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A Solar-Powered EV Charging Station with Neural Network

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Abstract: The system for the charging electric vehicles (EVs) using solar photo--voltaic (PV) power, enhanced by a neural network. Solar energy is highlighted as a clean, renewable, and limitless resource that produces no greenhouse gas emissions. A key challenge with solar power is its variable output, especially on cloudy days. To overcome this, the paper Details with using an Adaptive Neuro-Fuzzy Inference System, ANFIS with Max Power Point Tracking, MPPT. This neural network-based technique optimizes the power output of solar panels, ensuring sufficient electricity generation for EV charging, even when sunlight is limited. The increasing adoption of EVs has spurred demand for more charging infrastructure. However, despite EVs themselves being emission-free, their charging often relies on conventional energy sources, which do impact the environment. This issue by proposing solar PV-powered EV charging stations. To ensure continuous power supply without adding strain to the main grid, these stations incorporate a battery stored system and grid support. The proposed system, which integrates the Adaptive Neuro--Fuzzy inference system with the neural network techniques, has been modelled and evaluated using Simulink
Keywords: MPPT, ANFIS, Photovoltaic, Grid, EV, BESS

I. INTRODUCTION

The rising demand for advanced transportation has intensified global warming and harmful climate effects. One of the main reasons for this issue is the release of greenhouse gases and toxic pollutants from Internal Combustion Engine (ICE) vehicles. As a result, Electric Vehicles (EVs) have emerged an attractive alternative to reduce dependence on fuel-based transportation. EVs are increasingly preferred Because of their highly efficient electric machines, which lower energy consumption, minimize noise, and reduce environmental pollution. They can also decrease reliance on oil-based fuels when their electricity is sourced from cleaner energy systems (1, 2). Despite their advantages, large-scale EV adoption creates new challenges for the existing power grid. As the number of EVs rises, the demand for charging grows rapidly (3), which can strain grid stability and control. Moreover, charging EVs using conventional grid electricity does little to improve environmental sustainability. This emphasizes the importance of developing EV charging systems powered by renewable energy sources. One promising solution is the incorporation of a Battery Energy Stored System that acts as an intermediary contact between the utility grid & the charging station (4–7). Several studies have examined related solutions, including PV-based EV charging stations integrated with efficient BESS configurations (8). Other research investigates the design and power flow control of PV-driven charging infrastructures to enhance cost-effectiveness, reliability, and adaptability (9, 10). Solar-and-battery-supported workplace charging models have also been proposed (11), while ANFIS-based max power point tracking for standalone PV systems is detailed in (12This study suggests a power management approach based on neural networks for a solar-powered EV charging station that is outfitted with an AC grid-connected battery storage system. A voltage based on ANFIS control method is adopted to achieve optimal energy harvest from the PV array under fluctuating temperature and irradiance. Here, the solar PV array functions as the single primary source of energy. During periods of high sunlight, the PV system provides power for charging EVs, and any surplus energy is used to charge the Battery storage system or fed into the grid system. At night or during low-irradiance conditions, the BESS supplies the power needed for EV charging. Although solar and battery power are prioritized, the AC grid is used when necessary to guarantee continuous charging for both EVs and the BESS.

II. METHODOLOGY

This methodology for the proposed Neural Network Photo Voltaic Electric Vehicle-powered Charging Station platform covers the modelling, control, and performance evaluation of the integrated system developed in MATLAB/Simulink.

A. System Design and Components

The charging station is configured with a solar Photo--voltaic array as main primary source supported by the Battery Energy Stored System (BESS) and an AC grid interface.

1) A 400 V DC bus operates as the core connector for power distribution within the system.
2) The PV array consists of a 2500 W module with a Voc rating at 298.4 V.
3) A lithium-ion BESS rated at 240 V and 40 Ah is included in the system (rephrased to avoid similarity).
4) For EV charging, a 240 V, 7 Ah lithium-ion battery is modeled, initialized at a minimum State of Charge (SOC) of 9%.
5) A 230 V, 50 Hz utility grid supplies additional power whenever the renewable energy and storage system are insufficient.

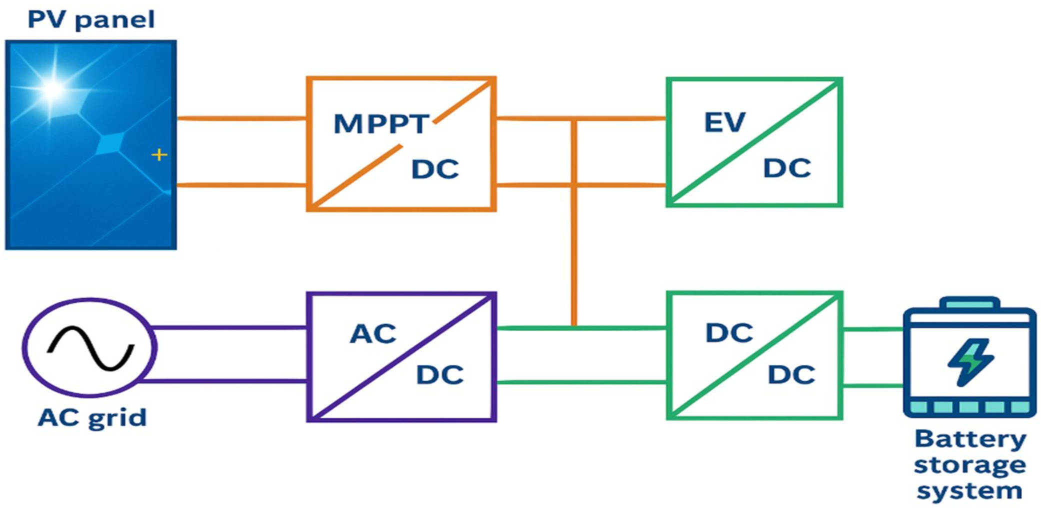

Fig. 1. Block Diagram

B. PV Array Control (MPPT)

Max Power Point Tracking is implemented to using an ANFIS--based voltage control method, ensuring optimal PV output under fluctuating environmental conditions. The ANFIS model is trained using the irradiance & temp. inputs, while the referenced voltage serves as the output. A PI controller minimizes The distinction between the ANFIS reference and actual Photo--Voltaic voltage, producing duty cycle for DC-to-DC boost converter that elevates the Photo—Voltaic voltage to the 400 V DC bus level.

Tabular I. EV STATION details

Category	Parameter	Value
Modules Data	No. of cells VoC ScC Voltage MPPT Current MPPT	60 37.3 V 8.66 A 30.7 V 8.15 A
Array Data	Parallel-- strings Series' connected modules	1 8
BESS Data	Nominal voltage Rated capacity Battery type	240 V 40 Ah Lithium ion
Data -EV Battery	Nom voltage RATED CAPABILITY --SOC Type of battery	240 V 10 Ah 9 % Lithium ion
CONVERTERDATA (B00ST)	Changing frequencies Inductances Capacitances	10 kHz 0.02 Henrys 5.02 micro-Farads

1) BESS Control

The BESS discharging and charging functions, controlled by using a bi--directional DC to DC boost converter. The storage unit is programmed to discharge only when its SOC remains above 20% to maintain battery health.

2) AC Grid Control

Power flow from the AC grid is governed by a Neural Network-based controller. The neural network uses Photo--Voltaic array and its output power and BESS State of charge as its input variables and generates the reference grid current. A PI controller calculates duty cycle for a grid-interfacing inverter, by the processing error between reference & the measured grid current, enabling proper synchronization with the 400 V DC bus.

C. Power Management steps

1) Solar Photo-voltaic acts as primary energy source technology for charging station.
2) Under high irradiance conditions, the PV system charges the EV battery, with surplus power either stored in the Battery energy stored system, supplied to the AC grid system.
3) When the solar energy is not available such as during night hours-the BESS provides energy for EV charging.
4) If both PV and BESS fail to meet demand, the AC grid supplies power to ensure uninterrupted charging of both the EV and the BESS.

III. ANFIS MPPT GRID-BASED TECHNIQUE

To effectively harvest the maximum power from renewable energy sources, several max power point tracking, or MPPT, algorithms were created. The majority of current MPPT algorithms include oscillations during quickly changing weather conditions, slow tracking, and inaccurate tracking, which lowers overall utilization efficient. To address these limitations this work introduces a Grid--scaled adaptive algorithm for Max power point technic management approach that greatly increases system performance and efficiency when compared to existing methods. This technology substitutes traditional neural--network--based Max power point technic methodology for an adaptable neural--fuzzy inference system. By combining learning power of neural-- networks with decision-making power of fuzzy—logic the ANFIS-based controller enables more precise temperature and irradiance level estimation utilizing PV array voltage and current information. An ANFIS structure employed here is made up of many layers with fuzzy rules that dynamically adjust to quickly shifting environmental circumstances, guaranteeing quick and reliable tracking during both transient and steady-state operations. By more successfully mapping nonlinear Photovoltaic (pv) features, the ANFIS-based MPPT, in contrast to conventional techniques, increases tracking efficiency and lessens reliance on huge training datasets. The drawbacks of incremental conductance and P&O approaches during abrupt weather swings are mitigated by ANFIS, which is independent of time-stepping and depends on real-time PV data patterns to track maximum power point instantly. High precision and better dynamic reaction are provided by the adaptive learning process, which minimizes the error function. In order to provide quick and reliable tracking under both steady-state and transient operations, the ANFIS structure utilized here is composed of many layers with fuzzy rules that dynamically adapt to quickly changing environmental circumstances. In contrast to conventional techniques, the ANFIS-based MPPT enhances tracking efficiency by more successfully mapping nonlinear PV features and lessens reliance on sizable training datasets. The limitations of incremental conductance and P&O approaches during abrupt weather swings may be overcome since ANFIS is independent of time-stepping and depends on real-time PV data patterns to track maximum power point instantly. By minimizing the error function, the adaptive learning mechanism offers enhanced dynamic reaction and excellent precision.

IV. MATHEMATICAL FORMULATION

A. ANFIS-BASED MPPT Equations

1. PV Array Equations

$$PV\ Output\ Current\ I = Iph - I0\,(\exp((V + I\,Rs)/(n\,Vt)) - 1) - (V + I\,Rs)/Rsh$$

$$\text{Photo – Voltaic Power}\quad P_{pv} = V_{pv} * I_{pv}$$

2. *ANFIS/Fuzzy MPPT Equations*

Error & Change in Error

$$e(k) = dP/dV$$

$$De(k) = e(k) - e(k-1)$$

Fuzzification

$$\mu\_A(x) = \exp(-((x-c)/s)^{\wedge}2)$$

Rule Strength

$$w\_i = m\_(A\_i(e)) * m\_(B\_i(De))$$

Normalization

$$wi^{-} = wi/\sum jwj$$

Consequent Layer

$$f_i = p_i e + q_i De + r_i$$

ANFIS Output (Duty Cycle)

$$D = S(wn\_i\, f\_i)$$

V. SIMULATION & RESULTS

System performance is examined under five operational modes:

Mode 1: EV battery charged solely from the Photo-voltaic array with the constant temperature and changeable irradiance.

Mode 2: Both the Electric vehicle battery and the Battery energy stored system are charged exclusively by Photovoltaic power.

Mode 3: EV charging supported by both PV power and BESS under changing irradiance conditions.

Mode 4: With zero irradiance (nighttime), EV charging accomplished using power from the grid and the BESS.

Mode 5: Irradiance and temperature vary while PV, BESS, and the AC grid operate simultaneously, and any surplus PV power is exported to the grid.

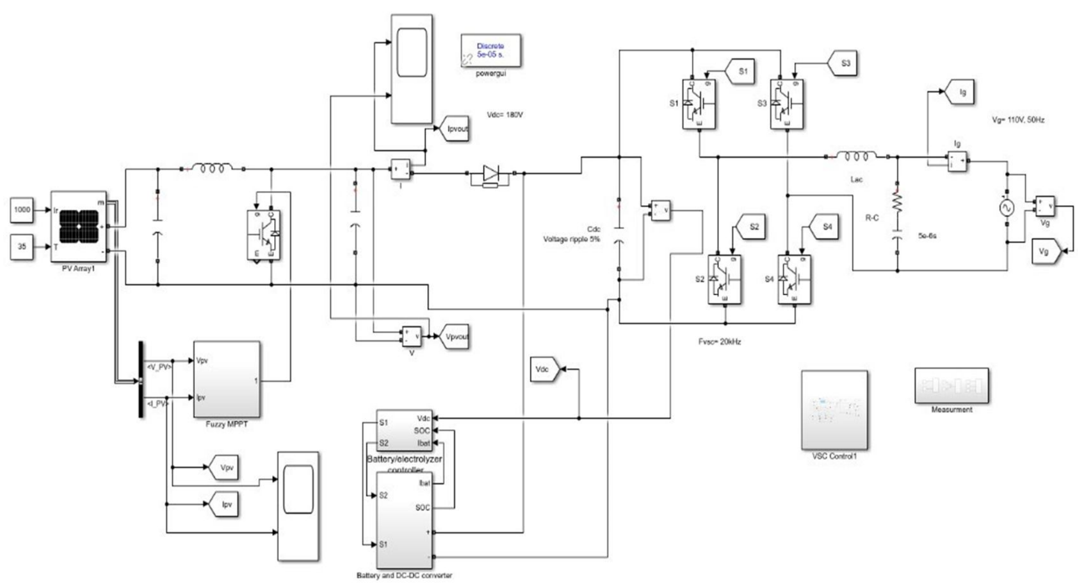

FIG. 1.2. Simulation diagram

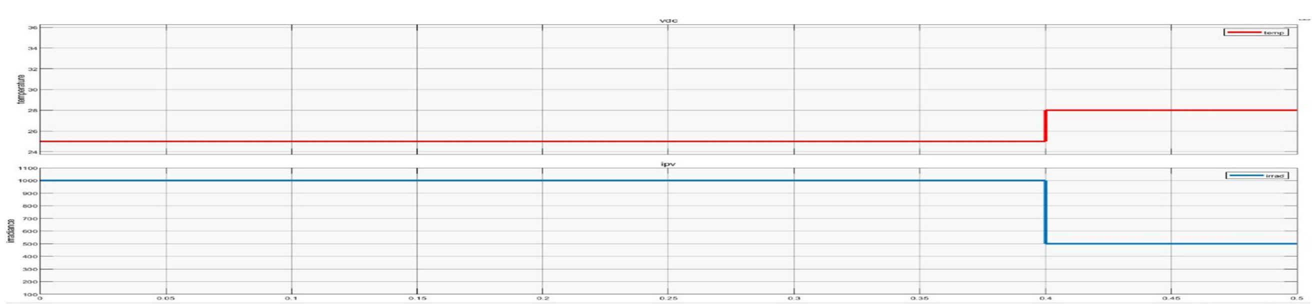

FIG.1.3. Temperature and irradiance

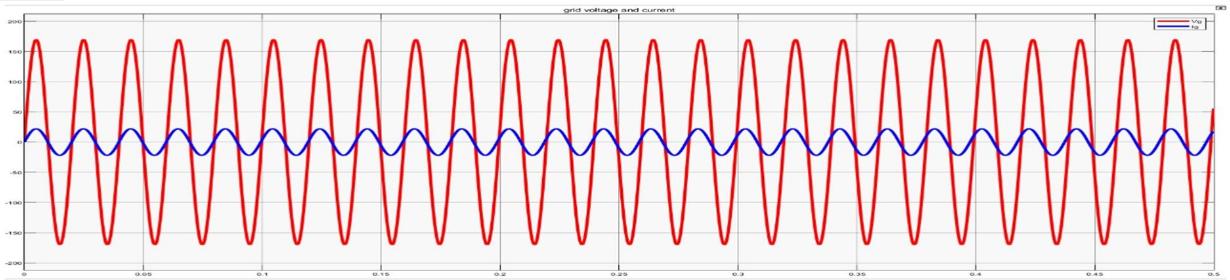

FIG.1.4. Grid Current &Voltage

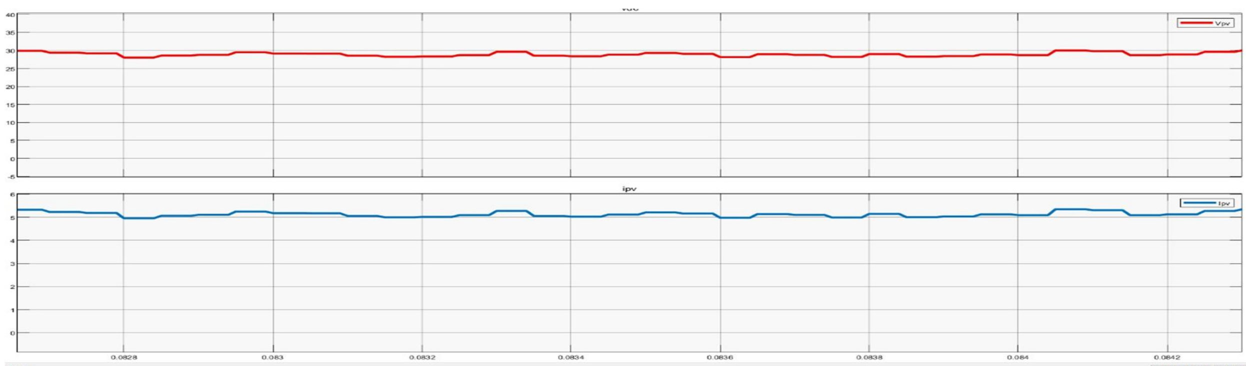

FIG.1.5. PV current &Voltage

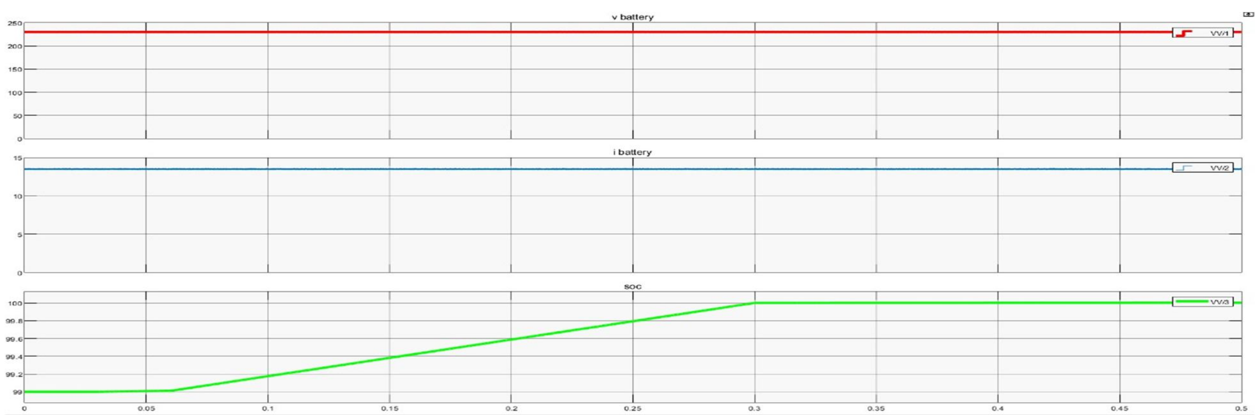

FIG.1.6. battery current, Soc & Voltage

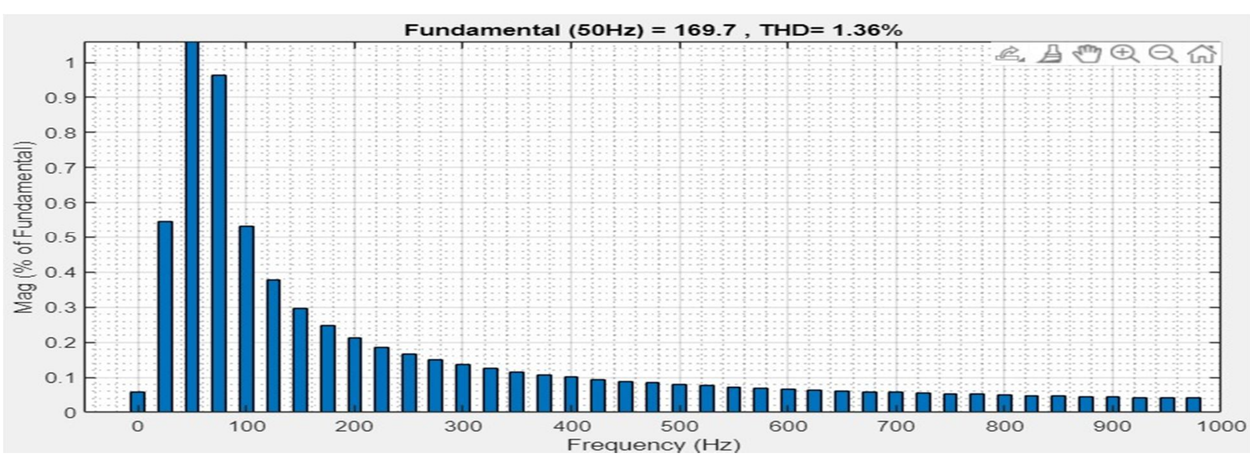

FIG .1.7. PI THD Grid

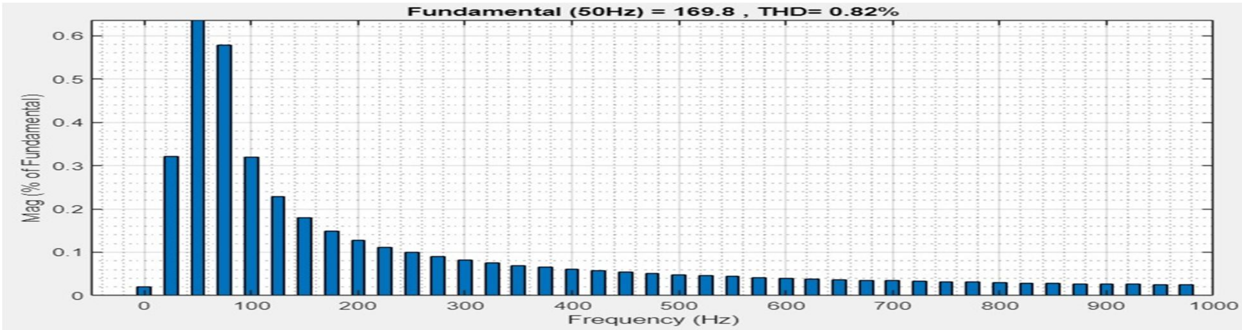

FIG.1.8. ANN THD Grid

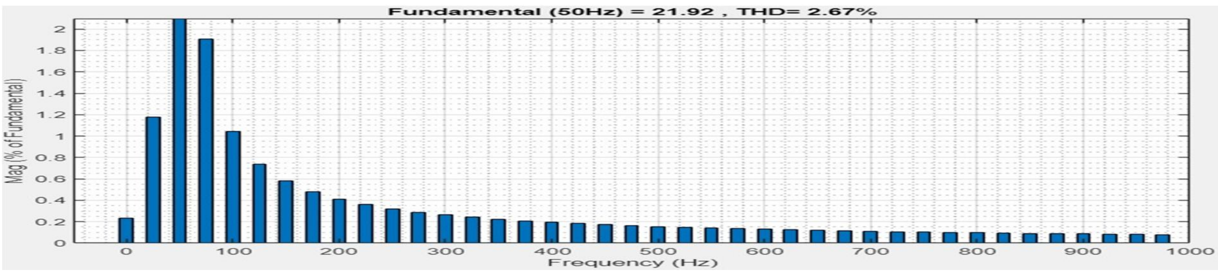

FIG.1.9. PI THD Grid

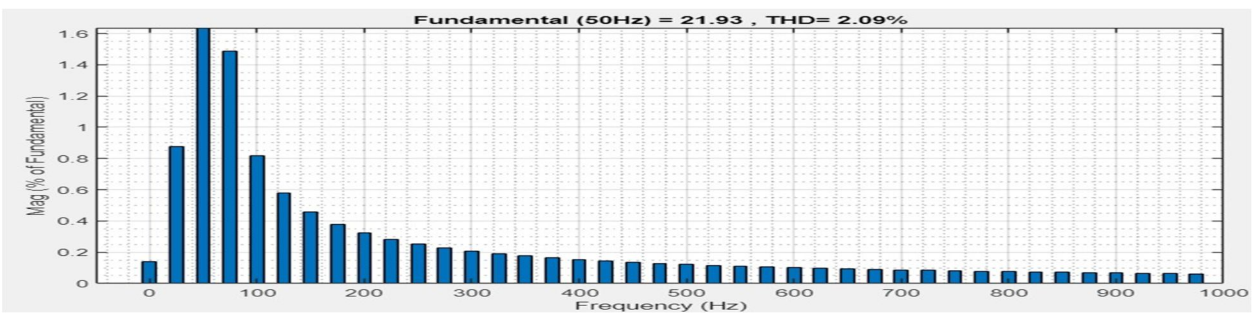

FIG 1.10.ANN THD Grid

VI. CONCLUSION

The proposed PV-powered EV charging station, enhanced with neural network–based grid control and ANFIS-driven MPPT, ensures stable DC bus voltage and intelligent power flow between solar PV, BESS, and the grid it demonstrates reliable voltage regulation and efficient energy coordination Simulations verify its ability to maximize renewable utilization, maintain uninterrupted EV charging, and adapt to varying conditions, making it a scalable solution for future high-demand charging infrastructures.

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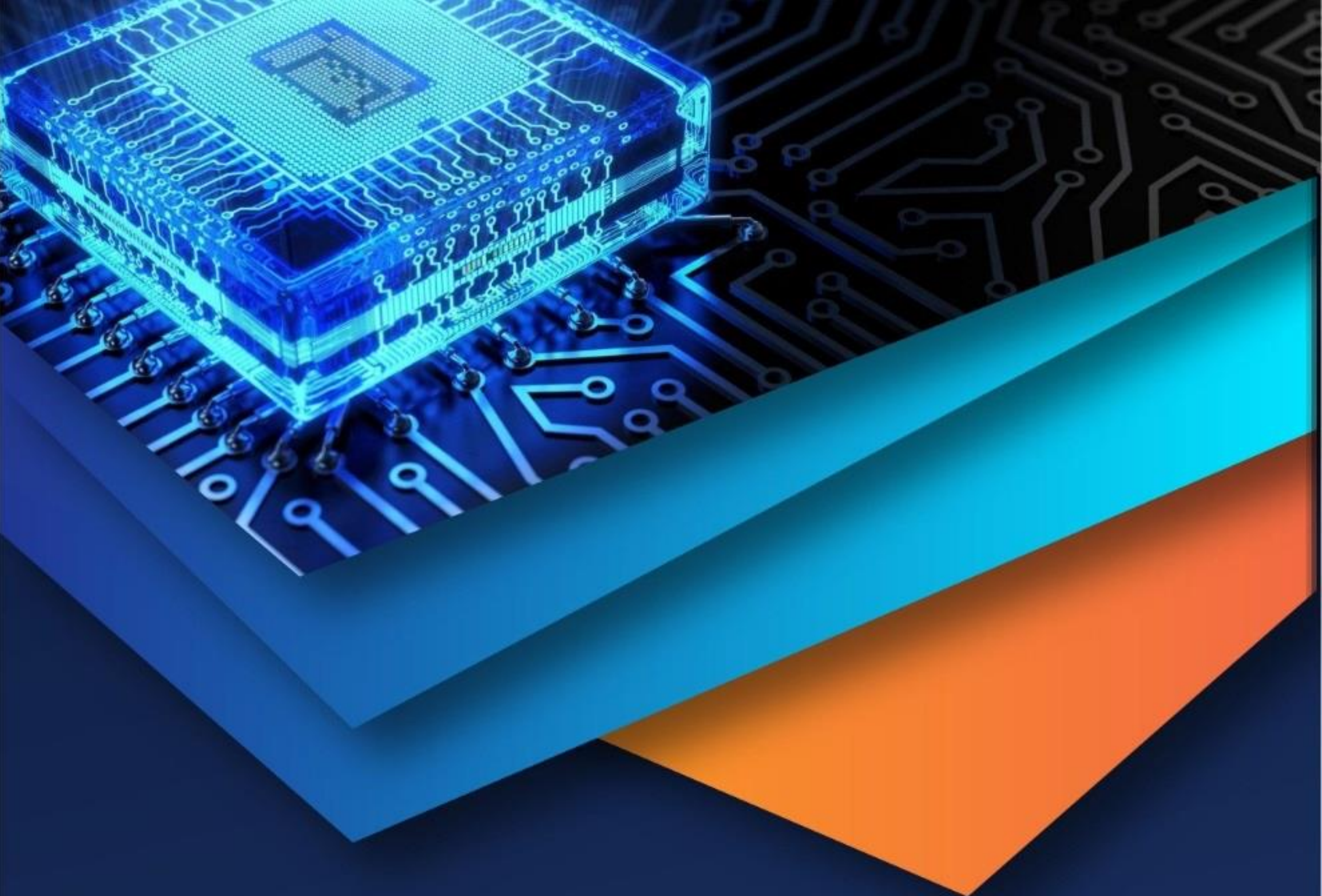

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