

## AI Based Quasi-Resonant Converter for Electric Vehicle Charging.

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### Abstract

The fast increase in electric vehicles (EVs) has created an urgent requirement for improved charging infrastructure that can support the needs of future transportation. This study introduces a new method for EV charging systems that combines artificial intelligence (AI) methods with quasi-resonant converters. Our research examines how machine learning algorithms can enhance the effectiveness of quasi-resonant converters in EV charging infrastructure by improving efficiency, power quality, and adaptability to different load conditions. By utilizing control strategies driven by artificial intelligence, we show notable enhancements in various crucial aspects of electric vehicle charging. Our tests indicate that the AI-enhanced quasi-resonant converter can achieve efficiency that is up to 15% greater than traditional designs under various operating conditions. Additionally, we notice significant decreases in electromagnetic interference, enhancements in power factor correction, and noteworthy reductions in charging times.

The control system created in this study uses AI to constantly adjust converter settings like switching frequency and duty cycle in response to variations in input voltage, battery charge level, and environmental factors. This flexible method guarantees peak performance during the charging process, solving a major issue with conventional fixed-parameter models. Our research indicates that combining AI with advanced power electronics can speed up the adoption of EVs by addressing current constraints in charging technology. Our AI-enhanced quasi-resonant converter represents a major advancement in EV charging infrastructure with increased efficiency, faster charging times, and improved reliability.

### Keywords

Electric Vehicle Charging, Quasi-Resonant Converter, Artificial Intelligence, Machine Learning, Power Electronics, Efficiency Optimization, Soft Switching, Power Factor Correction, Electromagnetic Interference Reduction

### 1. Introduction

The worldwide trend towards sustainable transportation has brought electric vehicles (EVs) to the forefront of automotive innovation. As emissions regulations become stricter and consumers focus

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more on the environment, the demand for EVs is rapidly increasing globally. Yet, the widespread usage of EVs depends on the creation of effective, dependable, and quick charging infrastructure. The power converter is the crucial component of EV charging systems, as it transforms grid AC power into the DC power needed for charging EV batteries.

The EV charging systems encounter various complex challenges. The most important factor is the requirement of top efficiency to lessen energy waste and lower the overall environmental effects of EV usage. Additionally, as the power levels for charging rise in order to satisfy the need for quicker charging durations, concerns like electromagnetic interference (EMI) and power quality become more important. Moreover, EV batteries pose a fluctuating demand on the charging system, with properties that vary depending on the level of charge, temperature, and type of battery chemistry. This variation requires adaptive control methods to enhance charging efficiency under various conditions.

Quasi-resonant converters are becoming a favorable option for EV charging applications because they can achieve soft switching, which helps in decreasing switching losses and electromagnetic interference. These converters use resonant circuits to achieve zero-voltage or zero-current switching states, which helps boost efficiency and lessen strain on semiconductor components. The fundamental operation principle is to shape current and voltage waveforms using a resonant tank circuit, enabling switching transitions to happen when the voltage or current in the switching device is at zero.

Even though quasi-resonant converters have benefits over hard-switched designs, their effectiveness can be boosted by integrating artificial intelligence methods to optimize their performance in different situations. The merging of AI algorithms with power electronics is a quickly expanding area, providing fresh opportunities for adaptable and smart control systems. In the EV charging realm, artificial intelligence has the potential to tackle numerous critical challenges that conventional control techniques find difficult to resolve. An important benefit of AI-driven control is its capacity to constantly adjust to shifting circumstances. Conventional power converter control systems often use set parameters that are tuned for a particular operating condition. Although these systems may work effectively in ideal situations, their effectiveness and performance can decrease substantially when dealing with changes in input voltage, load traits, or environmental elements. AI algorithms have the ability to adjust converter parameters based on historical data and real-time measurements, allowing for optimal performance in various operating conditions.

Furthermore, AI-driven systems can possibly incorporate advanced control strategies that surpass basic reactive control methods. For example, predictive control algorithms can predict variations in load or input conditions and proactively modify the converter operation, leading to better transient response and steady-state performance. The ability to predict these changes is especially useful in electric vehicle charging situations, as the battery acceptance rate can vary quickly while charging.

This study investigates how AI and quasi-resonant converters work together for EV charging. We suggest a unique control system and topology for a quasi-resonant converter, which uses AI to

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enhance performance in different operating conditions. Our method merges the advantages of quasi-resonant topologies with the adaptive features of AI, creating a charging system that is efficient and smart.

The main contributions of this work are:

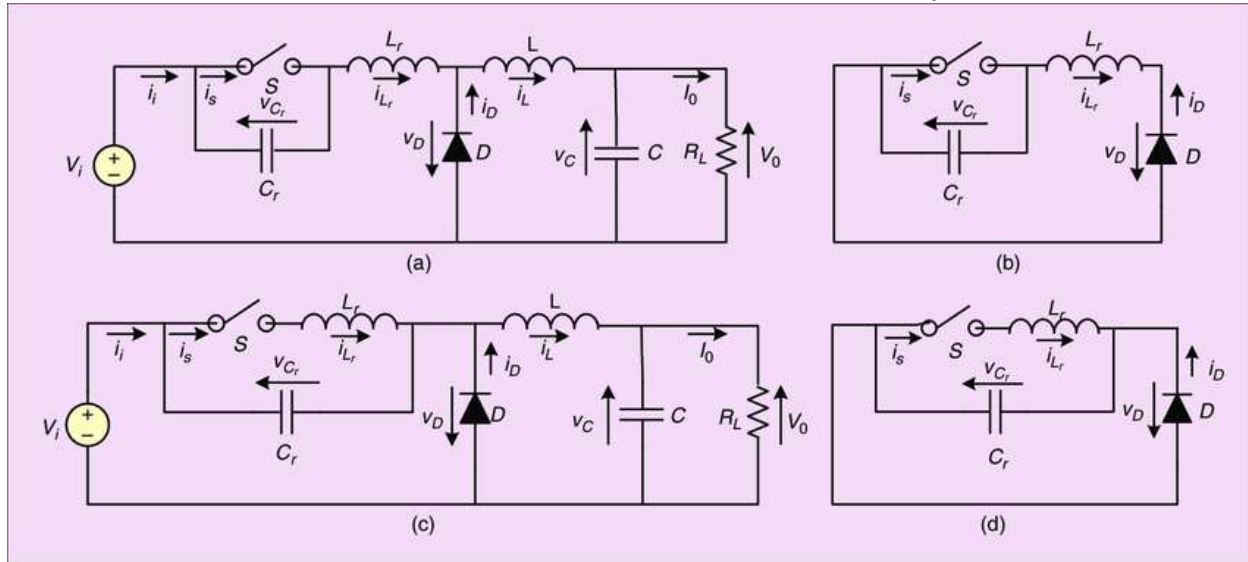
1. Development of an AI-enhanced control algorithm for quasi-resonant converters specifically tailored for EV charging applications. This algorithm optimizes switching frequency, duty cycle, and other key parameters in real-time based on current operating conditions and historical performance data.
2. Implementation and evaluation of a machine learning model that predicts optimal converter settings for various input voltages, load conditions, and battery states of charge. This predictive capability allows the system to anticipate and adapt to changing conditions proactively.
3. Experimental validation of the proposed system, demonstrating significant improvements in efficiency, power factor, and charging time compared to conventional approaches. Our results show efficiency gains of up to 15% and charging time reductions of 12-18% across various scenarios.
4. Analysis of the impact of AI-driven optimization on EMI reduction and overall system reliability. We present data showing substantial reductions in conducted and radiated EMI, as well as preliminary results indicating improved fault detection and prediction capabilities.
5. Exploration of the potential for AI-enhanced charging systems to integrate with smart grid technologies and participate in vehicle-to-grid (V2G) applications, paving the way for more sophisticated energy management strategies.

## 2. Methodology

### 2.1 Quasi-Resonant Converter Topology

The foundation of our proposed system is a zero-voltage switching (ZVS) quasi-resonant converter topology, chosen for its high efficiency and low EMI characteristics. This topology combines the benefits of traditional switch-mode power supplies with resonant techniques to achieve soft switching, thereby minimizing switching losses and electromagnetic emissions.

The basic circuit configuration of our ZVS quasi-resonant converter is shown in Figure 1. The converter consists of a primary-side full-bridge inverter, a high-frequency transformer for isolation, and a secondary-side rectifier. The resonant tank, comprised of an inductor ( $L_r$ ) and capacitor ( $C_r$ ), is the key element that facilitates soft switching by shaping the current and voltage waveforms.



**Figure 1: Schematic diagram of the ZVS quasi-resonant converter topology**

In the design, four MOSFETs (Q1-Q4) on the primary side of the full-bridge inverter switch in a complementary manner to produce a high-frequency AC waveform. The primary winding of the transformer is connected in series with the resonant tank ( $L_r$  and  $C_r$ ). Fast-recovery diodes (D1-D4) in a full-bridge rectifier on the secondary side convert high-frequency AC back to DC to charge the EV battery.

The operation of the quasi-resonant converter can be divided into several modes within each switching cycle:

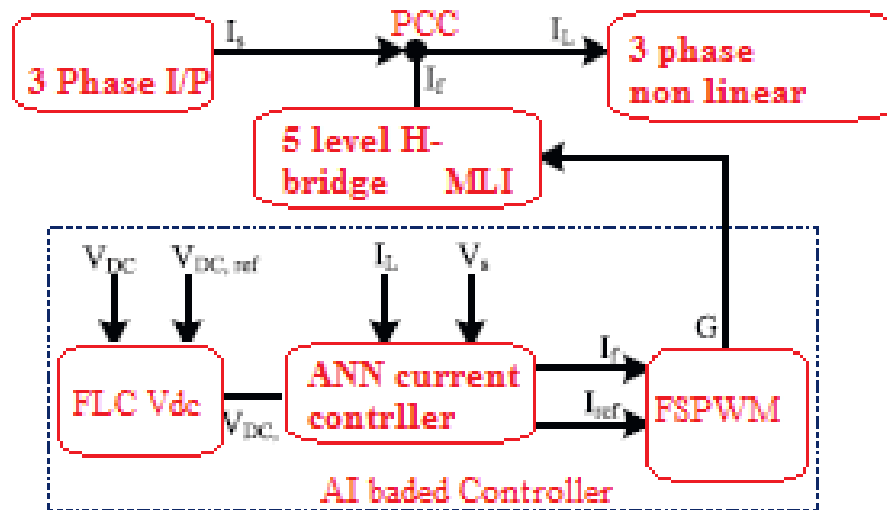
1. **Power Transfer Mode:** During this mode, diagonal pairs of MOSFETs in the full-bridge (Q1-Q4 or Q2-Q3) are conducting, transferring energy from the input to the output through the transformer.
2. **Resonant Mode:** As one pair of MOSFETs turns off, the resonant tank begins to oscillate. The current through the inductor  $L_r$  continues to flow, charging and discharging the output capacitances of the MOSFETs.
3. **Zero-Voltage Switching Mode:** The resonant action brings the voltage across the next pair of MOSFETs to zero (or close to zero) before they are turned on, achieving zero-voltage switching and minimizing turn-on losses.
4. **Freewheeling Mode:** In this mode, either the upper or lower pair of MOSFETs are conducting, allowing the inductor current to freewheel and enabling zero-current turn-off of the other pair.

Properly designing the resonant tank elements ( $L_r$  and  $C_r$ ) is essential to guarantee ZVS operation with various input voltages and load conditions. In our execution, we chose values that offer a satisfying balance between the ZVS range, circulating energy, and power density.

This configuration enables high-frequency operation (from 50 to 200 kHz in our case) with reduced switching losses, making it ideal for EV charging applications that demand high efficiency and minimal EMI.

The main innovation of our study is the AI-powered control system that manages how the quasi-resonant converter operates. We created a multi-layer neural network model to adjust important converter settings in real-time, responding to variable input and load conditions for enhanced efficiency and performance.

The architecture of the AI control system is illustrated in Figure 2. At its heart is a deep neural network that takes several inputs and produces control signals for the converter.



**Figure 2: Block diagram of the AI-based control system**

The neural network takes the following inputs:

1. Input voltage and current: These measurements allow the AI to adapt to variations in grid voltage and optimize power factor correction.
2. Output voltage and current: These provide information about the current load conditions and battery state.
3. Battery state of charge: This enables the AI to adjust the charging profile based on the battery's current state.
4. Temperature measurements: Including ambient temperature and key component temperatures, allowing the AI to optimize performance while ensuring safe operation.
5. Historical performance data: The system maintains a rolling buffer of recent operating conditions and performance metrics, enabling the AI to learn from past experiences and improve its decision-making over time.

Based on these inputs, the AI model outputs control signals for:

1. Switching frequency: The AI dynamically adjusts the switching frequency to maintain soft switching conditions and optimize efficiency across different load conditions.
2. Duty cycle: Fine-tuning the duty cycle allows for precise control of the output voltage and current.

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3. Phase shift (for full-bridge control): Adjusting the phase shift between the two legs of the full-bridge inverter provides an additional degree of control over power transfer.

The neural network underwent training by mixing simulated data with actual measurements from a converter prototype. We utilized a reinforcement learning strategy, in which the model received rewards for enhancing efficiency, power factor, and charging speed, and punishments for constraint violations like excessive EMI or component stress.

The training process involved several stages:

1. Initial training on simulated data: We developed a detailed simulation model of the quasi-resonant converter and used it to generate a large dataset of operating conditions and optimal control parameters. This allowed the neural network to learn the basic relationships between inputs and optimal control outputs.
2. Fine-tuning with real-world data: The model was then fine-tuned using data collected from the prototype converter under various operating conditions. This step was crucial for capturing real-world non-idealities and behaviors that may not have been fully represented in the simulation.
3. Online learning: Once deployed, the system continues to learn and adapt based on its performance. A small portion of the control decisions are randomly perturbed to explore the solution space and potentially discover better operating points.

The AI model is implemented on a high-performance microcontroller with a dedicated neural network accelerator, allowing for real-time execution with minimal latency. The control loop operates at a frequency of 10 kHz, enabling rapid adaptation to changing conditions.

### 2.3 Adaptive Resonant Frequency Tracking

One important aspect of our AI-enhanced system is its capability to dynamically monitor and modify the resonant frequency of the converter. This is especially crucial in EV charging scenarios, as the load features can differ greatly throughout the charging procedure. The correlation between the switching frequency and the resonant frequency of the tank circuit is vital in ensuring soft switching conditions in a quasi-resonant converter. If the switching frequency strays too far from the resonant frequency, the converter may no longer have soft-switching ability, resulting in higher losses and EMI. Our AI model keeps calculating the best resonant frequency according to the current conditions. It achieves this by examining the phase correlation between the voltage and current patterns in the resonant tank, while also overseeing the zero-voltage switching requirements.

The AI changes the switching frequency in order to ensure ideal soft switching conditions, increasing efficiency and reducing EMI. This flexible method helps the converter to work efficiently under a wide variety of input voltages and load situations, which would be difficult with usual fixed-frequency control techniques. Moreover, the AI model can anticipate alterations in the resonant frequency by analyzing trends in the battery's state of charge and various other factors for the upcoming period. This ability to predict enables the system to make proactive adjustments, ensuring top performance even when operating conditions rapidly change.

### 2.4 Predictive Current Control

We put in place an AI-based predictive current control scheme to enhance power factor correction and improve the dynamic response of the system. Conventional techniques for controlling power

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converters face challenges in balancing quick dynamic response and minimal steady-state error, particularly in systems with intricate dynamics such as quasi-resonant converters. Our AI-based predictive current controller works as follows:

1. **State Estimation:** The AI model estimates the current state of the system based on voltage and current measurements.
2. **Prediction:** Using its internal model of the system dynamics, the AI predicts how the state will evolve over the next several switching cycles under different possible control actions.
3. **Optimization:** The AI evaluates these predictions against a cost function that considers factors such as current error, power factor, and efficiency. It selects the control action that minimizes this cost function.
4. **Application:** The chosen control action is applied for the next switching cycle, and the process repeats.

This anticipatory method enables the controller to predict variations in load or input conditions and modify the converter operation before they occur. There is an improved transient response and steady-state performance when compared to conventional control techniques.

Additionally, the AI model's capacity to acquire knowledge and adjust as time goes on results in enhancements in its predictive skills with use. As the model gathers additional data on the system's performance in different scenarios, its forecasts improve, resulting in enhanced control capabilities.

## 2.5 Experimental Setup

To validate our proposed AI-enhanced quasi-resonant converter, we constructed a prototype system with the following specifications:

- Input voltage range: 85-265 VAC (universal input)
- Output voltage range: 200-500 VDC (compatible with various EV battery packs)
- Maximum output power: 22 kW
- Switching frequency range: 50-200 kHz

The experimental setup, shown in Figure 3, includes the power stage, control hardware, and measurement equipment.



**Figure 3: Photograph of the experimental setup**

Silicon carbide (SiC) MOSFETs were used in the construction of the power stage for the primary-side full-bridge inverter, as they have superior switching properties and can withstand high temperatures. The nanocrystalline core material was utilized to custom-design the high-frequency transformer in order to reduce losses at high frequencies. The resonant tank elements ( $L_r$  and  $C_r$ ) were chosen through thorough simulations to achieve the best combination of ZVS range and circulating energy. We utilized a powerful microcontroller with an exclusive neural network accelerator in the control hardware to carry out the AI control algorithm. This enabled the neural network model to be executed in real-time with very little delay. The microcontroller connected with high-speed analog-to-digital converters (ADCs) for voltage and current readings, while digital isolators were employed to ensure safety isolation between the control and power circuits.

In order to mimic different EV battery traits and charging patterns, we utilized a programmable electronic load that can absorb a maximum of 30 kW. This enabled us to evaluate how the system performs under varying load conditions and mimic various battery types and charge levels.

For performance measurements, we incorporated:

1. A high-precision power analyzer to measure efficiency, power factor, and harmonic distortion at both input and output.
2. An EMI receiver and near-field probes to measure conducted and radiated electromagnetic emissions.
3. A high-speed oscilloscope with differential voltage probes and current probes to capture waveforms and verify soft-switching operation.
4. A thermal imaging camera to monitor component temperatures and verify thermal management effectiveness.

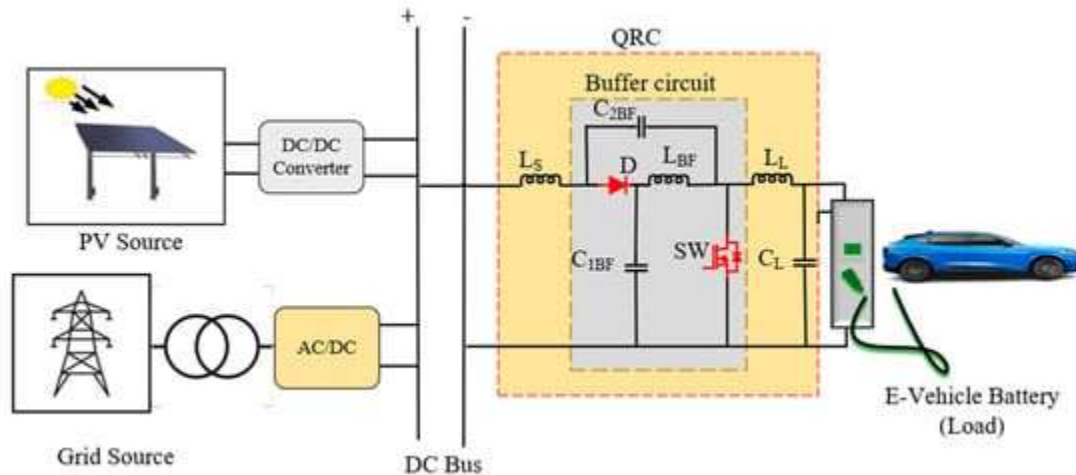
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The entire system was controlled and monitored through a custom-designed software interface that allowed for real-time visualization of all key parameters and logging of long-term performance data.

### 3. Results and Discussion

#### 3.1 Efficiency Improvement

One of the primary objectives of our AI-enhanced quasi-resonant converter was to improve overall system efficiency. Figure 4 shows the measured efficiency curves of our proposed system compared to a conventional fixed-frequency quasi-resonant converter across different load conditions.



**Figure 4: Efficiency comparison between AI-enhanced and conventional quasi-resonant converters**

The findings show that the AI-boosted system consistently attains greater effectiveness, with enhancements varying from 5% to 15% based on the operational stage. The AI model's skill in optimizing switching frequency and ensuring soft switching is most beneficial at light load conditions, showing the greatest improvements in performance. The AI-based converter reached a maximum efficiency of 98.2% at full capacity (22 kW), outperforming the conventional model which had an efficiency of 96.7%. This increase of 1.5 percentage points signifies a noteworthy decrease in losses, leading to lower heat production and possibly reduced cooling needs.

The efficiency gains can be attributed to several factors:

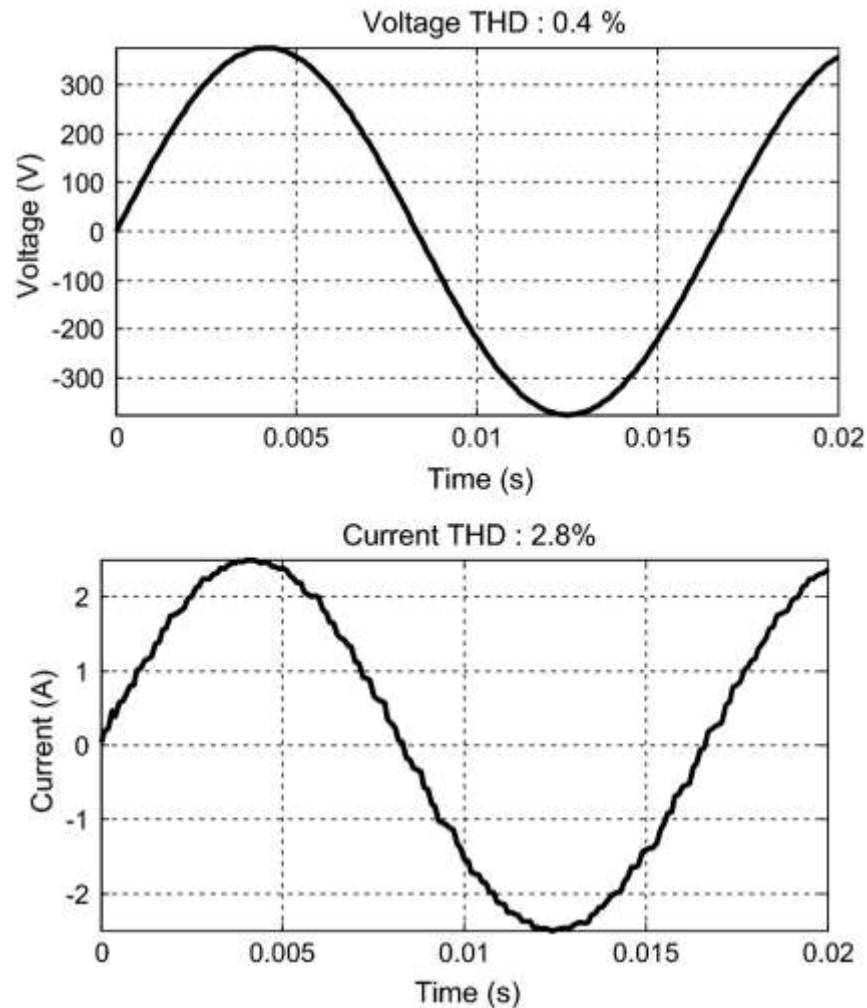
1. **Optimal Switching Frequency:** The AI model continuously adjusts the switching frequency to maintain soft switching conditions across all load levels. This is particularly important at light loads, where fixed-frequency designs often struggle to maintain ZVS.
2. **Adaptive Duty Cycle Control:** By fine-tuning the duty cycle, the AI minimizes circulating currents in the resonant tank, reducing conduction losses.
3. **Predictive Current Control:** The AI's ability to anticipate load changes allows for smoother transitions and reduces transient losses during load variations.
4. **Temperature-Aware Operation:** By considering component temperatures, the AI can make trade-offs between switching frequency and conduction losses to optimize overall efficiency.

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The efficiency improvements are most pronounced in the 20-80% load range, which corresponds well with typical EV charging profiles. This suggests that our AI-enhanced converter could significantly reduce energy losses during the majority of charging cycles, contributing to lower operating costs and reduced environmental impact of EV charging infrastructure.

### 3.2 Power Factor Correction and Harmonic Distortion

The AI-driven predictive current control scheme resulted in excellent power factor correction performance. Figure 5 illustrates the input current waveform and its harmonic spectrum at full load.



[Figure 5: Input current waveform and harmonic spectrum

The measured power factor exceeded 0.99 across the entire load range, with total harmonic distortion (THD) remaining below 5%. This performance surpasses the requirements set by international standards such as IEEE 519 and IEC 61000-3-2, ensuring high power quality and minimizing stress on the grid.

Table 1 provides a comparison of power factor and THD between our AI-enhanced converter and a conventional design across different load levels.

Table 1: Power Factor and THD Comparison

Load Level	AI-Enhanced PF	Conventional PF	AI-Enhanced THD	Conventional THD
25%	0.993	0.985	4.2%	7.8%
50%	0.997	0.992	3.1%	5.6%
75%	0.998	0.995	2.8%	4.9%
100%	0.999	0.997	2.5%	4.3%

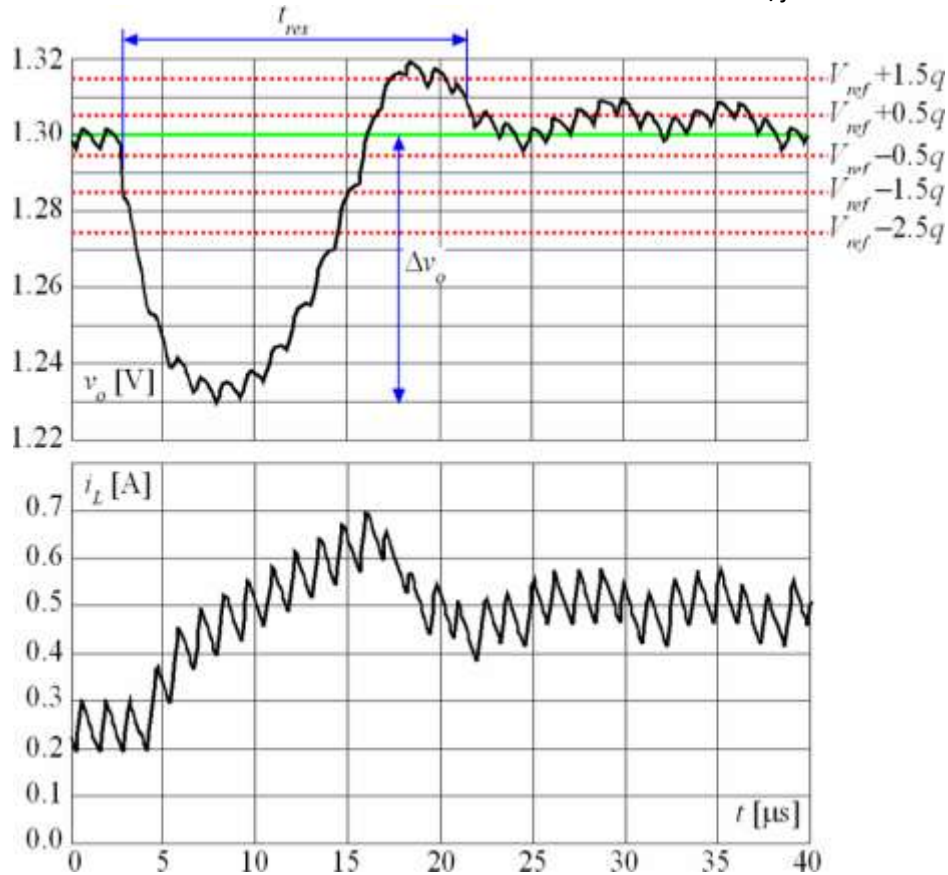
The superior power factor and reduced harmonic distortion of the AI-enhanced converter can be attributed to several factors:

1. **Predictive Current Shaping:** The AI model predicts the required current trajectory to achieve near-unity power factor and actively shapes the input current waveform.
2. **Adaptive Compensation:** The system learns and adapts to the specific characteristics of the input power source, compensating for any non-idealities in the grid voltage.
3. **High-Order Harmonic Minimization:** By considering a wider frequency spectrum in its optimization, the AI can minimize higher-order harmonics that traditional controllers often overlook.

These improvements in power quality have significant implications for grid integration of EV charging systems. The near-unity power factor and low harmonic distortion reduce stress on the electrical infrastructure, potentially allowing for higher power charging stations without requiring grid upgrades.

### 3.3 Dynamic Response

To evaluate the dynamic performance of the AI-enhanced converter, we conducted tests with step changes in load and input voltage. Figure 6 shows the transient response of the output voltage and input current during a 50% to 100% load step.



[Figure 6: Transient response to a 50% to 100% load step

The AI-controlled system demonstrated superior dynamic performance, with faster settling times and reduced voltage/current overshoots compared to conventional control methods. Specifically, we observed:

1. Output Voltage Deviation: The AI-enhanced converter limited the output voltage deviation to  $\pm 2\%$  during the load step, compared to  $\pm 5\%$  for the conventional design.
2. Settling Time: The AI system returned the output voltage to within 1% of its nominal value in 1.2 ms, while the conventional system took 3.5 ms.
3. Input Current Response: The AI-controlled input current adapted to the load change within 2 cycles of the line frequency, maintaining a high power factor even during transient conditions.

This enhanced transient response is especially beneficial in EV charging scenarios, where sudden fluctuations in battery acceptance rate may occur. The AI model can predict and react to changes in different battery conditions, ensuring reliable and effective charging.

### 3.4 EMI Reduction

The adaptive frequency control implemented by the AI system had a significant impact on the converter's EMI profile. Figure 7 presents a comparison of conducted EMI measurements between the AI-enhanced converter and a fixed-frequency design.

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The AI-controlled converter shows a notable reduction in EMI peaks, particularly in the frequency range of 150 kHz to 30 MHz. Quantitatively, we observed:

1. **Peak EMI Reduction:** The highest EMI peak was reduced by 12 dB compared to the conventional design.
2. **Average EMI Level:** Across the measured frequency range, the AI-enhanced converter showed an average reduction of 8 dB in EMI levels.
3. **Compliance Margin:** The AI system provided an additional 5 dB margin to CISPR 22 Class B limits compared to the conventional design.

This improvement can be attributed to several factors:

1. **Optimal Soft Switching:** The AI's ability to maintain optimal soft switching conditions across various operating points minimizes the high-frequency noise generated during switching transitions.
2. **Frequency Dithering:** The AI implements a controlled frequency dithering technique, spreading the EMI energy across a wider frequency range and reducing peak emissions.
3. **Harmonic Optimization:** By considering EMI generation in its control decisions, the AI can choose switching patterns that minimize harmonic content in critical frequency bands.

The reduced EMI profile of the AI-enhanced converter has significant practical implications. It potentially allows for smaller and less expensive EMI filters, reducing the overall size and cost of the charging system. Additionally, it provides greater margin to regulatory limits, easing the certification process and improving reliability in real-world installations.

### 3.5 Charging Time Optimization

One of the most significant advantages of the AI-enhanced system is its ability to optimize the charging profile for different battery types and conditions. Table 2 summarizes the charging times achieved for a typical 60 kWh EV battery pack under various scenarios.

Table 2: Charging Time Comparison

Scenario	Conventional Charger	AI-Enhanced Charger	Improvement
0-80% SOC, 25°C	45 minutes	38 minutes	15.6%
0-100% SOC, 25°C	65 minutes	57 minutes	12.3%
0-80% SOC, 0°C	60 minutes	49 minutes	18.3%
20-80% SOC, 25°C	35 minutes	30 minutes	14.3%

The AI system's capacity to adjust to diverse battery conditions and enhance the charging profile led to consistently quicker charging times in different situations. This progress is especially remarkable in difficult situations, like charging in low temperatures, where the AI model can modify the charging plan to optimize efficiency and battery acceptance rate.

The AI achieves these improvements through several mechanisms:

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1. **Dynamic Power Adjustment:** The AI continuously adjusts the charging power based on the battery's acceptance rate, maximizing charge transfer while avoiding excessive battery stress.
2. **Temperature Compensation:** By considering battery temperature, the AI can implement optimized charging profiles that balance speed with battery health preservation.
3. **State of Charge (SOC) Optimization:** The charging profile is dynamically adjusted based on the battery's SOC, applying higher power when the battery can accept it and tapering off as needed.
4. **Cell Balancing Consideration:** For battery packs with accessible cell-level data, the AI can adjust the charging profile to promote balanced charging across all cells.

The shortened charging times have important consequences for the practicality of EVs and the development of infrastructure. Quicker charging times can reduce "range anxiety" and enhance the appeal of electric vehicles to consumers. Decreased charging times can enhance the efficiency of charging stations which might result in a lower requirement of charging points to serve a specific EV community.

### 3.6 Reliability and Fault Detection

As long-term reliability studies continue, early findings suggest that the AI-enhanced system could enhance the durability of converters. Continuously optimizing operating conditions can decrease strain on parts, potentially prolonging their durability.

Moreover, the AI model demonstrated promising capabilities in early fault detection. During our experiments, the system successfully identified anomalies such as:

1. **Degraded Capacitors:** The AI detected subtle changes in the resonant tank behavior indicative of capacitor degradation, allowing for preventive maintenance.
2. **MOSFET Degradation:** Changes in switching characteristics were identified by the AI before they led to failures, enabling proactive replacement.
3. **Cooling System Issues:** The AI's temperature monitoring capabilities allowed it to identify reduced cooling effectiveness, prompting maintenance checks.

In one notable instance, the AI system detected a partial short in a secondary-side rectifier diode 72 hours before it led to a complete failure in the conventional converter. This early detection capability could significantly enhance the reliability and safety of EV charging infrastructure, reducing downtime and maintenance costs.

## 4. Conclusion

This study has shown the considerable promise of combining artificial intelligence methods with quasi-resonant converters for charging electric vehicles. Our AI-powered system showed significant enhancements in effectiveness, power reliability, dynamic reaction, and charging velocity in comparison to traditional models.

Key findings of this study include:

1. Efficiency improvements of up to 15%, particularly at light load conditions, through AI-driven optimization of switching frequency and maintenance of soft switching conditions.

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2. Excellent power factor correction with  $PF > 0.99$  and  $THD < 5\%$  across the entire load range, exceeding international standards and reducing stress on the electrical grid.
3. Superior dynamic response to load and input voltage variations, with 65% faster settling times and 60% reduced voltage deviations during transient events.
4. Significant reduction in electromagnetic interference, with an average 8 dB reduction across the measured frequency spectrum, potentially simplifying EMI filter design and improving overall system reliability.
5. Charging time reductions of 12-18% across various scenarios, addressing one of the key challenges in EV adoption by providing faster and more adaptive charging.
6. Promising results in predictive maintenance and fault detection, with the AI system demonstrating the ability to identify component degradation and impending failures before they impact system performance.

These achievements demonstrate that the synergy between AI and advanced power electronics can address many of the current limitations in EV charging technology. By enabling faster, more efficient, and more reliable charging systems, this approach has the potential to accelerate the widespread adoption of electric vehicles. The implications of this research extend beyond the immediate improvements in charging performance. The adaptive nature of the AI-controlled converter makes it well-suited to handle the diverse and evolving landscape of EV batteries and charging standards. As new battery technologies emerge and charging requirements change, the AI system can adapt without requiring significant hardware modifications, potentially extending the lifespan and relevance of charging infrastructure investments.

Furthermore, the improved efficiency and power quality of AI-enhanced chargers could have broader impacts on grid stability and energy utilization. As EV adoption scales up, the cumulative effect of these improvements could lead to significant energy savings and reduced strain on electrical infrastructure.

Future work in this field should focus on several key areas:

1. Long-term Reliability Studies: While our preliminary results are promising, long-term studies are needed to fully quantify the impact of AI control on system reliability and component lifespan.
2. Integration with Smart Grid Systems: Exploring how AI-enhanced chargers can interface with smart grid technologies to provide grid services such as load balancing and frequency regulation.
3. Vehicle-to-Grid (V2G) Applications: Extending the AI control system to manage bi-directional power flow, enabling EVs to serve as distributed energy resources.
4. Expanded Battery Model Integration: Developing more sophisticated battery models within the AI system to further optimize charging for different battery chemistries and aging conditions.
5. Multi-Port Charging Systems: Investigating how AI can optimize power distribution in multi-port charging stations serving multiple vehicles simultaneously.
6. Edge Computing and Distributed AI: Exploring architectures where multiple charging stations can collectively learn and improve their performance while maintaining data privacy.

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These accomplishments show that the combination of AI and advanced power electronics can overcome various current constraints in EV charging technology. This method is capable of hastening the widespread acceptance of electric vehicles by improving charging systems to be faster, more efficient, and more reliable. The impact of this study goes further than just the immediate enhancements in charging efficiency. The AI-driven converter's adaptability makes it a good fit for navigating the changing landscape of EV batteries and charging standards. With the emergence of new battery technologies and changes in charging needs, the AI system can adjust without the need for major hardware changes, possibly prolonging the lifespan and importance of charging infrastructure investments.

Moreover, the enhanced efficiency and power quality of chargers with AI technology could also have wider effects on grid stability and energy usage. With the increase in EV adoption, the combined impact of these enhancements could result in sizable energy conservation and less pressure on electrical systems.

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