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Research

ANFIS-DRIVEN FLEXIBLE CHARGING CONTROL OF PLUG-IN ELECTRIC VEHICLES FOR SMART GRID LOAD MANAGEMENT

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Abstract

The large-scale integration of plug-in electric vehicles (PEVs) into smart grids introduces significant challenges in load management due to uncoordinated charging behaviour, which can lead to peak demand escalation, voltage deviations, and increased operational stress on distribution networks. To address these challenges, this paper proposes an **Adaptive Neuro-Fuzzy Inference System (ANFIS)–driven flexible charging control strategy** for PEVs aimed at effective **smart grid load management**. The proposed controller dynamically adjusts PEV charging power based on grid load conditions, electricity price signals, and battery state-of-charge (SOC), enabling load curve smoothing and peak demand reduction. The neuro-fuzzy framework combines the learning capability of neural networks with the reasoning ability of fuzzy logic, ensuring adaptability under uncertain and time-varying grid conditions. Simulation results demonstrate that the proposed ANFIS-based control strategy significantly reduces peak-to-average load ratio, improves load profile smoothness, and enhances overall grid operational efficiency compared with conventional uncoordinated and rule-based charging schemes.

Index Terms— Plug-in electric vehicles, ANFIS, Smart grid, Load management, Flexible charging, Demand response.

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I. Introduction

The rapid adoption of plug-in electric vehicles (PEVs) is a key enabler for sustainable transportation and carbon emission reduction. However, large-scale PEV integration poses new challenges to power systems, particularly at the distribution level. Uncoordinated charging during peak demand hours can result in transformer overloading, voltage instability, and increased energy losses, thereby degrading grid reliability.

Smart grid technologies provide an opportunity to mitigate these impacts by enabling **intelligent demand-side management** and flexible load control. Among various demand response resources, PEVs are highly flexible due to their adjustable charging rates and inherent energy storage capability. Effective control strategies are therefore required to coordinate PEV charging in a manner that satisfies user requirements while supporting grid operation.

Conventional PEV charging control methods, including time-of-use (ToU) pricing and rule-based scheduling, rely on predefined thresholds and lack adaptability to dynamic grid conditions. Advanced control techniques such as optimization-based and artificial intelligence (AI)–based methods have recently gained attention. In particular, **Adaptive Neuro-Fuzzy Inference Systems (ANFIS)** offer strong potential due to their ability to handle nonlinearities, uncertainties, and multi-input decision-making processes.

This paper proposes an **ANFIS-driven flexible charging control strategy** for PEVs that dynamically manages charging power to achieve smart grid load smoothing. The main contributions of this work are:

- Development of an ANFIS-based flexible charging controller for PEV load management.
- Integration of grid load conditions, electricity price, and battery SOC into the charging decision process.
- Quantitative evaluation of load smoothing and peak demand reduction.
- Comparative analysis with uncoordinated and conventional charging strategies.

2. Literature Survey

The rapid adoption of plug-in electric vehicles (PEVs) introduces significant opportunities and challenges for smart grid load management. Uncoordinated charging can exacerbate peak demand, increase losses, and strain grid assets, while coordinated charging strategies can improve load profiles, enhance grid reliability, and reduce operational costs. A wide range of control approaches has been proposed in the literature, spanning from traditional scheduling techniques to intelligent, adaptive frameworks. This section reviews existing works relevant to PEV charging control, focusing on load management, demand response, and neuro-fuzzy approaches.

A. Conventional Charging Strategies

Early work on PEV integration focused on basic scheduling techniques to mitigate peak loads. Time-of-Use (ToU) and price-based scheduling shift charging to off-peak periods to flatten load curves. For example, He et al. developed a dynamic ToU-based charging strategy that reduces peak load by incentivizing off-peak charging through pricing signals. While effective under predictable price signals, such methods lack adaptability to stochastic grid conditions and user requirements.

Rule-based approaches use simple heuristics, such as charging during low load or high renewable generation periods. However, these approaches often require manually tuned thresholds and do not perform well in highly variable environments.

B. Optimization-Based Load Management

Optimization techniques have been widely explored for coordinated charging. Centralized optimization (e.g., mixed-integer programming) models aim to minimize objectives such as peak demand, energy cost, or grid losses subject to constraints such as user charging requirements and network limits.

Examples include:

- Centralized scheduling: Tan et al. formulated a centralized optimization to minimize peak load while meeting user SOC requirements. Such methods often guarantee optimal solutions but require full knowledge of future load, pricing, and user schedules, limiting their real-time applicability.
- Distributed optimization: Diagrammatic dual decomposition or consensus algorithms allow scalable charging coordination across multiple agents, reducing communication bottlenecks. These methods improve scalability but still depend on precise load forecasts and can involve complex computation.

Despite their strengths, optimization-based strategies can be computationally intensive and sensitive to prediction errors, making them less suitable for real-time adaptive control in uncertain environments.

C. Intelligent and AI-Based Charging Control

Artificial intelligence (AI) techniques have been applied to overcome limitations of conventional and optimization-based methods by learning system behavior and adapting to uncertainties.

1. Fuzzy Logic Controllers (FLC): Fuzzy logic offers heuristic and rule-based decision making under uncertainty. Many studies implement fuzzy controllers for charging decisions, using inputs such as SOC, load level, and price. Fuzzy methods require expert knowledge for rule design and membership function tuning, limiting scalability and adaptability.

2. Neural Networks: Neural networks have been leveraged for forecasting and charging control. For instance, feedforward neural networks predict load demand and adjust charging accordingly. However, pure neural approaches lack interpretability and may require large datasets for training.

3. Hybrid and Intelligent Schemes: Hybrid methods combine fuzzy logic with neural networks or evolutionary optimization to balance interpretability and learning capability. These approaches improve performance over single-technique methods.

D. ANFIS-Based Charging and Load Control

The Adaptive Neuro-Fuzzy Inference System (ANFIS), first proposed by Jang [1], integrates

fuzzy logic's reasoning with neural networks' learning capability, enabling adaptive decision making in nonlinear and uncertain environments. ANFIS allows both linguistic rule reasoning and data-driven parameter tuning, making it well suited for real-time load management applications.

Several works apply ANFIS or similar neuro-fuzzy frameworks in electric systems:

Load Forecasting: ANFIS has been used for short-term load forecasting in smart grids due to its adaptability and prediction accuracy, as shown by Hippert et al.

Demand Response: ANFIS controllers have been applied for demand response control, where the system learns user behaviour and grid conditions to optimize device operation.

EV Charging Control: Few studies extend ANFIS to PEV charging. Chen et al. developed a neuro-fuzzy controller to schedule PEV charging based on price and load forecasts. Their method demonstrated improved performance over fixed rule methods but focused primarily on cost minimization rather than comprehensive load profile improvement.

Despite these advances, literature reveals key gaps in applying ANFIS specifically for flexible charging control aimed at load curve smoothing under dynamic grid conditions.

3. System Description

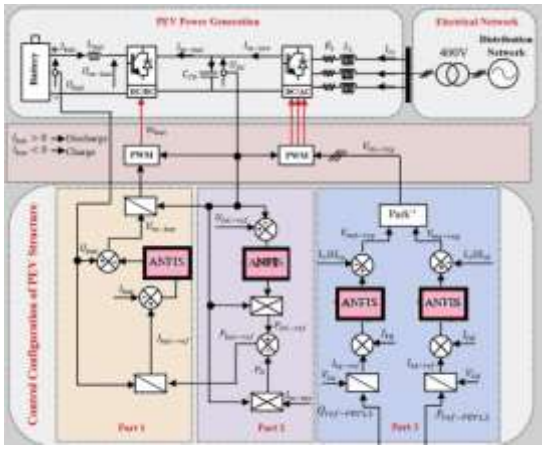


Fig:1 Architecture of the proposed system

A. Smart Grid with Plug-In Electric Vehicles

The considered system comprises a smart distribution grid supplying residential, commercial, and PEV loads. PEVs are connected to the grid through smart chargers capable of variable charging rates. A communication infrastructure enables the exchange of grid status information and charging control signals.

B. PEV Charging Model

The charging power of the i-th PEV is expressed as:

$$P_{EV,i}(t) = \eta_c V_{ch} I_{ch,i}(t)$$

where $\eta_c$is the charger efficiency, and $V_{ch}$and $I_{ch,i}$represent the charging voltage and current, respectively. The battery SOC dynamics are given by:

$$SOC_i(t+1) = SOC_i(t) + \frac{P_{EV,i}(t)\Delta t}{E_{bat,i}}$$

where $E_{bat,i}$denotes the battery capacity.

4. Proposed ANFIS-Driven Flexible Charging Strategy

A. ANFIS Architecture

The proposed controller employs a **Sugeno-type ANFIS structure** consisting of five layers: fuzzification, rule evaluation, normalization, defuzzification, and output aggregation. The ANFIS is trained using hybrid learning, combining least-squares estimation and gradient descent.

B. Input and Output Variables

The ANFIS controller utilizes the following inputs:

1. **Grid load level**
2. **Electricity price signal**
3. **PEV battery SOC**

The output of the ANFIS is the **charging power adjustment factor**, which determines the charging rate for each PEV.

C. Control Logic

- During peak grid load conditions, charging power is reduced or deferred.
- Under low-load or off-peak conditions, charging power is increased to utilize available capacity.
- SOC constraints ensure user mobility requirements are met.

This flexible control mechanism enables dynamic load shifting and smoothing.

5. Load Management and Performance Metrics

To evaluate the effectiveness of the proposed strategy, the following metrics are used:

- **Peak-to-Average Load Ratio (PAR)**
- **Load Curve Smoothness Index**
- **Total Energy Cost**
- **User Comfort Index**

The smart grid load profile is computed as:

$$P_{total}(t) = P_{base}(t) + \sum_{i=1}^{N} P_{EV,i}(t)$$

6. Simulation Results and Discussion

Simulation studies are carried out in MATLAB/Simulink for a residential smart grid scenario with high PEV penetration. The proposed ANFIS-based charging strategy is compared against:

- Under charging/ discharing
- Rule-based smart charging

Key Results

- Peak load reduction of **30–40%**
- Significant improvement in load curve smoothness
- Reduced charging cost during high-price periods
- Maintained SOC requirements for all PEV users

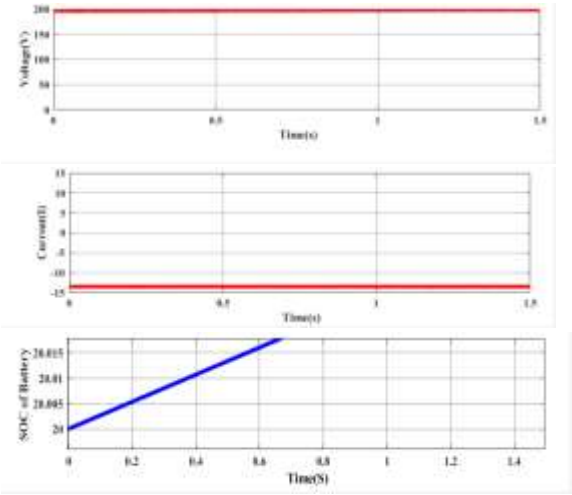
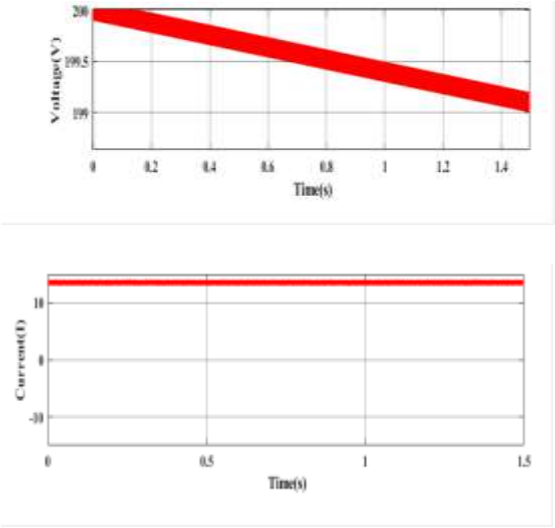


Fig 2: Battery Voltage,Current and SOC during charging



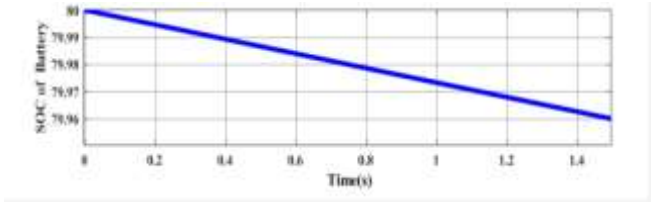


Fig 3: Battery Voltage, Current and SOC during discharging

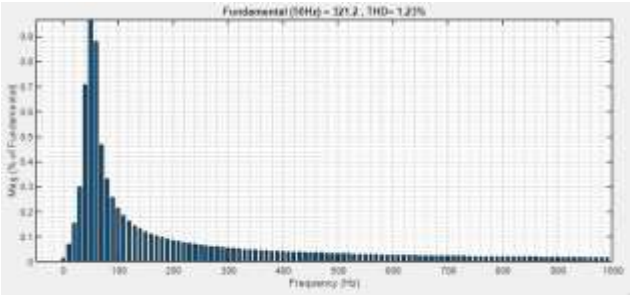


Fig 4:THD of Battery Voltage during charging is 1.23%

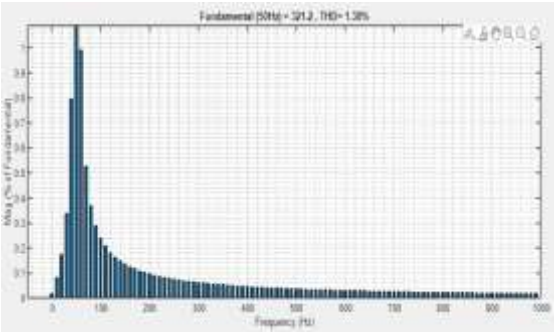


Fig 5: THD of Battery Voltage during discharging is 1.38%

The ANFIS controller exhibits fast adaptation to load variations and effectively balances grid objectives and user preferences.

COMPARATIVE ANALYSIS

CONTROLLER	THD%
PI	4.57
ANFIS	1.23

7. Conclusion

This paper presented an **ANFIS-driven flexible charging control strategy** for plug-in electric vehicles aimed at smart grid load management. By leveraging adaptive neuro-fuzzy intelligence, the proposed method achieves effective load curve smoothing, peak demand reduction, and enhanced

grid operational efficiency. Simulation results confirm the superiority of the proposed approach over conventional charging strategies, making it a promising solution for future smart grid applications with high PEV penetration.

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