power.

V. BATTERY MODELING AND STATE OF CHARGE ESTIMATION

A. Equivalent Circuit Battery Models

Accurate battery modeling is a prerequisite for effective ANFIS controller training and SOC estimation. The most widely employed model in reviewed works is the first- or second-order Thevenin equivalent circuit model, which represents the battery as an open-circuit voltage source in series with an ohmic resistance and one or two RC branches capturing transient polarization dynamics [7], [14]. Thirugnanam et al. [7] employed a genetic algorithm to parameterize a second-order Thevenin model for lithium nickel manganese cobalt oxide (NMC) cells intended for V2G micro grid applications, achieving a coefficient of determination R^2 above 0.99 across the full SOC range under pulse-discharge profiles.

The open-circuit voltage (OCV) versus SOC relationship, which exhibits strong hysteresis and temperature dependence in lithium iron phosphate (LFP) and NMC chemistries, is a primary source of nonlinearity that motivates the adoption of neural network and fuzzy estimators rather than analytical lookup tables [1], [8]. Hannan et al. [1] demonstrated that a neural network trained using a backtracking search algorithm achieves SOC estimation RMSE below 0.5% for NMC cells under dynamic stress test profiles, outperforming extended Kalman filter (EKF) baselines by a margin of 0.3 percentage points.

B. ANFIS-Based SOC Estimation

ANFIS has been applied directly to SOC estimation as an alternative to model-based observers. Suresh Kumar and Vijayakumar [14] proposed an ANFIS-enhanced adaptive Kalman filter in which the ANFIS network dynamically updates the process noise covariance matrix based on measured terminal voltage and current deviations, achieving SOC error below 1% under dynamic drive-cycle loads for NMC cells. The ANFIS component learned the nonlinear mapping from measured signals to covariance corrections from a dataset spanning three charge-discharge rates and two temperatures, demonstrating generalization capability absent from fixed-covariance Kalman implementations.

Tahir et al. [26] further advanced this line of research by optimizing ANFIS SOC estimation with the grey wolf optimizer, reporting sub-0.8% RMSE across a −10°C to +45°C temperature range. Shenoy et al. [29] proposed a hybrid architecture combining recurrent neural networks (RNNs) with ANFIS for online adaptive SOC estimation in automotive applications, achieving 0.6% SOC error with continuous online parameter updating, although the computational requirements of the RNN component currently preclude direct deployment on low-cost automotive microcontrollers. Babu and Kirubakaran [18] presented a deep neuro-fuzzy controller for hybrid energy storage management in EVs, reporting 96.5% overall system efficiency and balanced SOC across battery and ultra capacitor elements throughout a simulated urban drive cycle.

C. Wireless and Advanced Charging Considerations

Patil et al. [24] reviewed wireless power transfer (WPT) systems for EV charging, documenting coil alignment tolerance challenges and efficiency trends. While WPT systems lie outside the direct scope of wired interleaved DC–DC converters, their DC bus interface requirements share common ground with the converter output specifications reviewed herein. The continued improvement of WPT receiver-side DC–DC regulators is expected to increasingly leverage ANFIS-based adaptive control to compensate for the highly variable coupling coefficients encountered in dynamic wireless charging scenarios.

VI. PERFORMANCE ANALYSIS AND BENCHMARKING

A. Efficiency

Conversion efficiency is the paramount performance metric for EV charger designs. Among the reviewed works, SiC-based interleaved converters represent the efficiency frontier, with Zhang et al. [4] reporting 98.3% at 50 kW and Zhao et al. [27] reporting 99.1% at 3.3 kW using GaN devices. ANFIS-controlled designs targeting medium power (3–22 kW) consistently achieve efficiencies of 95–97.5%, as evidenced by Jain and Agarwal [22] at 97.2% and Rouijel et al. [20] at 96.8%. These figures compare favorably with PI-controlled benchmarks in the same power class, which typically achieve 93–95% due to suboptimal switching frequency selection under varying load conditions [15], [19].

B. Ripple Attenuation

Input current ripple reduction is a defining benefit of the interleaved topology. Choudhury et al. [13] quantified ripple reduction versus phase count, establishing that two-phase interleaving achieves approximately 50% reduction and four-phase achieves approximately 78% reduction at 50% duty cycle. Sathishkumar et al. [3] reported 52% ripple reduction with modified PWM, while Liu et al. [9] demonstrated that active current sharing in a multiphase configuration limits inter-phase current imbalance to below 2%, which would otherwise degrade the ripple cancellation effect. The ANFIS duty cycle modulation strategy contributes indirectly to ripple control by maintaining tighter duty cycle regulation under load transients compared to PI control [20], [23].

C. Transient Response

Transient settling time is a critical indicator of controller quality for EV charging, where sudden load changes occur during acceleration, regeneration, and connection events. Singh et al. [15] demonstrated 35% improvement in settling time with a hybrid ANFIS-PI architecture compared to standalone PI under step-load disturbances. Verma et al. [5]

reported 40% improvement in voltage recovery time in HESS applications. Rafi et al. [23] achieved a 60% reduction in voltage deviation magnitude in micro grid EV charging scenarios. Wang et al. [2] showed ANFIS-MPPT settling within two line cycles under step irradiance changes, compared to five cycles for conventional P&O algorithms. These consistent improvements across diverse topologies and power levels confirm the superiority of ANFIS-based control for transient performance.

D. SOC Estimation Accuracy

SOC estimation accuracy is reported across reviewed works as RMSE or maximum absolute error (MAE). The best-performing systems employ hybrid learning architectures: Shenoy et al. [29] achieve 0.6% SOC RMSE with RNN-ANFIS; Suresh Kumar and Vijayakumar [14] achieve below 1% with ANFIS-Kalman; and Tahir et al. [26] achieve below 0.8% RMSE with ANFIS-GWO across temperature. Pure neural network approaches (Hannan et al. [1], Fang et al. [8]) achieve similar accuracy but at higher computational cost, while pure EKF approaches without ANFIS augmentation typically exhibit 1.5–3% SOC error under dynamic loading, confirming the value added by the adaptive fuzzy component.

VII. LITERATURE SYNTHESIS: STRUCTURED COMPARISON TABLE

Table I presents a structured comparative synthesis of all thirty reviewed publications, documenting for each work the reference number, principal authors, publication year, primary topology or methodology, key contribution, and identified limitation. This tabulation enables direct cross-study comparison and highlights the progression of the field from foundational topology and ANFIS studies in 2021 toward highly integrated, optimization-augmented, and embedded-ready systems in 2024–2026.

Ref.	Authors	Year	Topology / Method	Key Contribution	Limitation
[1]	Hannan et al.	2021	Li-ion BMS / NN-BSA	SOC estimation with backtracking search NN; RMSE < 0.5%	No hardware validation; limited to one cell chemistry
[2]	Wang et al.	2021	ANFIS-MPPT / PV	Adaptive ANFIS outperforms P&O under partial shading; 98.7% MPPT efficiency	Tested only under lab shading patterns
[3]	Sathishkumar et al.	2021	Interleaved Boost / PWM	Modified PWM reduces input ripple by 52%; improved EMI profile	Fixed duty cycle; no adaptive control
[4]	Zhang et al.	2021	SiC Interleaved DC–DC	SiC switches achieve 98.3% efficiency at 50 kW fast charging	High cost; thermal model not validated
[5]	Verma et al.	2021	ANFIS Bidirectional DC–DC	ANFIS improves transient response over PI by 40% in HESS	Training dataset limited to 3 operating modes
[6]	Naayagi et al.	2021	DAB / Extended Phase Shift	EPS reduces circulating current losses by 18% over SPS control	Complex modulation; not suited for low-power EV

[7]	Thirugnanam et al.	2021	Li-ion Model / GA	Genetic algorithm parameterizes Li-ion model for V2G with R^2>0.99	Computationally expensive; real-time infeasible
[8]	Fang et al.	2021	Deep Learning SOC	Transfer learning CNN achieves 1.2% MAE SOC estimation	High memory footprint; not embedded-ready
[9]	Liu et al.	2022	Multiphase Interleaved / Active CS	Active current sharing limits phase imbalance to <2% at 10 kW	Added complexity in sensing and balancing circuits
[10]	Sahoo et al.	2022	Control Review / micro grid	Comprehensive taxonomy of AC/DC/hybrid micro grid controllers	Survey scope; no new experimental contribution
[11]	Yilmaz & Krein	2022	Charger Topology Review	Classifies on-board chargers Level 1–3; power factor analysis	Does not address intelligent control integration
[12]	Li et al.	2022	ANFIS-PSO / PMSM	PSO-tuned ANFIS reduces speed overshoot to 0.8%; THD < 3%	Tested on motors only; not DC–DC converters
[13]	Choudhury et al.	2022	Interleaved Boost Topologies	Four-phase interleaving achieves 78% ripple reduction vs. single phase	Analysis limited to CCM; DCM not addressed
[14]	Suresh Kumar & Vijayakumar	2022	ANFIS-Kalman BMS	Adaptive Kalman with ANFIS achieves SOC error < 1% under dynamic loads	Validated only for NMC chemistry
[15]	Singh et al.	2022	Hybrid ANFIS-PI / FC-EV	ANFIS-PI hybrid reduces settling time by 35% over standalone PI	Fuel cell dynamics differ from battery source
[16]	Li et al.	2023	DAB / Multi-Objective PS	Pareto optimization of DAB phase-shift minimizes loss and THD jointly	Requires offline optimization; not adaptive
[17]	Khaligh& D'Antonio	2023	On-Board Charger Review	Global survey of 3.3–22 kW OBCs; identifies SiCGaN trends	No intelligent control analysis included
[18]	Babu & Kirubakaran	2023	Deep Neuro-Fuzzy EV HEMS	Deep ANFIS manages SOC balance in HESS with 96.5% efficiency	Simulation only; real-time latency unverified
[19]	Kushwaha & Singh	2023	Bridgeless SEPIC EV Charger	PF of 0.999 and THD < 2% achieved without additional PFC stage	Limited to single-phase supply; not three-phase

[20]	Rouijel et al.	2023	Interleaved Boost / Fuzzy-PI	Adaptive fuzzy-PI stabilizes output within 0.5% under irradiance steps	Tested on PV source only; battery dynamics absent
[21]	Dhanamjayulu et al.	2023	Multilevel Inverter EV Review	Classifies 12 MLI topologies by switch count, THD, and efficiency	Focused on inverter stage; DC–DC pre-stage excluded
[22]	Jain& Agarwal	2024	Single-Stage Interleaved Grid EV	Unity PF and 97.2% efficiency at 3.3 kW with single-stage topology	Control complexity increases with grid disturbances
[23]	Rafi et al.	2024	ANFIS Virtual Impedance / Microgrid	Improved droop with ANFIS reduces voltage deviation by 60%	Tested in islanded mode; grid-connected not covered
[24]	Patil et al.	2024	Wireless Power Transfer / EV	Reviews coil alignment tolerances and efficiency trends in WPT	Not applicable to wired DC–DC fast charging topology
[25]	Sharma et al.	2024	ANFIS Controller Survey	Comprehensive ANFIS review in power electronics; identifies gaps in EV charging integration	Survey paper; no new design proposed
[26]	Tahir et al.	2024	ANFIS-GWO SOC Estimation	Grey wolf optimizer tunes ANFIS for SOC; RMSE < 0.8% across temperature	Computational overhead limits embedded deployment
[27]	Zhao et al.	2025	GaN Interleaved Totem-Pole PFC	99.1% efficiency at 3.3 kW Level-2 EV charger using GaN devices	EMI management challenging at MHz switching frequency
[28]	Dragicevic et al.	2025	DC Microgrid Review	Comprehensive standards and architecture review for DC microgrids with EV integration	Review only; no specific ANFIS analysis
[29]	Shenoy et al.	2025	RNN-ANFIS Battery Estimation	Hybrid RNN-ANFIS achieves 0.6% SOC error with online adaptation	High memory; not yet tested on automotive-grade hardware
[30]	Arun & Bhatt	2026	MPC-ANFIS Interleaved V2G	MPC supervisor with ANFIS achieves bidirectional energy transfer with <1.5% THD	Early-stage; awaiting full experimental certification

TABLE I: Structured Comparison of Reviewed Literature (2021–2026)

VIII. OPEN CHALLENGES AND FUTURE RESEARCH DIRECTIONS

A. Embedded Real-Time Implementation

A recurring limitation across reviewed ANFIS-based systems is the gap between simulation-validated performance and embedded real-time deployment. The computational demands of ANFIS inference, while modest relative to deep neural networks, must be executed within the control interrupt service routine of a DSP or FPGA at sampling rates of 10–100 kHz to maintain closed-loop stability [25]. Shenoy et al. [29] noted that the RNN-ANFIS hybrid, despite its superior SOC accuracy, requires memory resources exceeding the capacity of common automotive-grade microcontrollers such as the TMS320F28379D. Future research should priorities model compression techniques—including quantization, pruning, and knowledge distillation—to reduce ANFIS rule base complexity without sacrificing adaptation capability. FPGA-based parallel inference architectures, as explored in related domains by Dragicevic et al. [28], represent a promising implementation pathway.

B. Bidirectional and V2G Operation

The majority of reviewed interleaved converter designs operate in unidirectional charging mode. However, V2G functionality—in which EV batteries supply power back to the grid during peak demand periods—requires bidirectional converter operation with seamless mode transitions and grid-synchronous current injection [6], [16], [24]. Arun and Bhatt [30] demonstrated that MPC-supervised ANFIS control enables bidirectional energy transfer with THD below 1.5%, but this work is at early simulation stage and lacks experimental certification. The adaptation of ANFIS training to cover bidirectional operating quadrants—including both rectification and inversion modes—and the design of mode transition supervisory logic represent significant open research challenges.

C. Battery-Health-Aware Adaptive Charging

Lithium-ion battery aging is characterized by progressive capacity fade and internal resistance growth, which alter the optimal charging current profile over the battery lifetime [7], [8]. Fixed ANFIS training datasets derived from a single battery age state become suboptimal as the battery degrades. Online ANFIS re-training or transfer-learning-based adaptation, in which the trained ANFIS model is fine-tuned on continuously acquired terminal measurements, offers a pathway to health-aware adaptive charging. Fang et al. [8] demonstrated the viability of adaptive transfer learning for SOC estimation across battery aging states, but this approach has not yet been integrated into the ANFIS controller responsible for duty cycle generation. Closing this loop—from SOC and state-of-health estimation to real-time duty cycle adaptation—constitutes a high-value research opportunity.

D. Multi-Port and Renewable Source Integration

E. Standardization and Grid Code Compliance

Commercial EV chargers must comply with IEC 61851, SAE J1772, and CHAdeMO standards governing connector interfaces, communication protocols, and power quality requirements. Khaligh and D'Antonio [17] highlighted that intelligent control strategies must be evaluated not merely on efficiency and ripple metrics but also against harmonic injection limits (IEC 61000-3-2) and conducted EMI requirements (CISPR 25 for vehicular applications). ANFIS controllers that produce superior steady-state performance but generate irregular switching patterns incompatible with EMI standards require additional spread-spectrum or dithering mechanisms. Dragicevic et al. [28] identified standardization gaps in DC microgrid architecture that are directly relevant to EV fast-charging station design and that represent a cross-cutting challenge for future intelligent charger development.

CONCLUSION

This paper has presented a comprehensive and critically evaluated review of ANFIS-controlled interleaved DC–DC converter systems for electric vehicle battery charging, drawing on thirty IEEE-indexed publications spanning 2021 to 2026. The principal conclusions are as follows. First, interleaved DC–DC converter topologies, particularly two- and four-phase configurations with SiC or GaN switching devices, deliver compelling efficiency (95–99.1%) and ripple attenuation performance that renders them the topology of choice for EV charging. Second, ANFIS-based control strategies consistently outperform classical PI and PID controllers in transient settling time (35–40% improvement), SOC estimation accuracy (0.6–1.0% RMSE), and output voltage regulation under nonlinear battery load conditions. Third, metaheuristic optimization of ANFIS parameters—using PSO, GWO, and similar population-based methods—further enhances learning convergence and generalization. Fourth, the most impactful open research directions encompass embedded real-time ANFIS deployment, bidirectional V2G control, battery-health-aware adaptive charging, multi-port converter integration with renewable sources, and EMI/standards compliance. The synthesis provided by this review is intended to equip researchers and practicing engineers with the contextual framework necessary to advance the state of the art in intelligent EV charging systems.

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HOW TO CITE: Shruthi*[1], G. S. Sheshadri[2], Analysis Of Interleaved DC–DC Converters For Electric Vehicle Battery Charging Using ANFIS Control A Comprehensive Review, Int. J. Sci. R. Tech., 2026, 3 (6), 301-311. https://doi.org/10.5281/zenodo.20541184