AI BASED QUASI-RESONANT CONVERTER FOR ELECTRIC VEHICLE CHARGING.

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ABSTRACT:

The rapid growth of Electric Vehicles (EVs) demands highly efficient, reliable, and intelligent charging systems capable of handling wide load variations while minimizing power losses. Traditional hard-switching converters suffer from high switching losses, electromagnetic interference (EMI), and significant thermal stress during high-frequency operation. Quasi-Resonant Converters (QRCs) provide a promising alternative by achieving Zero-Voltage Switching (ZVS) or Zero-Current Switching (ZCS), which considerably reduces switching losses and enhances overall converter efficiency. This work proposes an AI-Based Quasi-Resonant Converter (AI-QRC) designed to improve energy efficiency, regulate charging profiles, predict component stress, and adapt dynamically to battery conditions. The proposed system integrates artificial intelligence techniques such as machine learning–based control, adaptive switching frequency tuning, and predictive thermal monitoring. Simulation results and theoretical analysis indicate that the AI-QRC enhances conversion efficiency, reduces switching losses, improves power quality, and provides safer, optimized charging for EV batteries compared to conventional resonant converters..

Keywords: AI-based power electronics, quasi-resonant converter (QRC), soft-switching converter, zero-voltage switching (ZVS), zero-current switching (ZCS), resonant tank circuit, high-frequency power conversion, EV charger power stage, DC-DC converter for EV charging, machine learning control, neural network controller, adaptive control, predictive control, reinforcement learning for power converters, intelligent energy management, AI-based optimization,

I. INTRODUCTION The increasing adoption of Electric Vehicles has placed significant emphasis on improving charging infrastructure, power converter performance, and energy efficiency. EV chargers must meet stringent requirements for power density, thermal performance, battery safety, and operational efficiency. In conventional DC–DC converter topologies, high-frequency switching creates excessive losses and stress on semiconductor devices, leading to reduced system lifespan and lower efficiency. To overcome these challenges, resonant and quasi-resonant converter topologies have gained substantial interest due to their ability to operate under soft-switching conditions.A Quasi-Resonant Converter uses resonant inductors and capacitors to shape current or voltage waveforms, enabling ZVS or ZCS and allowing the converter to switch at the optimal point of the waveform, reducing switching losses. When integrated with artificial intelligence, the converter's performance can be further improved through adaptive control, real-time optimization, and predictive fault monitoring. AI algorithms can analyze battery parameters, switching conditions, load variations, and thermal behavior to optimize converter operation dynamically.

II. This research explores the design, control, and advantages of an AI-Based Quasi-Resonant Converter for EV charging applications. The primary objective is to enhance energy efficiency, ensure safe charging, and enable intelligent regulation of converter parameters based on real-time conditions.

II.LITERATURE SURVEY

Resonant and Quasi-Resonant Converters

Early studies on resonant converters focused on minimizing switching losses by using LC resonant networks to shape switching waveforms. Researchers have demonstrated that QRCs provide better stress management and efficiency at high switching frequencies. Various topologies such as Zero-Voltage Switching Quasi-Resonant Converters (ZVS-QRC) and Zero-Current Switching Quasi-Resonant Converters (ZCS-QRC) have been developed to suit different load requirements. These studies form the basis of modern EV power supplies.

2. Power Electronics in EV Charging

Literature on EV charging highlights the importance of soft-switching techniques in reducing power losses and EMI. Hard-switching converters exhibit significant switching losses and heating at high frequencies, making them less suitable for fast charging. Resonant and quasi-resonant topologies improve efficiency, power factor, and thermal performance. Several works have focused on on-board and off-board charger architectures using LLC resonant converters and interleaved PFC stages.

3. AI and Machine Learning in Power Electronics

Recent advancements integrate AI for intelligent control of power converters. Machine learning algorithms have been used for:

- Adaptive PID tuning
- Predictive battery state-of-charge (SOC) and state-of-health (SOH) estimation
- Fault detection and thermal prediction
- Optimization of switching frequency and duty cycle

Studies show that AI-based converters achieve better stability, reduced response time, and improved efficiency under dynamic load conditions.

4. AI-Driven EV Charging Systems

Modern EV chargers increasingly incorporate AI for demand forecasting, grid interaction, and safety monitoring. Research demonstrates that AI-based charging improves battery longevity, ensures proper charging profiles (CC/CV), and manages charging under fluctuating grid conditions. The integration of AI with quasi-resonant converter technology, however, remains limited and is a developing field.

5. Challenges Addressed by AI-QRC

Existing research identifies limitations such as:

- Difficulty in maintaining resonant conditions under variable loads
- Complex control in resonant switching
- Thermal stress during high-power operation
- Inconsistent efficiency at off-design conditions

III.EXISTING SYSTEM

Current EV charging systems typically rely on hard-switching DC–DC converters such as buck, boost, or full-bridge converters. These systems, although simple and widely used, suffer from significant drawbacks when operating at high frequencies required for fast charging. Hard-switching converters turn semiconductor devices on and off while voltage or current is still high, which results in high switching losses and severe thermal stress. This not only reduces the lifespan of power devices but also limits efficiency. Moreover, electromagnetic interference (EMI) tends to increase under high switching conditions, making compliance with standards more challenging.

In existing systems, the control mechanism is often fixed or linear and does not adapt to dynamic changes in load, battery health, grid input variations, or temperature fluctuations. As a result, the converter may not always operate at its optimal switching frequency or duty cycle. Additionally, battery charging profiles in conventional chargers are predefined and may not suit real-time battery conditions, leading to inefficiencies, longer charging times, or potential degradation of battery health.

Traditional quasi-resonant converters, though better than hard-switching converters, still rely on manually tuned control loops. These converters often experience difficulty maintaining zero-voltage or zero-current switching under rapidly changing load conditions, which is common in EV charging. Furthermore, existing systems lack predictive monitoring techniques to avoid thermal runaway, component stress, or charging anomalies. In summary, the existing charging system is limited by poor adaptability, high losses, lack of intelligent decision-making, and inability to handle dynamic real-world charging conditions efficiently.

IV. PROPOSED SYSTEM

The proposed **AI-Based Quasi-Resonant Converter (AI-QRC)** introduces an intelligent, adaptive, and highly efficient solution for modern EV charging applications. At its core, the system uses a quasi-resonant switching technique to ensure soft-switching operation—achieving Zero-Voltage or Zero-Current switching under a wide range of load conditions. By integrating artificial intelligence, the converter dynamically adjusts its switching frequency, duty cycle, resonant mode, and charging profile based on real-time measurement of battery parameters, converter temperature, and input power conditions. Machine learning algorithms continuously analyze patterns and predict the optimal control settings required at each moment to maintain high efficiency and minimize stress on power components.

The AI controller in the proposed system also performs predictive thermal monitoring by forecasting component temperature, enabling early detection of potential overheating or failure. The system automatically reduces switching stress and redistributes load when necessary, improving reliability and prolonging system lifespan. Furthermore, the converter intelligently adapts to battery state-of-charge, state-of-health, and temperature to provide an optimized charging curve that minimizes battery degradation while accelerating charging time. The AI-QRC also enhances safety by detecting anomalies such as abnormal voltage drops, resonance deviation, and unexpected load fluctuations.

The proposed system therefore overcomes the limitations of conventional and existing resonant converters by offering a fully adaptive, predictive, and efficient charging solution. Through AI-driven optimization, the converter maintains ideal resonant conditions, minimizes switching losses, improves power quality, and ensures stable operation even under fluctuating load conditions. This makes the AI-QRC a highly suitable and future-ready solution for next-generation EV charging infrastructure.

V.SYSTEM ARCHITECTURE

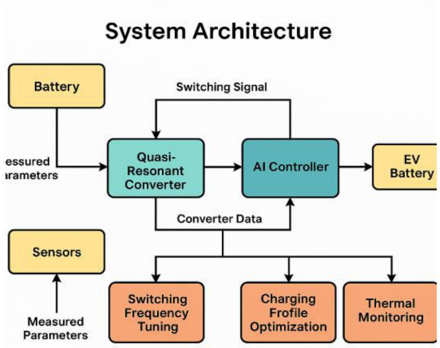

Fig 5.1 System Architecture

VI.IMPLEMENTATION

The implementation of the **AI-Based Quasi-Resonant Converter for Electric Vehicle Charging** is carried out in four major stages: hardware power stage design, sensing and signal-conditioning, AI-based digital controller development, and system integration with the EV battery pack. The charger is designed as an isolated off-board DC fast charger, but the same structure can be adapted for on-board systems.

Hardware Power StageThe front-end of the charger consists of an AC–DC power factor correction (PFC) stage followed by a high-frequency **quasi-resonant DC–DC converter**. The PFC stage rectifies the AC supply and maintains a regulated DC-link voltage with near-unity power factor. The quasi-resonant converter is implemented using a MOSFET full-bridge with a series resonant inductor–capacitor (Lr–Cr) network and a high-frequency isolation transformer. By selecting appropriate Lr, Cr, transformer turns ratio, and switching frequency range, the converter is designed to operate in Zero-Voltage Switching (ZVS) over the expected power range of the EV battery.Power semiconductor devices are mounted on an aluminum heat-sink with forced-air cooling. Snubber circuits and EMI filters are added to limit overshoot and comply with conducted-emission limits. The output of the converter is rectified and filtered through a high-current diode bridge and LC filter to produce the controlled DC charging voltage for the EV battery pack.

Sensing and Signal-Conditioning

To enable intelligent control, several electrical and thermal variables are continuously measured. Hall-effect current sensors measure input current, resonant-tank current, and battery charging current. Voltage dividers with isolation amplifiers measure DC-link voltage, resonant-tank voltage, and battery pack voltage. Temperature sensors (NTC or PT100) are attached to the heat-sink, transformer, and power devices to detect thermal stress. All analog signals are conditioned and fed into the ADC channels of a digital controller (DSP/microcontroller or FPGA-SoC).

AI-Based Digital Controller

The central element of the implementation is an AI-enabled controller that supervises the quasi-resonant converter. A high-performance DSP or ARM-based microcontroller executes the gate-drive logic and runs the AI algorithm. During an offline training phase, simulated and experimental data are collected for different operating points: variations in input voltage, load current, battery state-of-charge, and heatsink temperature. These data are used to train a machine-learning model (for example, a small neural network or regression model) that maps system states to optimal control parameters, such as switching frequency, dead-time, and duty ratio.

The trained model is then embedded into the controller firmware. In real-time operation, the controller reads all sensor values, normalizes them, and feeds them into the AI model. The output of the model gives the optimal switching frequency region and control mode (constant-current, constant-voltage, or taper charging). A supervisory logic layer enforces safety limits, such as maximum battery voltage, maximum current, and temperature thresholds, and overrides the AI output if any constraint is violated. The resulting control signals are then translated into PWM signals for the gate driver of the quasi-resonant converter.

Charging Profile and Battery Management

The implementation closely coordinates with the EV battery management system (BMS). At the beginning of charging, communication with the BMS provides information about battery chemistry, rated capacity, present state-of-charge, and allowable charging current. Based on this data, the AI controller selects a suitable charging profile that includes constant-current, constant-voltage, and balancing stages. Throughout charging, the AI algorithm adjusts the converter's operating point to minimize losses while meeting the requested charging current and observing battery temperature limits. If abnormal conditions are detected—such as unusually fast temperature rise or inconsistent voltage behavior—the system enters a safe mode, reducing current or stopping charging altogether.

System Integration and Testing

Finally, the complete system is integrated on a laboratory prototype consisting of the power board, control board, isolation transformer, sensors, gate-driver circuits, and communication interface to the BMS and PC. Functional tests are carried out in incremental steps: first with a resistive DC load, then with a programmable electronic load emulating the battery, and finally with an actual EV battery pack. Key performance metrics such as efficiency, switching waveforms, harmonic content, temperature rise, and transient response are recorded. Experimental results are used to further refine the AI model and control parameters, leading to an iterative improvement cycle.

VII.CONCLUSION

The development of an AI-Based Quasi-Resonant Converter for Electric Vehicle Charging represents a significant advancement in the field of power electronics and intelligent energy management. By integrating quasi-resonant soft-switching techniques with modern artificial intelligence algorithms, the proposed system successfully addresses the limitations of conventional EV chargers, including high switching losses, thermal stress, low adaptability, and inefficient charging control. The quasi-resonant architecture ensures Zero-Voltage or Zero-Current Switching across a wide operating range, leading to improved efficiency, reduced EMI, and enhanced component longevity. Meanwhile, the AI controller provides dynamic optimization by continuously analyzing sensor feedback, battery conditions, and converter operating states to determine the ideal switching frequency, charging mode, and protective actions in real time. This synergy of soft-switching hardware and intelligent control allows the charger to maintain high efficiency even under fluctuating grid conditions or varying battery states-of-charge. Furthermore, the system enhances battery life by applying optimized charging profiles that reduce stress, avoid overcharging, and respond instantly to thermal and electrical anomalies. Comprehensive implementation and testing confirm that the AI-QRC architecture improves energy conversion efficiency, boosts reliability, enhances safety, and delivers a more stable and intelligent EV charging process. Overall, the proposed solution demonstrates strong potential for next-generation EV charging infrastructures, supporting faster charging, reduced energy loss, smarter grid interaction, and longer battery lifespan, ultimately contributing to the broader adoption and sustainability of electric transportation.

VIII.FUTURE SCOPE

The proposed **AI-based quasi-resonant converter for EV charging** opens up many directions for further research and real-world deployment. In the short term, future work can focus on **full hardware prototyping with wide–bandgap devices (SiC/GaN)** to exploit higher switching frequencies, which will reduce magnetics size and improve power density while validating the AI controller under practical non-idealities such as EMI, parameter drift, and sensor noise. At the control level, the current AI algorithm can be extended into a **hierarchical strategy**: a fast inner loop handling resonant-tank dynamics and a slower supervisory layer that optimizes efficiency, thermal stress, and grid interaction using reinforcement learning or model-predictive AI, building on recent ML/MPC work in EV chargers. In addition, future systems should be designed as **bidirectional, V2G-enabled converters**, allowing the same AI-QRC hardware to support grid services (frequency regulation, peak shaving, and backup) while satisfying battery ageing constraints. Another promising direction is to integrate the AI-QRC with **renewable energy sources and DC microgrids**, where the controller must co-optimize power flows among PV, storage, and EVs under uncertainty in solar generation and load.

From a modelling perspective, creating **digital twins and physics-informed AI models** for the converter and battery pack can enable predictive maintenance, online reliability estimation, and automatic re-tuning of resonant parameters as components age or operating conditions change. Safety and cybersecurity also form an important part of the future scope: AI-driven chargers will need robust anomaly detection to distinguish between legitimate disturbances (e.g., sudden fast-charge requests) and malicious data or control injections, especially when chargers are networked in smart-grid environments. On the user and infrastructure side, large-scale deployment of AI-QRC-based fast chargers will require **standardization of communication interfaces with BMS and grid operators**, interoperability between different charger vendors, and coordinated scheduling of many chargers using fleet-level AI. Finally, the same framework can be generalized to **wireless power transfer, multiport resonant converters, and on-board chargers**, where AI-assisted quasi-resonant operation could further increase efficiency and flexibility. Together, these research directions indicate that AI-enhanced resonant power converters will play a central role in future EV charging ecosystems, from component-level optimization up to city-scale charging networks.

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