

Article

Adaptive Neuro Fuzzy Inference System (ANFIS)-Based Control for Solving the Misalignment Problem in Vehicle-to-Vehicle Dynamic Wireless Charging Systems

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Abstract: Vehicle-to-vehicle dynamic wireless charging (V2V-DWC) represents a modern advancement in electrified transportation, where a specialized charging vehicle delivers power to another vehicle on the move. The rising popularity of this technology can be attributed to the gradual advancements in energy storage technologies and the scarcity of plug-in charging infrastructure. V2V wireless power transfer provides a solution for electric vehicles (EVs) to recharge their batteries while in transit. The existing literature confirms the empirical validation of this concept through analytical and experimental studies, yet the challenge of misalignment remains insufficiently explored. Achieving optimal power transfer in V2V systems necessitates precise alignment of the inductive coils. Lateral misalignment (LTM) occurs due to the deviation of the coils from the proper alignment, leading to significant energy losses. Additionally, the development of effective controllers to address the V2V misalignment problem remains inadequate. This study proposes the development of a neural network-based adaptive fuzzy logic controller (ANFIS) to alleviate the misalignment issues in V2V-DWC systems. A comparative analysis is conducted between the proposed ANFIS controller and the conventional fuzzy logic controller (FLC) to evaluate their performance across various degrees of LTM. The performance of the proposed ANFIS controller is evaluated through simulations in MATLAB/Simulink, supplemented by experimental testing. The results indicate that the proposed ANFIS controller surpasses the FLC in both simulation and experimental contexts in addressing the V2V misalignment challenge.

Keywords: dynamic wireless charging (DWC); electric vehicle (EV); fuzzy logic controller; adaptive neuro fuzzy inference system (ANFIS); lateral misalignment (LTM)



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1. Introduction

The electric vehicle (EV) has emerged as a fitting solution to the worldwide fuel crisis [1]. Presently, EVs are predominantly charged through plug-in modes at charging stations, drawing energy from the grid through various wires and connectors. Nonetheless, there are notable disadvantages associated with EVs that are impeding their extensive adoption. These drawbacks include a limited driving range, commonly referred to as “range anxiety”, extended charging durations, prolonged waiting times at charging stations, and a larger battery size, which increases manufacturing costs compared to traditional automobiles [2]. This issue becomes more problematic when embarking on trips that necessitate multiple stops for recharging, as this can consume a significant portion of the overall travel time.

Furthermore, the charging process can be vulnerable to adverse weather conditions because of the management of high-voltage cables. Dynamic wireless charging (DWC) technology [3–5] offers a viable solution to address the drawbacks associated with EVs. While DWC technology can effectively eliminate concerns like range anxiety, extended waiting times at charging stations, and the substantial initial manufacturing expenses tied to large battery sizes, it relies on advanced controllers to ensure that the EV accurately stays in the charging lane. Otherwise, it may encounter misalignment issues.

The system in [6] comprises a charging vehicle designed to wirelessly charge a user vehicle while both are in motion on a highway. As the user's vehicle advances along its journey, it can opt to initiate a vehicle-to-vehicle recharge (VVR) request when its battery's state of charge (SOC) drops to a lower threshold. An innovative method is proposed to navigate electric vehicles (EVs) around mobile energy disseminators (MEDs) within the road network, utilizing constraint logic programming and optimization via a graph-based shortest path algorithm [7]. The technique leverages inter-vehicle communications to environmentally optimize the routes of EVs. A collaborative approach combining vehicle-to-charging infrastructure (V2C) and vehicle-to-vehicle (V2V) power transfer has been developed to reduce the total infrastructure cost and alleviate range anxiety by 50% [8].

A novel holistic energy management framework has been suggested, offering potential solutions to various aspects of V2V charging challenges at different stages [9]. The article in [10] explores the challenges of routing, scheduling, and aligning vehicles in a vehicle-to-vehicle (V2V) wireless power transfer (WPT) platform within an energy–time expanded network and proposes a dynamic programming method to efficiently solve these issues. Ref. [11] introduces the core theory of multi-turn coil design with an angular offset to improve the coupling factor and enhance system efficiency. An enhanced WPT coil design, which has been optimized to improve transfer efficiency, coupling separation, and tolerance to misalignment, was introduced in [12].

While the concept of V2V charging involving communication protocols, efficient coil design, routing, and scheduling can be found in the existing literature, there is still a gap in addressing the misalignment issue, which remains unexplored in the literature. Misalignment leads to reduced mutual inductance between the coils, resulting in diminished power transfer from the source to the receiver. Recent research on simultaneous wireless power and data transfer (SWPDT) systems emphasizes the importance of misalignment tolerance and vertical distance adaptation. Developments in anti-series coil design, mutual inductance stabilization, and the use of compensation capacitors have notably improved performance while reducing power interference [13–15]. Consequently, the system's efficiency decreases, and the EV receiver fails to receive the necessary power. Moreover, there is a notable absence of controllers identified for addressing the misalignment issue in V2V-DWC systems in the existing literature.

Building on this background, this paper proposes developing appropriate controllers to solve the lateral misalignment (LTM) problem in V2V charging. The primary objective behind the development of these controllers is to regulate the input power level, ensuring that it matches the vehicle's power requirements, especially when facing abrupt fluctuations in the coupling coefficient between the coils. The existing literature shows that the fuzzy logic controller (FLC) has good performance in addressing misalignment issues and alleviating the reduced power transfer phenomenon caused by it [16,17]. The FLC's reliance on expert knowledge for rule creation and parameter tuning can be time-consuming and subjective, limiting its adaptability to changing environments. This drawback motivates us to explore a new controller that is adaptive to dynamic conditions.

This study develops an Adaptive Neuro-Fuzzy Inference System (ANFIS) that enhances adaptability and robustness by combining the learning capabilities of neural net-

works with the interpretability of fuzzy logic, making it ideal for dynamic wireless charging systems, particularly in resolving misalignment issues through its ability to self-adjust and optimize control parameters based on real-time input data. The rationale for selecting the ANFIS controller for the system lies in its capacity to adapt effectively to a range of dynamic scenarios, effectively managing misalignment by adjusting the pulse width modulation (PWM) duty cycle of the inverter. It learns in real time, improving its efficiency in handling nonlinear relationships and disturbances without needing precise mathematical models. The system enhances power transfer efficiency and robustness, ensuring reliable operation even with external perturbations. Its ability to continuously optimize performance reduces energy losses and offers a seamless user experience. Overall, neuro-fuzzy control is ideal for maintaining the required power levels in dynamic and complex charging scenarios.

A comparative analysis between the two controllers was performed to evaluate their suitability for this application. Using the MATLAB/Simulink environment, simulations were conducted to design the proposed ANFIS controller, considering both the mutual inductance and dynamic behavior of vehicles. Also, the designed ANFIS controller was validated through small scale experimental setup. The main contributions of this work include the following:

- Developing the ANFIS controller to mitigate the misaligned cases in the V2V charging system.
- Analysis of the proposed controller's performance compared to the existing fuzzy controller based on control system indicators.
- A comparative assessment of both controllers for their compatibility within the DWC-V2V system.

This article is structured as follows: Section 2 discusses the primary challenges encountered in a dynamic wireless power transfer (DWPT) system and analyzes their impact on system parameters. Section 3 focuses on the design of the controller. Sections 4 and 5 provide the simulation results and experimental findings, respectively. Finally, Section 6 offers concluding remarks and outlines directions for future research.

2. Problem Statement

Vehicle-to-vehicle (V2V) charging is based on the inductive power transfer (IPT) method. A typical representation of a V2V charging system is depicted in Figure 1, where the charger vehicle is equipped with a substantial battery pack that serves as a source of power for the receiving vehicle. A DC battery serves as the input source for a full-bridge inverter, which is controlled using phase-shift modulation and operates at a frequency of 20 kHz. This inverter generates a high-frequency square wave, which is then fed through an LCL-T type compensation network. This network is designed to tune the circuit to resonate at a specific frequency and filter out all higher harmonics, leaving only the fundamental component. Consequently, primary coil current is produced as a pure sinusoidal waveform with fundamental harmonic content only.

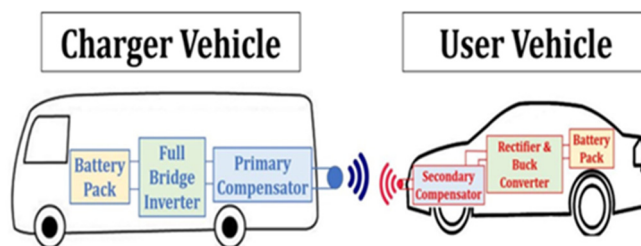


Figure 1. Schematic of a vehicle-to-vehicle dynamic wireless charging system.

The equivalent circuit diagram for the vehicle-to-vehicle dynamic wireless charging (V2V-DWC) process is illustrated in Figure 2. In this diagram, the primary side corresponds to the circuits within the charger vehicle, while the secondary side represents the user vehicle.

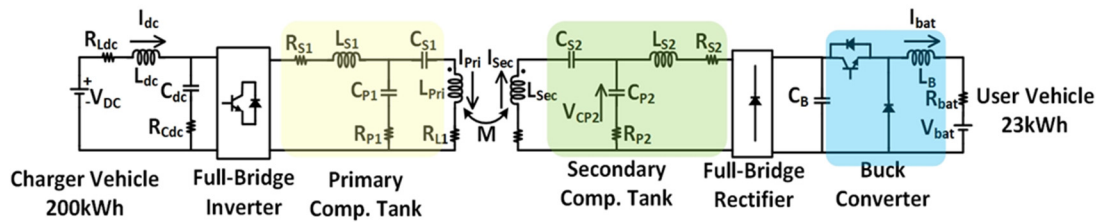


Figure 2. V2V-DWC process equivalent circuit diagram [16].

The power transferred to the secondary side can be understood using the straight-forward inductive circuit depicted in Figure 3 [16]. The power that is transferred to the secondary side is expressed as (1).

$$P_{out} = w_s * M^2 * I_1^2 * \frac{Q}{L_L} \quad (1)$$

Here, system operating frequency is represented by w_s , M denotes the mutual coupling between the pair of coils, the current in the primary coil is shown by I_{pri} , Q represents the quality factor of the receiver side, L_L is the inductance of the receiver side, and P_{out} denotes to the power sent to the receiver EV. According to Equation (1), the output power P_{out} can be adjusted by manipulating w_s , M , I_{pri} , or Q .

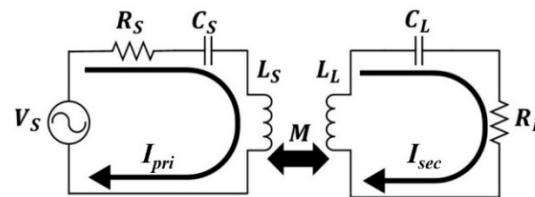


Figure 3. Mutual coupling between two coils [16].

2.1. Misalignment Issue

A DWPT system is highly sensitive to misalignment. This means that if the pair of coils are not completely aligned, the mutual inductance (M), which influences the coupling factor (k) as described by the equation ($M = k \sqrt{L_S L_L}$), will change significantly if the secondary coil of the user EV cannot effectively follow the charger EV. The value of M is influenced by lateral misalignment (LTM), longitudinal misalignment (LNM), angular misalignment (AM), and vertical misalignment (VM). Among these four types of misalignments, LNM, VM, and AM have minimal impact on M for an EV. In contrast, LTM primarily causes the loss of transferred power. As LTM increases, the coupling factor between the coils decreases, leading to a reduction in mutual impedance, as illustrated in Figure 4. This reduction is a crucial factor in determining the output power, as seen in Equation (1). Figure 4 is based on a circular receiver coil (radius = 35 cm) and experimental results [16]. “Degrees of Lateral Misalignment (Normalized)” refers to the normalized measure of the side-to-side offset between the transmitter and receiver, scaled to a standard range for efficient processing in control systems. In the context of wireless power transfer in a V2V scenario, a maximum allowable lateral misalignment (LTM) of 15 cm between two coils was considered. A normalized LTM of 10% corresponds to an actual misalignment of 1.5 cm. Similarly, a 20% normalized LTM represents a 3 cm lateral displacement, illustrating

how the system quantifies and handles deviations from ideal alignment to ensure efficient power transfer.

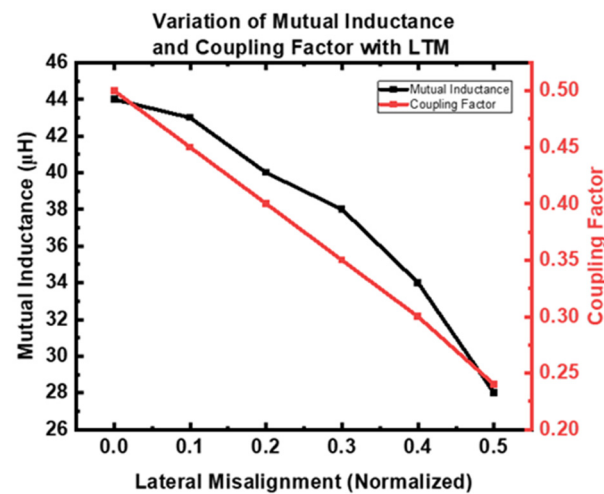


Figure 4. Mutual inductance and coupling factor variation with LTM.

2.2. Impact of LTM on Power Rating of Electronic Devices

In cases of significant misalignment or when multiple EVs pass over the primary coil, the required primary current will increase, potentially exceeding the power rating of the electronic devices involved. To address this limitation, it is essential to restrict the primary current to a specified maximum value. Table 1 illustrates the variation in DWPT parameters for a fully aligned coil (Case 1) compared to different lateral misalignment scenarios (Cases 2–6). The DWPT system is designed to deliver 25 kW (P_{out}) with a switching frequency of 20 kHz ($\omega_s = 2\pi \times 20 \text{ kHz}$). All other system parameters were sourced from [18]. The most effective method to address the reduction in power transfer is to increase the primary coil current (I_{pri}). The concept behind controlling the primary current is rooted in the principles of magnetically coupled circuits. When the primary coil carries a higher current, it produces a greater magnetic flux, which in turn attempts to induce a higher voltage in the secondary coil. Therefore, it is crucial to regulate the primary current (I_{pri}) to maintain consistent power transfer within a specified range of misalignment conditions. This realization drives us to investigate a new controller to tackle the misalignment challenges in DWC for EVs.

Table 1. System parameters for different degrees of LTM.

Case No.	DWPT System Parameters			
	Degrees of LTM (Normalized)	Coupling Factor (k)	Mutual Inductance (M in μH)	Required Primary Current (Amps)
1	0 (fully aligned)	0.241	42.10	55.27
2	0.1	0.236	41.20	56.48
3	0.2	0.232	40.39	57.61
4	0.3	0.216	37.66	61.78
5	0.4	0.193	33.53	69.40
6	0.5	0.161	27.89	83.43

3. Control Methodology

In V2V charging systems, controllers can be located on either the primary side (source vehicle) or the secondary side (receiver vehicle). In this study, the controllers were implemented on the primary side to control misalignment. The significance of regulating the primary current I_{pri} to mitigate the effects of variations in mutual inductance is further highlighted in Equation (1). Figure 5 illustrates the concept of the proposed ANFIS controller, focusing on the primary side segment. It is crucial to manage the duty cycle (phase shift angle of the full bridge converter) to effectively control the primary current.

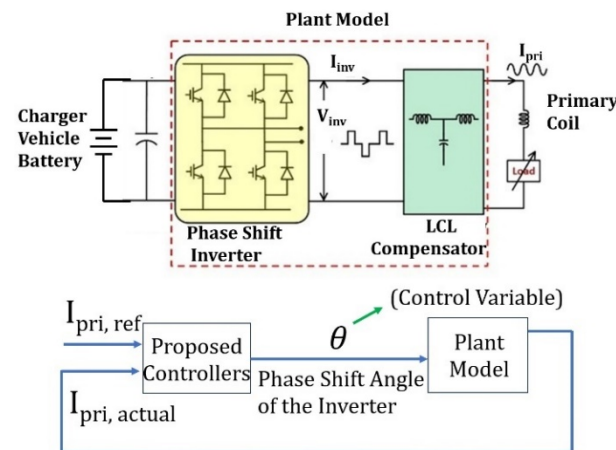


Figure 5. Concept of the proposed controller.

3.1. Proposed Adaptive Neuro-Fuzzy Inference System (ANFIS) in V2V Scenario

The Adaptive Neuro-Fuzzy Inference System (ANFIS) integrates the capabilities of neural networks and fuzzy logic, forming a robust and flexible control system. Leveraging the learning power of neural networks and the interpretability of fuzzy logic, ANFIS excels at modeling intricate systems and making informed decisions in uncertain settings. ANFIS is an adaptive neural network approach that synchronizes artificial neural networks (ANNs) with fuzzy inference systems (FIS). This predictive model works with real-world data, customized for specific applications, often structured using rules and input parameters derived from actual data. By assigning appropriate membership functions to fuzzy data inputs, ANFIS calculates input parameters (ANFIS input). Employing hybrid techniques like the least squares estimator and backpropagation gradient descent, the antecedent parameters are iteratively optimized to reach the final values. Throughout the learning process, real-world data, including both forward and backward passes, are fed to the ANFIS model repeatedly across several iterations. In each iteration, modifications are made to both premise and consequent parameters.

Moreover, the adaptive NN-based fuzzy logic controller (FLC) is well suited to a V2V-DWC system due to its ability to manage the system's inherent uncertainties and nonlinear behaviors. Unlike traditional controllers, ANFIS does not require an exact mathematical model, making it ideal for handling dynamic factors such as misalignment, load fluctuations, and varying coupling conditions. Its rule-based framework allows for intuitive and adaptive control, like human decision-making. This adaptability ensures that the ANFIS can effectively maintain stable power transfer, even as operating conditions change, which is essential for delivering consistent power to the receiving EV.

3.1.1. Modeling of ANFIS

In 1993, J.S. Roger Jang introduced the ANFIS, which is recognized as a fuzzy system and global estimator derived from the Takagi–Sugeno fuzzy model [19]. This model functions as a Type 3 fuzzy inference system, where the rule outputs are formed by a linear

mixture of input parameters and a constant term. The final result is calculated by averaging the weighted outputs of all the rules [20]. ANFIS is a sophisticated integration of an artificial neural network and a fuzzy inference system, offering a powerful and integrated solution to complex engineering problems by leveraging the strengths of both models [21–23]. Figure 6 presents a schematic diagram of the ANFIS architecture, demonstrating how the system effectively combines the learning capabilities of a neural network with the fuzzy logic system to model the output–input relationships of real-world systems.

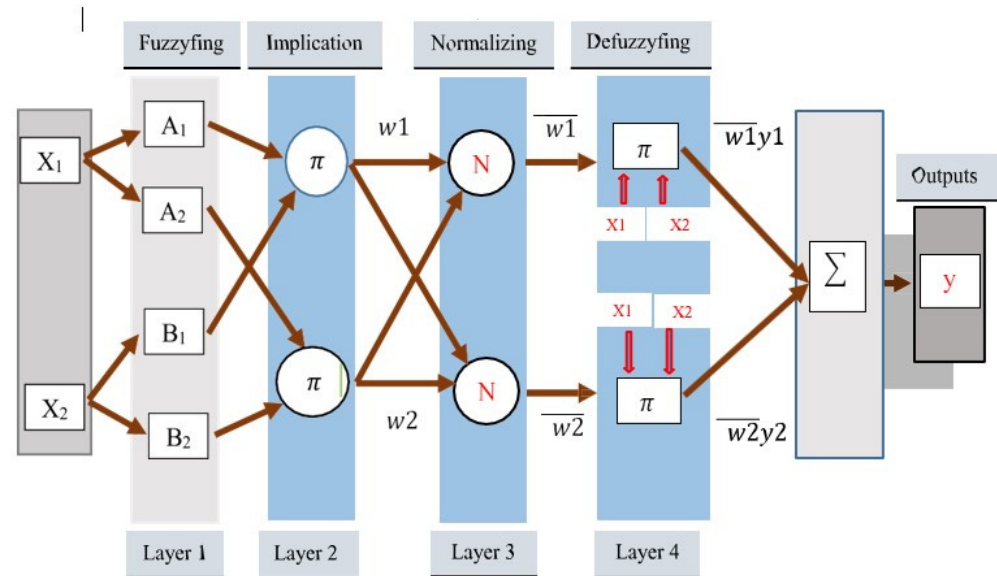


Figure 6. Schematic diagram of the structure of ANFIS.

The fundamental ANFIS rule, that processes two inputs, X_1 and X_2 , to generate a single output, y , is described as follows:

Rule 1: if X_1 is A_1 and X_2 is B_1 , then the output is given by $y_1 = p_1X_1 + q_1X_2 + r_1$.

Rule 2: if X_1 is A_2 and X_2 is B_2 , then the output is given by $y_2 = p_2X_1 + q_2X_2 + r_2$.

The parameters A_j and B_j correspond to each input fuzzy sets for the premise part, while the parameters p_j , q_j , and r_j are the linear variables in the consequent part. The ANFIS architecture for a single output–two input network consists of five distinct layers:

- (1) Fuzzification Layer: In this layer, each node j is considered an adaptive node, and the output is computed as [24]

$$O_j^1 = \mu_{A_j}(x_1), \text{ for } j = 1, 2 \quad (2)$$

$$O_j^1 = \text{for } j = 3, 4 \quad (3)$$

- (2) Implication Layer: In this layer, the nodes are fixed and represented by π , meaning they function as simple multipliers. Each node's output introduces w_j , the rule firing strength, which is computed based on the incoming signals as

$$O_j^2 = w_j = \mu_{A_j}(x_1) \mu_{B_{j-2}}(x_2), \text{ for } j = 1, 2 \quad (4)$$

- (3) Normalization Layer: In this layer, each node is a fixed node, labeled as N . The output signal $\bar{w}_j$ for the j th node is calculated by the division of the firing strength of the j th rule by the sum of all the rules' firing strengths:

$$O_j^3 = \bar{w}_j = \frac{w_j}{w_1 + w_2} \text{ for } j = 1, 2 \quad (5)$$

- (4) Defuzzification Layer: Each node j in this layer is adaptive, with the node function involving the parameters (p_j, q_j, r_j) and w_j . The firing strength is expressed as a normalized value, as follows:

$$O_j^4 = \bar{w}_j y_j = \bar{w}_j (p_j X + q_j X + r_j), \text{ for } j = 1, 2 \quad (6)$$

- (5) Combination Layer: The final layer consists of a single fixed node, labeled Σ , which sums all the input signals to compute the total final output as

$$O_j^5 = y = \sum_j (\bar{w}_j y_j) = \frac{\sum_j (w_j y_j)}{\sum_j w_j} \quad (7)$$

3.1.2. Evaluation Parameter

ANFIS learning uses two algorithms to determine the membership function: the backpropagation method and a hybrid algorithm that integrates the least squares method with gradient descent techniques. In particular, this study employs the gradient descent method to adjust nonlinear input parameters, while the least squares technique is used to fit nonlinear output parameters. This combined algorithm is recognized for its high efficiency [22]. The root mean square error is calculated by squaring the gap between predicted and observed values, averaging this over the sample, and then taking the square root. Mathematically, this can be expressed as (8)

$$RMSE = \sqrt{\frac{1}{n} \sum_{k=1}^n [n(k) - \hat{n}(k)]^2} \quad (8)$$

Let n be the test vectors. Here, $\hat{n}(k)$ refers to the expected (measured) value, while $n(k)$ denotes the value generated. The RMSE follows a quadratic error rule, where the differences are first averaged and then squared. This approach assigns a relatively higher weight to larger errors [25–29].

3.1.3. Generating Fuzzy Inference System and Training of ANFIS

For V2V misalignment application, at first, the PI controller is developed to tune the system in the desired level. As the PI controller exhibits an oscillatory pattern in higher LTMs, the PI controller input (error in primary current) and output (phase angle of the inverter) are extracted from the simulation. The dataset is then used for training the ANFIS. In total, 80,000 data points are used to train the neural network. This is a SISO (single input–single output) network, as shown in Figure 7. In the wireless power transfer system for V2V charging, key feedback parameters such as received voltage, current, and power levels are monitored on the receiving side. These parameters serve as indicators of the system's performance, helping to identify any inefficiencies or misalignments that may occur during the power transfer process. Specifically, variations in these parameters can signal phase misalignment (dephasing) between the transmitting and receiving coils, which directly impacts the efficiency of the power transfer.

The primary goal of the Adaptive Neuro-Fuzzy Inference System (ANFIS) algorithm is to utilize the feedback parameters to detect and resolve dephasing issues in real time. By continuously adjusting the phase and duty cycle of the PWM converter on the transmitting side, the algorithm ensures optimal alignment and efficient power transfer. The ANFIS algorithm dynamically compensates for misalignments and varying conditions, maintaining effective power transmission despite the challenges posed by the dynamic V2V charging environment.

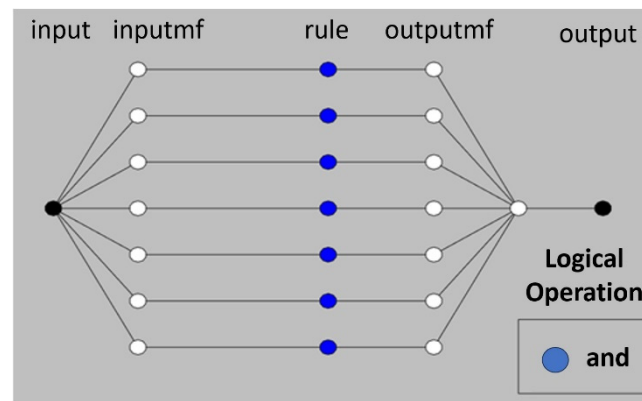


Figure 7. ANFIS model structure.

Using the grid partitioning technique, the fuzzy inference system is generated with seven trapezoidal membership functions (MFs). The details of the training parameters are summarized in Table 2. To ensure that ANFIS functions effectively, we need to pick membership functions that effectively show how the system behaves but are not too complicated. By finding the right balance between accuracy and simplicity, we can make sure that ANFIS performs well in different situations through trial and error and by cleaning the dataset for neural network training.

Table 2. Training of ANFIS.

Training Parameters of ANFIS	Details
Fuzzy Inference System	Grid Partitioning Method
No. of Membership Functions	7
Membership Function Type	Trapezoidal
No. Of Fuzzy rules	7
No of input	1
No of output	1
Error Tolerance	0.001
Optimization Technique	Hybrid Method
No of Epochs for training	100

After training is performed with the extracted dataset, the following results are obtained based on the training (Figure 8) and validation dataset (Figure 9).

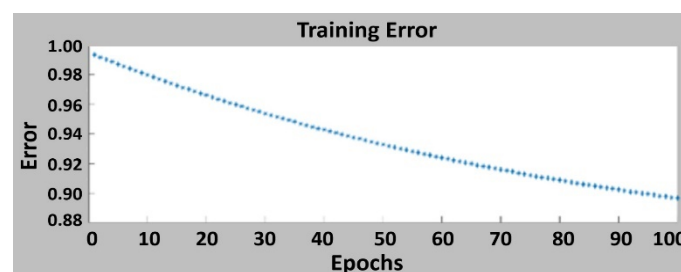


Figure 8. Training error of the proposed ANFIS (mean squared error: 0.9 after 100 epochs).

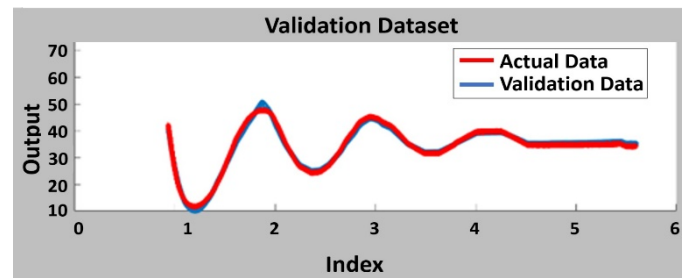


Figure 9. Validation of ANFIS structure.

The algorithm is designed to maintain constant power on the receiving side of the wireless power transfer system, even under conditions of high misalignment. When misalignment increases, the coupling factor between the transmitter and receiver coils decreases, which leads to a drop in the receiver voltage. To compensate for this, the algorithm increases the current on the primary side, thereby generating more magnetic flux. This increased flux induces a higher voltage on the receiver side, allowing the system to maintain the same power output, as described by Equation (1).

While this approach can effectively maintain constant power, such as 25 kW on the receiver side, it is not without its challenges. Power efficiency can decrease due to higher losses associated with increased primary current, and thermal constraints become a critical factor in ensuring the system's safe operation. Nonetheless, our analysis and simulations indicate that, despite these constraints, it is possible to maintain constant power delivery at high misalignment by carefully controlling the primary current and managing the system's thermal conditions. This demonstrates the robustness of the algorithm in adapting to dynamic conditions to ensure optimal power transfer to the receiver EV.

3.2. Comparison with Existing State-of-the-Art Neuro Fuzzy System

The latest state-of-the-art design of a neuro-fuzzy controller is presented in [30] within a microgrid system, where hydrogen fuel cell energy is converted to AC power. By utilizing a neuro-fuzzy inference controller, smooth voltage regulation and efficient power generation can be achieved. Although our system focuses on V2V-DWC, it can be compared to the existing ANFIS controller in terms of design and performance. Table 3 offers a concise comparison of the two systems.

Table 3. Comparison of proposed ANFIS and existing neuro-fuzzy controller.

Features	ANFIS (Proposed for V2V-DWC System)	Neuro Fuzzy Controller (for Renewable Microgrid)
Input-Output Membership Functions	7	3
Algorithm Complexity	No of epochs: 100	No of epochs: 50
Training Time	1–2 min	Not mentioned in [30]
Cost	Processors: Core i9	Processors: Core i9
Accuracy	RMSE: 0.05%	RMSE: 0.03%
Input-Output Numbers	Input: 1, Output: 1	Input: 2, Output: 1
Rules	7	9
Efficiency of Systems	356,008 samples	522,064
Number of Hidden Layers	4	5
Controller Approach Speed	System Settling time: 300 ms	System Settling time: 400 ms

The proposed ANFIS controller demonstrates notable advancements over the existing ANFIS model in various aspects. It achieves a faster settling time of 300 ms compared to 400 ms, improving responsiveness for real-time applications. While using 100 epochs instead of 50, it strikes a balance between complexity and performance, converging to more precise results. The model is simplified by reducing the number of rules from nine to seven and the number of hidden layers from five to four, lowering computational demands without sacrificing performance.

Furthermore, the proposed ANFIS is more cost-efficient, operating on systems with two mid-range processors (e.g., Intel Core i5) instead of the four high-end processors (e.g., Intel Core i7) required by the existing model, resulting in substantial cost savings. Despite processing fewer samples (356,008 vs. 522,064), it still meets practical requirements effectively. These improvements make the proposed ANFIS a superior choice, offering enhanced speed, accuracy, cost-efficiency, and simplicity, making it highly suitable for real-time control scenarios.

3.3. Fuzzy Logic Controller

The proposed ANFIS-based controller is compared with the FLC method that was reported in [16]. In formulating the fuzzy logic controller design, the input and output parameters are identified as the error in the primary coil current (ΔI) and the phase shift angle of the full bridge inverter, denoted as θ , respectively. Figure 10 displays triangular membership functions [31–35] that represent the linguistic variables NB (Negative Big), NS (Negative Small), Z (Zero), PS (Positive Small), and PB (Positive Big) for the input. Similarly, Figure 11 presents triangular membership functions [36–38] that represent the variables VS (Very Small), S (Small), M (Medium), L (Large), and VL (Very Large) for the output.

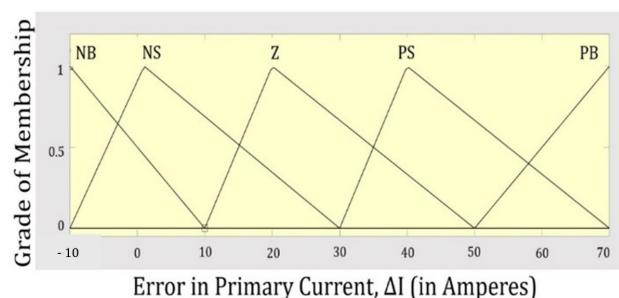


Figure 10. Membership functions for the FLC input (ΔI).

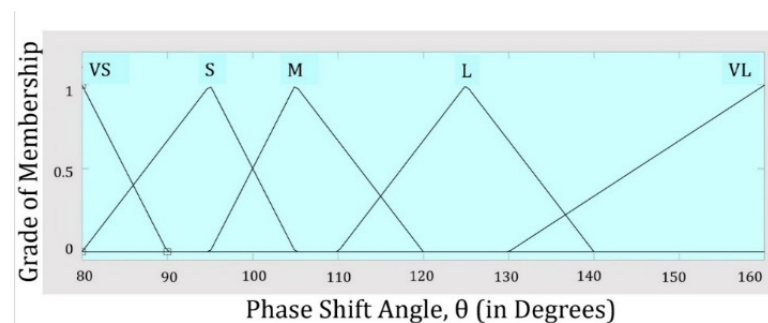


Figure 11. Membership functions for the FLC output (θ).

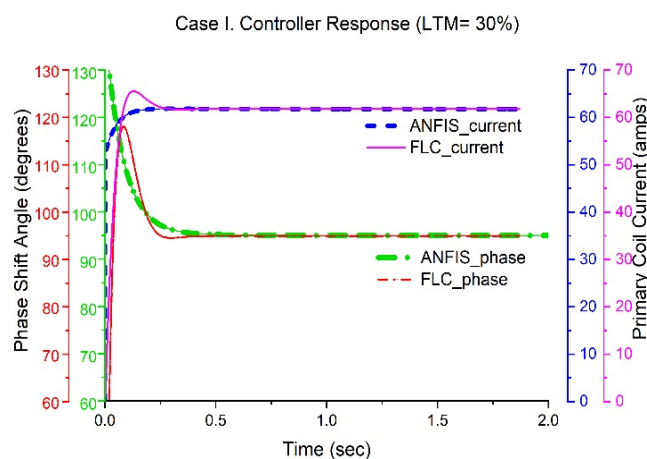
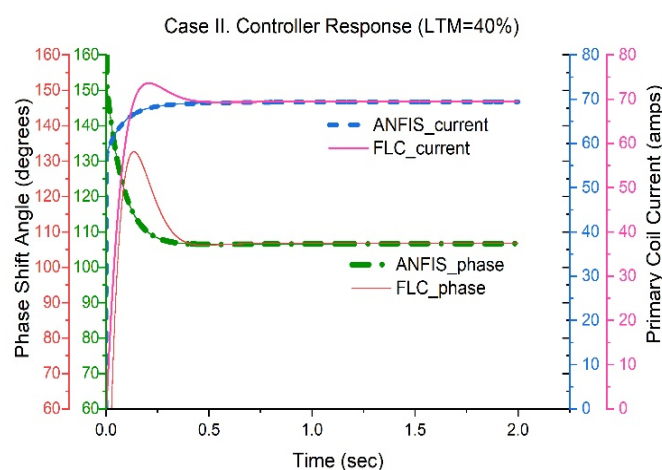
The control strategy being proposed is defined by only five control rules, as shown in Table 4, which illustrate the relationship between the controller input and output. A detailed explanation of this controller can be found in [16,39,40].

Table 4. Fuzzy Rule.

Fuzzy Input (ΔI)	Fuzzy Output (θ)
NS	S
PS	L
Z	M
NB	VS
PB	VL

4. Simulation Results and Discussion

In this study, a V2V-DWC system is developed, and the model's characteristics are evaluated through simulations in MATLAB/Simulink. It is considered that the two coils cannot maintain the same distance from each other, and even if they maintain the distance, they are not always perfectly aligned. In both cases, the coupling factor (k) is changed abruptly. Three case scenarios, namely Case I (LTM = 30%), Case II (LTM = 40%), and Case III (Varying LTM), are explained in Figures 12–14.

**Figure 12.** Comparison between FLC and ANFIS controller response (for LTM = 30%).**Figure 13.** Comparison between FLC and ANFIS controller response (for LTM = 40%).

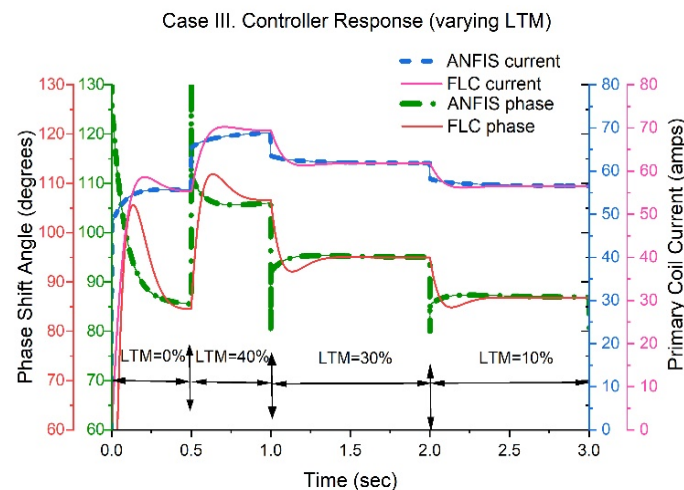


Figure 14. Comparison between FLC and ANFIS controller response (for varying LTM).

Figure 12 depicts the comparative performance of FLC and ANFIS. It presents controller responses for Case I (LTM = 30%). Both FIS and ANFIS achieve a primary current response reaching the reference value of 61.78 amps at 300 ms, displaying slight overshoot and a negligible steady-state error. Subsequently, both responses exhibit minimal vibration, with the ANFIS controller demonstrating slightly better performance compared to the FIS controller. When observing the control input (phase shift angle) for the ANFIS, it consistently follows a decreasing pattern, eventually stabilizing at 95 degrees. On the contrary, the FLC's control input sees an abrupt drop followed by oscillations before settling at 95 degrees at 50 ms.

Figure 13 shows the comparable performance between the two controllers in the scenario of higher misalignment (Case II). Once again, ANFIS outperforms the FLC, demonstrating minimal overshoot and swift settling. ANFIS gradually tracks the reference current measure of 69.40 amps with negligible overshoot, while FLC has an overshoot of 6.07%.

Figure 14 illustrates the responses of the controllers for Case III, where the LTM varies between 0 and 40%. The ANFIS controller adeptly tracks the primary current reference values of 55.40 amps, 61.78 amps, and 69.40 amps, displaying minimal overshoot and steady-state error. It smoothly transitions during the LTM changes at $t = 0.5$ s, 1 s, and 2 s. In contrast, the fuzzy controller, while noteworthy, exhibits a 30 ms delay in response to the immediate LTM change points, responding to the reference current values.

Table 5 provides a summary of the simulation results presented in Figures 12–14, comparing the performance of the controllers in terms of rise time, settling time, overshoot (%), and steady-state error. In all cases, the ANFIS controller outperforms the FLC, exhibiting shorter rise and settling times, lower overshoot, and negligible steady-state error.

Table 5. Existing fuzzy controller and proposed ANFIS controller comparison.

Case	Comparison Between Controllers		
	Performance Indicators	Fuzzy Logic Controller	Adaptive Neuro Fuzzy Controller
Case-1 (LTM = 30%)	Settling Time	400 ms	300 ms
	Overshoot (%)	1.39%	Negligible (approximately 0%)
	Steady-State Error (%)	0.2%	0.05%
Case-2 (LTM = 40%)	Settling Time	500 ms	350 ms

Table 5. Cont.

Case	Comparison Between Controllers		
	Performance Indicators	Fuzzy Logic Controller	Adaptive Neuro Fuzzy Controller
Case-2 (LTM = 40%)	Overshoot (%)	6.07%	Negligible (approximately 0%)
	Steady-State Error (%)	0.2%	0.05%
Case-3 (Varying LTM)	Settling Time	120 ms (each transition)	50 ms (each transition)
	Overshoot (%)	3.5%	Negligible (approximately 0%)
	Steady-State Error (%)	0.15%	0.05%

4.1. Inverter Efficiency Analysis

To analyze the efficiency of an inverter in a V2V-DWC system, it is assessed by comparing the output power to the input power. It is important to test the inverter under different load conditions and consider different LTM scenarios, as these factors can affect the overall performance and efficiency of the inverter in the system. Figure 15 presents data on inverter efficiency across six different cases, corresponding to varying degrees of lateral misalignment (LTM) and duty cycles of 0.44, 0.47, 0.5, 0.55, 0.6, and 0.65. For LTM = 0 (duty cycle = 0.44), the inverter efficiency is at its highest, at 99.84%, with an input power of 25,464 W and an output power of 25,424 W. As the duty cycle increases with higher LTM values, the inverter efficiency decreases slightly. For LTM = 0.1 (duty cycle = 0.47), the efficiency drops to 99.64%. At LTM = 0.2 (duty cycle = 0.5), the efficiency further reduces to 99.31%.

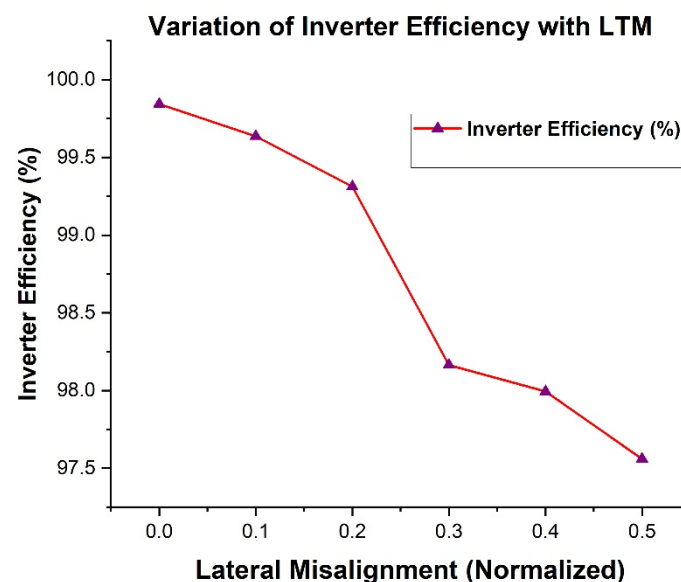


Figure 15. Inverter efficiency for different LTM scenarios.

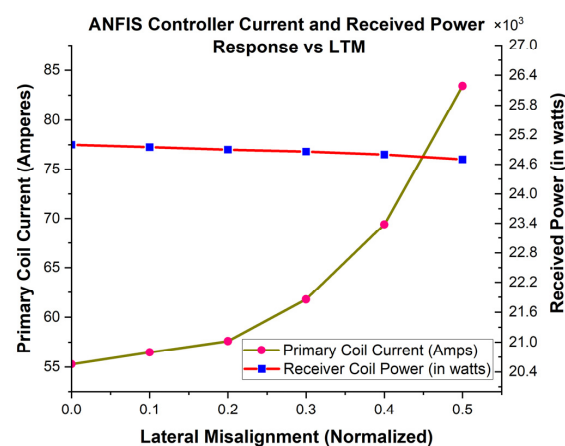
This trend continues with a gradual decline in efficiency as the duty cycle increases: LTM = 0.3 (duty cycle = 0.55) shows an efficiency of 98.16%, LTM = 0.4 (duty cycle = 0.6) has an efficiency of 97.99%, and for LTM = 0.5 (duty cycle = 0.65), the efficiency is 97.56%. These results indicate that while the inverter maintains high efficiency across all cases, higher duty cycles, which correspond to greater misalignments, lead to a small reduction

in efficiency. This showcases the inverter's ability to adapt to varying conditions while minimizing efficiency losses.

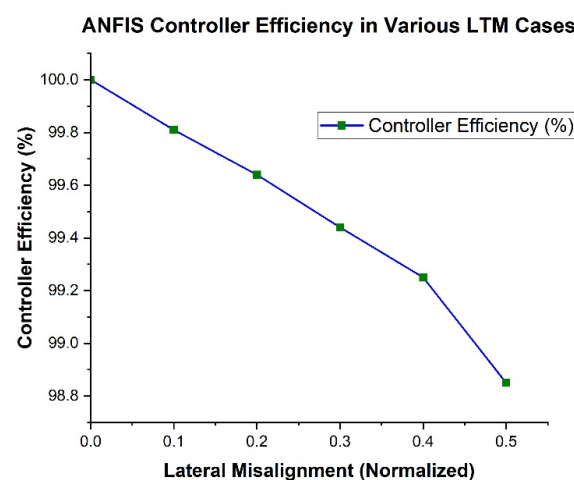
4.2. ANFIS Controller Efficiency Analysis

The efficiency of a controller in a V2V dynamic wireless charging (DWC) system is assessed by its ability to maintain the desired output power, in this case, 25 kW, by effectively adjusting the controlling parameters. These parameters include the phase shift angle of the inverter and the primary coil current. The controller's task is to dynamically adapt these inputs to compensate for variations, such as lateral misalignment between coils, ensuring consistent power delivery to the receiver. High efficiency is achieved when the controller can minimize power losses while maintaining the output power close to the target value. This analysis focuses on how the ANFIS controller manages these adjustments to sustain optimal performance across different misalignment scenarios.

The simulation results (Figure 16) demonstrate the ANFIS controller's capability to regulate the primary coil current to maintain a consistent output power of 25 kW at the receiver coil, despite varying lateral misalignments (LTM) from 0 to 0.5. At LTM = 0, the controller achieves the maximum efficiency of 100% with a primary coil current of 55.27 A and an output power of 25,000 W. As LTM increases, the primary coil current gradually rises to compensate for the misalignment and maintain the desired output power.



(a)



(b)

Figure 16. (a) ANFIS controller current response and receiver coil power output. (b) Controller efficiency for different LTM scenarios.

For LTM = 0.1, the primary current increases slightly to 56.48 A, resulting in a minor efficiency drop to 99.80%. At LTM = 0.2, the current further rises to 57.61 A, with an efficiency of 99.60%. As the misalignment increases to LTM = 0.3, the controller adjusts the current to 61.78 A, achieving 99.44% efficiency. For higher misalignments, such as LTM = 0.4 and 0.5, the primary current increases to 69.4 A and 83.43 A, respectively, with corresponding efficiencies of 99.20% and 98.80%. These results highlight the ANFIS controller's effectiveness in maintaining high efficiency while adapting to varying misalignments, ensuring stable power delivery of around 25 kW to the receiver coil.

4.3. Mean Time to Failure (MTTF) Analysis

Reliability analysis can be conducted for any system to assess the performance of its components under various conditions over a defined time [41,42]. Factors such as humidity and temperature are examples of these conditions. For each electronic component, specific equations are used to determine its failure life. Ultimately, the failure lives of all components are aggregated to calculate the system's mean time to failure (MTTF). This section provides all the necessary equations and calculations for conducting reliability tests.

A. Capacitors

The capacitor parameter can be determined from [43] as follows (9):

$$\lambda_P = \lambda_b \pi_{CV} \pi_Q \pi_E \text{ failures}/10^6 h \quad (9)$$

In this equation, λ_P represents the failure life of the capacitor. The thermal life of the capacitor is denoted by π_b , while π_{CV} , π_Q , and π_E correspond to the temperature, quality, and environmental factors, respectively. The value of λ_P is set to 0.00037. Since two capacitors with values of 0.51 μF and 1.22 μF are used in the system, and with $\pi_{CV} = 1.4 \text{ C}^{0.12}$, this factor is calculated as 0.2460 for the 0.51 μF capacitor and 0.2732 for the 1.22 μF capacitor. Both π_Q and π_E are assumed to be 10, representing the fixed ground and unknown screening level for the converter. Therefore, the failure life for both capacitors can be determined using Equation (9).

$$\lambda_P = \begin{aligned} &0.00037 * 0.2460 * 10 * 10 = 0.009104 \text{ for } C_{S1} = 0.51 \mu\text{F} \\ &0.00037 * 0.2732 * 10 * 10 = 0.0101086 \text{ for } C_{P1} = 1.22 \mu\text{F} \end{aligned}$$

B. Inductors

For an inductor, this parameter can be determined from (10) as follows:

$$\lambda_P = \lambda_b \pi_C \pi_Q \pi_E \text{ failures}/10^6 h \quad (10)$$

The variables are the same as described above. Accordingly, the value of λ_P is as follows:

$$\lambda_P = \begin{aligned} &0.0023 * 0.5 * 3 * 6 = 0.009104 && \text{for } L_{S1} = 0.62 \mu\text{H} \\ &0.0023 * 1.5 * 3 * 6 = 0.0101086 && \text{for } L_{P1} = 173.7 \mu\text{H} \end{aligned}$$

C. Power Mosfets

The failure life of a Power MOSFET [44] can be expressed as follows (11):

$$\lambda_P = \lambda_b \pi_C \pi_Q \pi_E \text{ failures}/10^6 h \quad (11)$$

Here, π_T is the thermal factor and all other parameters are the same. According to Equation (11), the value of $\lambda_P = 0.0083 * 3 * 5.5 * 2 = 0.2739 \text{ failures}/10^6 \text{ h}$.

D. MTTF Calculation for the System

The system's failure rate can be determined by summing the failure rates of all its components.

$$\lambda_{CONVERTER} = (4 * \lambda_{MOSFET}) + 2 (\lambda_{CP1} + \lambda_{CS1}) + 2(L_{P1} + L_{S1}) \quad (12)$$

$$= 1.29978 \text{ failure}/10^6 \text{ h}$$

The meantime to failure (*MTTF*) is calculated for this converter as follows (13):

$$MTTF = \frac{1}{\lambda_{CONVERTER}} \text{ h} = 769360.9688 \text{ h} \quad (13)$$

The value of *MTTF* for this electrical system is quite acceptable.

5. Experimental Setup

To validate the simulation results, a laboratory-scale model was developed to demonstrate the impact of misalignment and its mitigation in a DWC scenario between two EVs in a V2V system. The simulation parameters were designed to replicate real-world conditions, while the experimental setup employed a small-scale model. Despite the difference in scale, the experiment aimed to compare the performance of different controllers in both environments. This approach highlights the controllers' effectiveness regardless of application size. The primary goal was to improve the reliability of DWC by assessing the controllers' ability to track the reference current and adjust the PWM signal to deliver a constant power of 50 watts to the receiving EV under coil misalignment conditions.

The experimental setup included an IRFZ44n MOSFET-based H-bridge inverter, an IRS2184 gate driver, an Arduino Mega 2560 microcontroller (Texas Instruments, Dallas, TX, USA), and MATLAB 2023b software for generating a PWM signal based on lateral misalignment. Additionally, it comprised transmitting and receiving coils attached to the source (MED) and receiving (User) EVs, a rectifier circuit, and a battery pack, as shown in Figure 17. The system parameters used in the experiment are summarized in Table 6. Before beginning the experiment, the Arduino microcontroller was configured to interface with MATLAB, and the gate driver's functionality was validated to ensure proper transmission of signals to the MOSFETs.

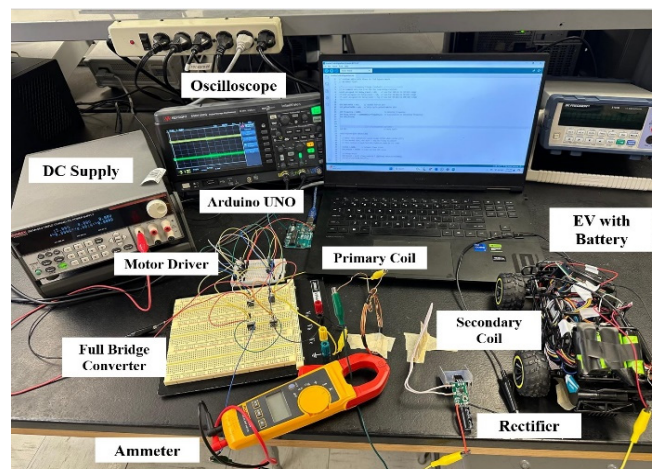


Figure 17. Experimental setup for small-scale V2V DWC process.

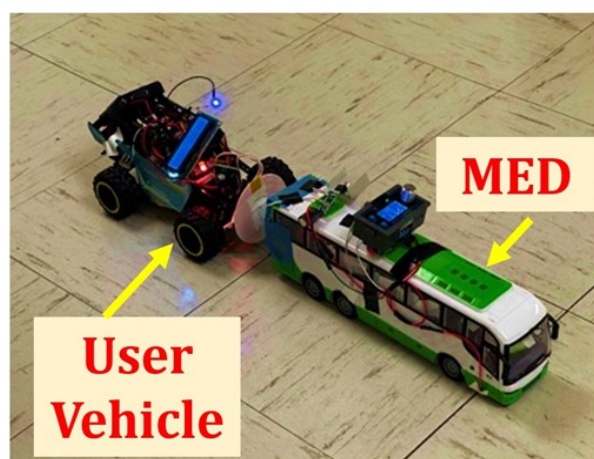
Table 6. System parameters for the DWC experiment.

Parameters	Value
DC Input Voltage, VDC	20 volts
DC-Link Capacitor, CDC	100 nF
Resonant Frequency, FS	10 kHz
Primary Coil Inductance, LS	578 μ H
Primary Side Compensator, CS	107 nF
Vehicle Coil Inductance, LL	287 μ H
Vehicle Side Compensator, CL	328 nF
Rectifier Smoothing Capacitor, CBAT	1200 μ F
Vehicle Battery Level	20 volts
Transferred Output Power	50 watts
Transmitting Power Capacity	200 watts
Coil Radius	15 cm
Maximum Allowable LTM	20 cm

The two EVs were placed 30 cm apart at a fixed distance, while the lateral displacement between the centers of the transmitting and receiving coils varied, indicating misalignment. To measure this lateral misalignment, ultrasonic sensors were strategically placed on both the transmitting and receiving coils of the two EVs. These sensors were mounted on the sides of the coils to measure the horizontal distance between them. Initially, the system was calibrated by perfectly aligning the coils and recording the sensor readings as a reference.

As the EVs moved, the ultrasonic sensors continuously monitored the lateral displacement. If the coils shifted laterally, the sensors detected the change in distance. The lateral displacement was calculated by taking the difference between the distance readings from the left and right sensors on both coils. The receiving EV, equipped with a 700 mAh battery, a rectifier circuit, and a receiving coil, followed the lead vehicle. When the receiving EV was aligned with the transmitting coil, the degree of misalignment was measured to be 40%.

An LED confirmed the successful DWC process, and the battery voltage and receiver coil voltage were displayed on an attached LCD screen (Figure 18). Under perfect alignment (with no lateral misalignment), the PWM inverter's duty cycle was set to 0.5. To adjust for the 40% misalignment, the ANFIS controller modified the PWM duty cycle from 0.5 to 0.65 within 200 microseconds, whereas the FLC took 500 microseconds, as illustrated in Figures 19 and 20.

**Figure 18.** EV charging status during DWC process.

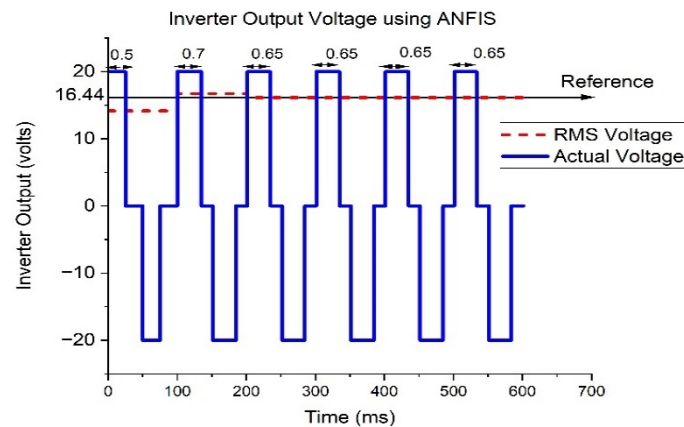


Figure 19. Inverter output voltage using the ANFIS controller.

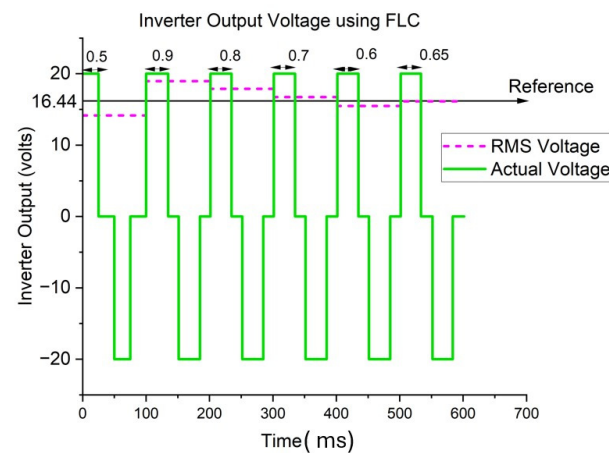


Figure 20. Inverter output voltage using the fuzzy logic controller.

In the simulation, the reference current for a lateral misalignment (LTM) of 40% was 69.40 amps, as shown in Figure 13, while the experimental setup recorded a current of 4.78 amps. This discrepancy is due to the difference in system scale—the simulation was designed for a 25 kW DWC application, whereas the laboratory experiment was scaled down to 50 watts. Additionally, the system parameters used in the simulation and the experimental setup were not identical, contributing to the variation in current values. Figure 21 demonstrates the current response of both controllers, where the ANFIS controller stabilized the primary coil current to 4.78 amps at 150 milliseconds, while the FLC showed oscillations, overshoot, and a slower convergence time. It settled down to its required current value at 350 ms.

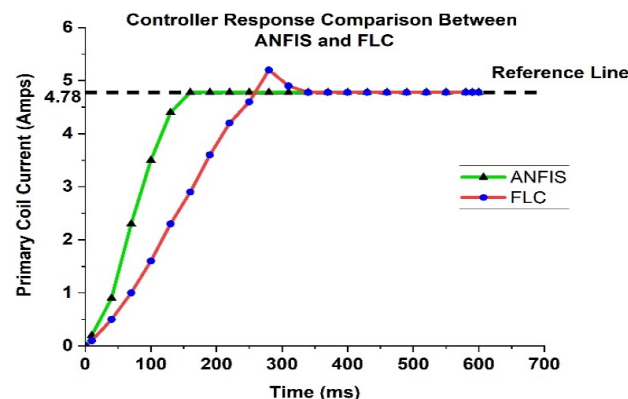


Figure 21. Current response comparison between ANFIS and FLC (LTM = 40%).

6. Conclusions

In this study, the ANFIS controller has been developed to regulate the primary coil current, accommodating various degrees of lateral misalignment of the V2V-DWC system within a millisecond timeframe while mitigating power loss effects. The study effectively showcases ANFIS's superiority in addressing coil misalignment challenges in the DWC-EVs compared to the FLC. The key findings of the paper are as follows:

- The Adaptive Neuro-Fuzzy Inference System (ANFIS) greatly enhanced the system's ability to track the reference current and adjust the PWM duty cycle during misalignment with faster response times and improved accuracy. It highlights the effectiveness of ANFIS controller in significant misalignment scenarios, demonstrating a seamless performance during the transition phases between different levels of lateral misalignment.
- Additionally, a comparative table illustrates the relative performance of the proposed ANFIS controller with the existing FLC across various performance parameters.
- Since the dynamic behavior of the system is highly nonlinear, the neural network-based fuzzy logic controller (ANFIS) outperforms in this application.
- The improved and stable tracking accuracy and rapid response of ANFIS highlights its potential for improving the efficiency and reliability of DWC.

It is important to emphasize that the parameters of the proposed ANFIS controller will be adjusted using established optimization techniques in future work. Also, a more sophisticated, model-based controller will be explored that is capable of comprehensively capturing system dynamics, accurately predicting system behavior, and subsequently implementing precise control actions. This direction is reserved for future research.

For vehicle-to-vehicle DWC, efficient data exchange between vehicles is crucial. The use of 5G technology in this context offers significant advantages, such as faster communication, improved charging efficiency, strengthened reliability, and more flexibility compared to previous technologies like 4G, 3G, or even optical fiber connections. While dedicated short-range communication (DSRC) has been explored for its low latency [17], 5G surpasses it by providing superior bandwidth, higher throughput, and broader coverage, making it ideal for real-time data exchange between vehicles and enabling efficient wireless power transfer.

Future work could focus on optimizing the integration of 5G in vehicle-to-vehicle DWC systems, exploring its potential to enhance inter-vehicle data exchange, coordination, and power sharing. Additionally, research could aim to develop advanced cybersecurity measures specifically tailored for V2V wireless charging networks, ensuring the secure operation of critical systems and building trust in this evolving EV technology.

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