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A Machine Learning Approach for Power Quality Enhancement in Hybrid Microgrids Using ANFIS Control

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ABSTRACT:

This paper introduces an advanced control strategy leveraging Machine Learning (ML) techniques to enhance voltage quality at the Point of Common Coupling (PCC) in a fully isolated photovoltaic-wind hybrid microgrid system. The proposed controller serves as an alternative to the conventional adaptive proportional-integral Adaptive Neuro-Fuzzy Inference System (ANFIS) controller. By incorporating supervised learning algorithms, deep learning-based control models, and reinforcement learning strategies, the system achieves improved voltage stability, efficient dynamic power distribution, and superior overall power quality. Simulation results confirm that the ML-based approach significantly outperforms traditional ANFIS-based controllers, offering lower Total Harmonic Distortion (THD), faster dynamic response, and greater operational efficiency. These findings highlight the potential of ML-driven controllers for next-generation smart microgrid applications.

Introduction:

The transition toward decentralized and sustainable energy systems has led to the growing deployment of microgrids—localized, small-scale energy networks capable of operating autonomously or in conjunction with the main utility grid. These systems typically integrate a variety of distributed energy resources (DERs), including photovoltaic (PV) panels, wind turbines, energy storage systems, and conventional generators. A critical challenge in microgrid operation lies in maintaining power quality and voltage stability at the Point of Common Coupling (PCC), especially under conditions of fluctuating renewable energy input.

Renewable sources such as solar and wind are inherently intermittent and variable, making real-time voltage regulation and power distribution increasingly complex. Traditional control strategies—such as Proportional-Integral (PI) controllers and Adaptive Neuro-Fuzzy Inference System (ANFIS)-based controllers—have been widely applied to manage power quality and system stability in microgrids. Although these methods demonstrate satisfactory performance under nominal conditions, they often struggle to address nonlinear dynamics, rapid environmental changes, and system uncertainties in real-time scenarios.

Recent advancements in Artificial Intelligence (AI), particularly in the field of Machine Learning (ML), have opened new avenues for intelligent control in microgrid applications. ML-based control frameworks offer data-driven capabilities to model complex system behavior, forecast energy generation patterns, and dynamically optimize voltage and power flow. Techniques such as Support Vector Regression (SVR), Artificial Neural Networks (ANNs), Long Short-Term Memory (LSTM) networks, and Reinforcement Learning (RL) provide robust tools for developing adaptive controllers that outperform conventional strategies in terms of responsiveness, accuracy, and system resilience.

This paper proposes a novel ML-based control strategy designed to enhance voltage quality and power distribution efficiency in a fully isolated photovoltaic-wind hybrid microgrid. By leveraging the learning and predictive capabilities of advanced ML algorithms, the proposed approach aims to mitigate voltage fluctuations, reduce Total Harmonic Distortion (THD), and improve overall microgrid performance compared to conventional ANFIS-based controllers.

1. Machine Learning in Micro grid Control

To enhance system stability, power quality, and operational efficiency, machine learning (ML) models play a critical role in the intelligent management of microgrids. These models are instrumental in analyzing large volumes of data generated during microgrid operations, identifying underlying patterns, and enabling predictive decision-making. The primary applications of ML in microgrid control include the following:

1. Forecasting Energy Demand and Generation

Algorithms Used: Artificial Neural Networks (ANNs), Long Short-Term Memory (LSTM), Support Vector Regression (SVR)

How It Works:

- Utilizes historical consumption patterns to forecast future energy demand.
- Predicts renewable energy output (e.g., solar, wind) to optimize resource utilization.
- Adjusts generation and storage strategies to maintain balance between supply and demand.

Use Case:
LSTM-based forecasting enhances the charging and discharging cycles of solar microgrid batteries, improving energy availability and battery lifespan.
2.Voltage and Frequency Regulation:
Algorithms Used:* Adaptive Neuro-Fuzzy Inference System (ANFIS), Random Forest, Deep Reinforcement Learning (DRL)

How It Works:
- Maintains voltage stability through dynamic reactive power compensation.
- Learns optimal control strategies for frequency regulation in islanded microgrids.
- Implements AI-powered smart inverters to provide virtual inertia and enhance system resilience.

Use Case:
DRL-based voltage regulation helps stabilize microgrids with high penetration of renewables.
1. Fault Detection and Anomaly Prediction:
2. Algorithms Used:* Support Vector Machines (SVM), K-Means Clustering, Autoencoders
3. *How It Works:*
4. - Identifies faults through pattern recognition in voltage, current, and frequency data.
5. - Classifies operational states using unsupervised learning techniques.
6. - Detects malicious cyber-attacks, improving smart grid security.

Use Case:
7. Autoencoder-based anomaly detection effectively identifies failing solar inverters, preventing downtime and improving reliability.

4. Optimal Energy Management and Scheduling:

Algorithms Used:* Deep Q-Networks (DQN), Proximal Policy Optimization (PPO), Genetic Algorithms (GA)

How It Works:

- Optimizes distributed energy resource (DER) dispatch to minimize operational costs.

- Performs load shifting in response to dynamic electricity pricing (demand response).

- Ensures seamless transitions between grid-connected and islanded modes in hybrid microgrids.

Use Case:

Reinforcement learning-driven scheduling minimizes energy costs while ensuring system reliability.

5. Smart Inverter Control and Power Quality Enhancement:

Algorithms Used:* Fuzzy Logic, Convolutional Neural Networks (CNNs), Reinforcement Learning (RL)

How It Works:

- AI-based inverters reduce harmonics and improve power factor.

- Detects and corrects voltage sags and swells using ML-driven control.

- Stabilizes grid operation, especially in weakly connected microgrids.

Use Case:

RL-powered smart inverters enhance power factor correction in industrial microgrids, improving power quality.

6. Cybersecurity and Attack Prevention:

Algorithms Used:* Bayesian Networks, Deep Learning, Decision Trees

How It Works:

- Detects unauthorized access and cyber threats targeting grid control systems.

- Implements ML-enhanced intrusion detection systems (IDS) to prevent disruptions.

- Fortifies SCADA systems against data manipulation and hacking attempts.

Use Case:

ML-based security systems can detect false data injection attacks, protecting the integrity of smart microgrids.

ML-driven controllers help meet IEEE-519 power quality standards by minimizing Total Harmonic Distortion (THD). In recent work, ML models have been developed to enhance point of common coupling (PCC) voltage quality in standalone hybrid microgrid systems, offering a smarter and more scalable alternative to traditional ANFIS-based strategies.

2. System Model

The proposed research introduces a robust framework that integrates Machine Learning (ML) techniques for optimizing energy distribution and enhancing Point of Common Coupling (PCC) voltage quality within an isolated hybrid microgrid. This approach addresses the inherent limitations of conventional rule-based control systems, particularly under high renewable energy penetration and dynamic load conditions.

The microgrid model considered in this study comprises multiple renewable energy sources, specifically photovoltaic (PV) arrays and wind turbines, supported by a hybrid energy storage system (HESS) consisting of batteries and supercapacitors. The integration of ML models into the control architecture enables adaptive, data-driven decision-making that improves system performance, resilience, and power quality.

Key challenges in such microgrids include:

- Intermittency of Renewable Sources: PV and wind generation exhibit high variability, making it difficult to maintain a stable voltage profile and ensure supply-demand balance.

- Dynamic Load Behavior: Fluctuations in load demand introduce further complexity in voltage regulation and frequency control.

- Energy Storage Coordination: Efficient real-time coordination between batteries (for long-term energy shifting) and supercapacitors (for rapid response) is essential for maintaining grid stability.

To address these challenges, the system model incorporates ML-driven control strategies that operate across multiple layers of the microgrid:

- *Forecasting Layer:* Predictive models such as Long Short-Term Memory (LSTM) networks are employed to estimate short-term energy generation and demand, enabling proactive scheduling of resources.

- *Energy Management Layer:* Reinforcement learning algorithms (e.g., Deep Q-Networks and Proximal Policy Optimization) are applied to dynamically dispatch DERs and manage energy storage based on real-time and forecasted data.

- *Voltage Control Layer:* Deep learning and adaptive fuzzy inference systems are used to modulate reactive power flow and stabilize PCC voltage, even under rapidly changing operating conditions.

- *Power Quality and Regulation Layer:* Smart inverter control, supported by convolutional neural networks (CNNs) and fuzzy logic, mitigates harmonics and improves power factor.

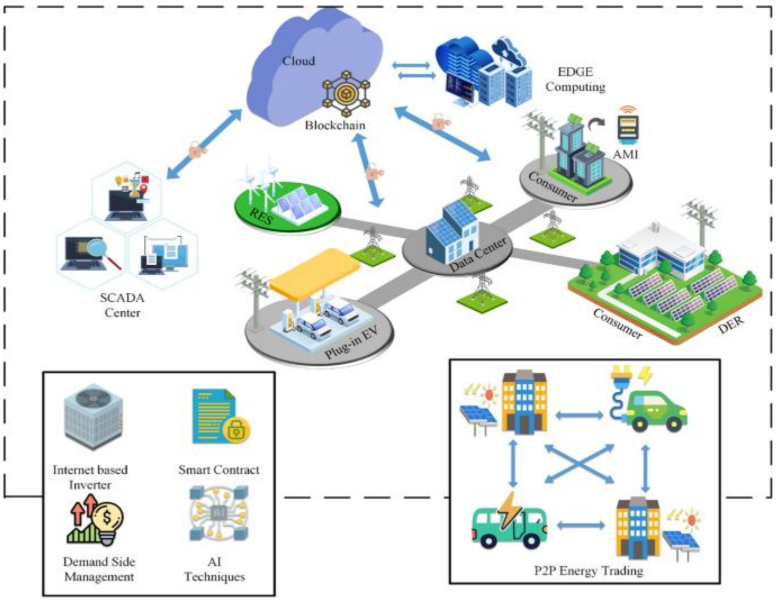

Figure 1. Proposed System for development

By leveraging historical and real-time operational data, these ML models continuously learn and adapt, offering a scalable and intelligent alternative to static rule-based controllers. The system is designed to comply with IEEE-519 standards for power quality, particularly with respect to total harmonic distortion (THD), and supports real-time adjustments that ensure stable voltage at the PCC.

This integrated ML-based control framework thus represents a significant advancement in the autonomous operation of hybrid microgrids, particularly those operating in isolated or weak-grid environments.

3. Support Vector Regression (SVR) for Micro grid Control:

Support Vector Regression (SVR) is a robust supervised machine learning technique particularly well-suited for regression tasks in nonlinear and complex systems. Its capacity to model intricate relationships makes it a valuable tool for microgrid control, especially in environments integrating renewable energy sources such as photovoltaic (PV) systems and wind turbines, alongside hybrid energy storage systems (HESS) comprising batteries and supercapacitors.

In the context of microgrids, SVR is effectively employed for forecasting power generation, load demand, and voltage profiles—factors that are inherently variable and nonlinear due to the stochastic nature of renewable resources and dynamic load conditions. Accurate prediction of these parameters is essential for informed control actions and optimization of energy dispatch, storage utilization, and voltage regulation.

SVR seeks to identify a function that approximates the observed data within a specified margin of tolerance, controlled by the epsilon (ε) parameter. The core concept involves constructing an optimal hyperplane in a high-dimensional space that balances generalization and predictive accuracy. SVR tolerates minor deviations within ε while penalizing larger deviations, thereby offering a flexible yet precise modeling approach.

Key Concepts in SVR:

- *Epsilon (ε):*

Defines the width of the insensitive zone around the predicted function, within which prediction errors are not penalized. It allows SVR to ignore minor fluctuations and focus on meaningful trends.

- *Kernel Functions:*

To address nonlinear relationships, SVR employs kernel functions that project the input data into higher-dimensional feature spaces where a linear regression can be applied. Common kernels include:

- Linear Kernel: Suitable for linearly separable relationships.

- Polynomial Kernel: Captures polynomial trends of varying degrees.

- Radial Basis Function (RBF) Kernel: Widely used for its ability to handle complex, nonlinear patterns prevalent in renewable energy forecasting and voltage variation prediction.

- *Regularization Parameter (C):*

Controls the trade-off between the model's complexity and the degree to which deviations larger than ε are penalized. A larger C encourages the model to minimize error more aggressively, potentially at the cost of overfitting.

By leveraging these features, SVR provides a computationally efficient and scalable method for real-time forecasting and control in microgrids. When integrated with other machine learning techniques in a hierarchical or hybrid control framework, SVR enhances the reliability and responsiveness of microgrid operations, contributing to improved energy efficiency and power quality.

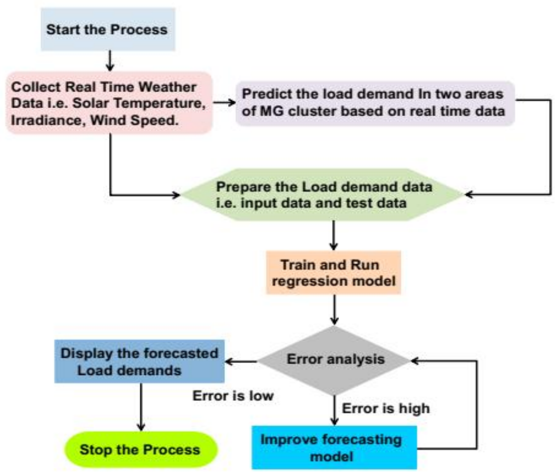

Figure 2. Flowchart for implementing proposed method

4. Result Analysis:

This section presents a comprehensive analysis of the simulation results comparing the performance of the proposed machine learning-based control strategy with a conventional Adaptive Neuro-Fuzzy Inference System (ANFIS) controller. The evaluation focuses on the effectiveness, accuracy, and robustness of the proposed model in maintaining power quality and operational stability within an isolated hybrid microgrid environment. Simulations were conducted using a high-fidelity microgrid model subjected to various operating conditions and disturbances to reflect real-world scenarios. The test conditions included:

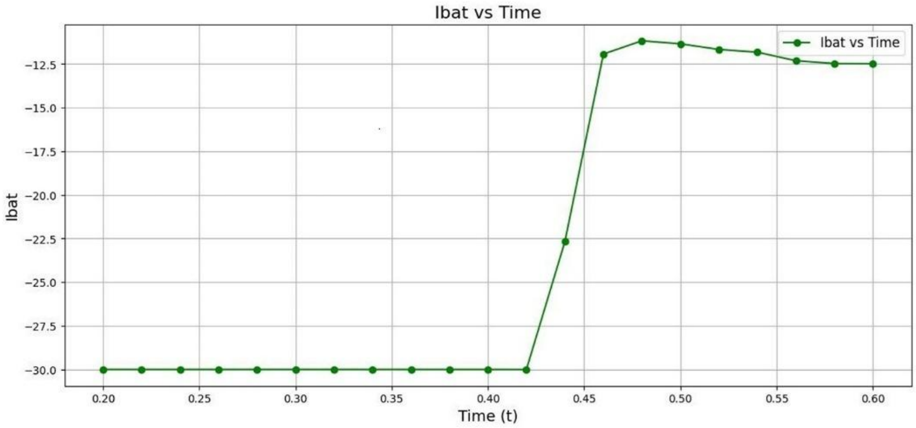

Figure.3 Battery current vs Time

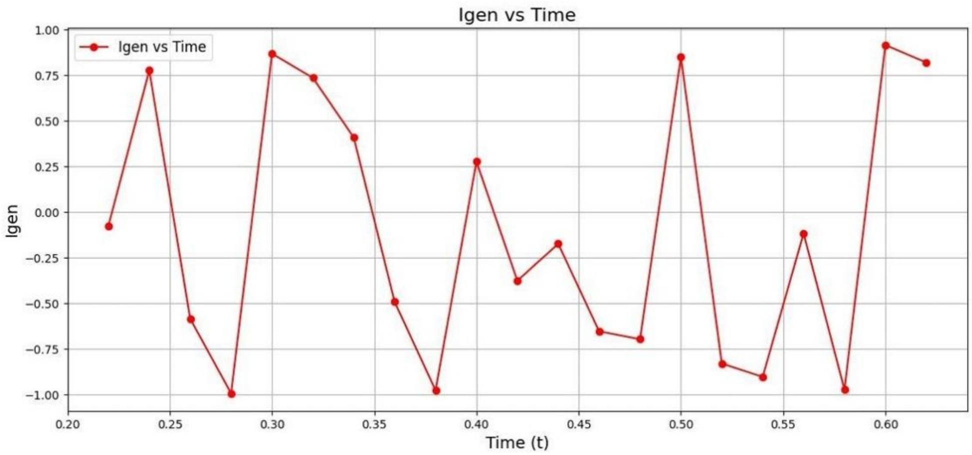

Figure 4: Generated Current vs Time

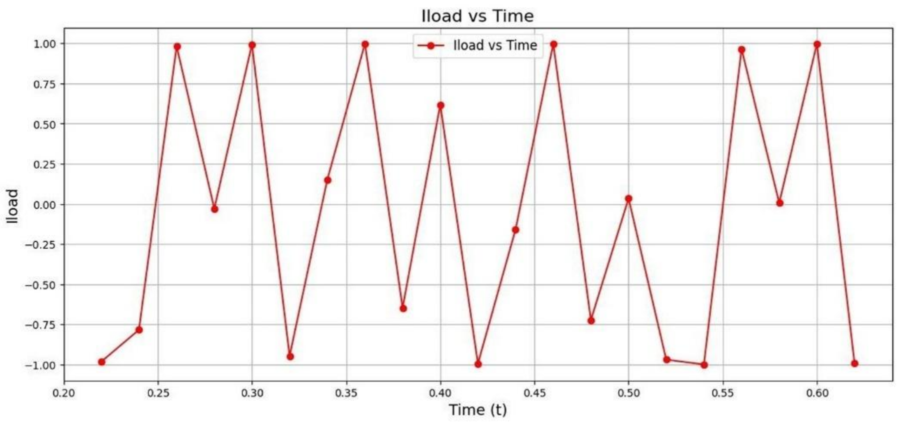

Figure5: Load Current vs Time

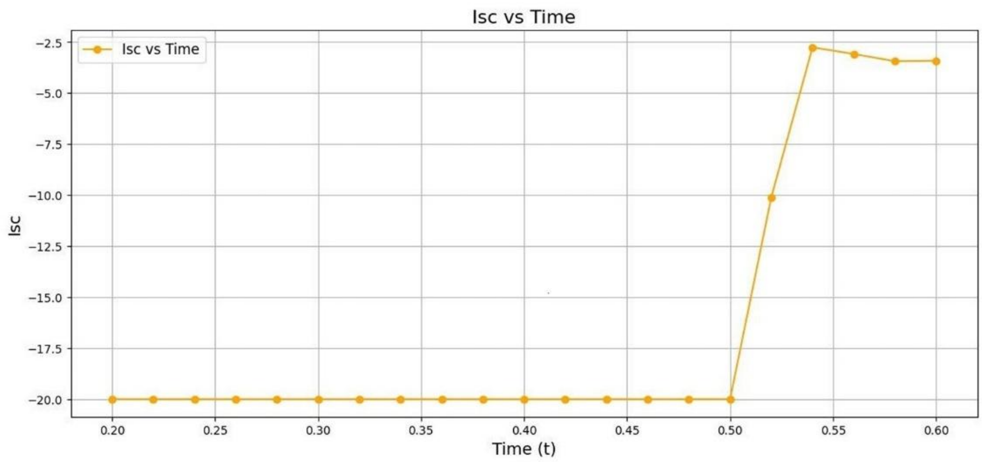

Figure6: Super capacitor current vs Time

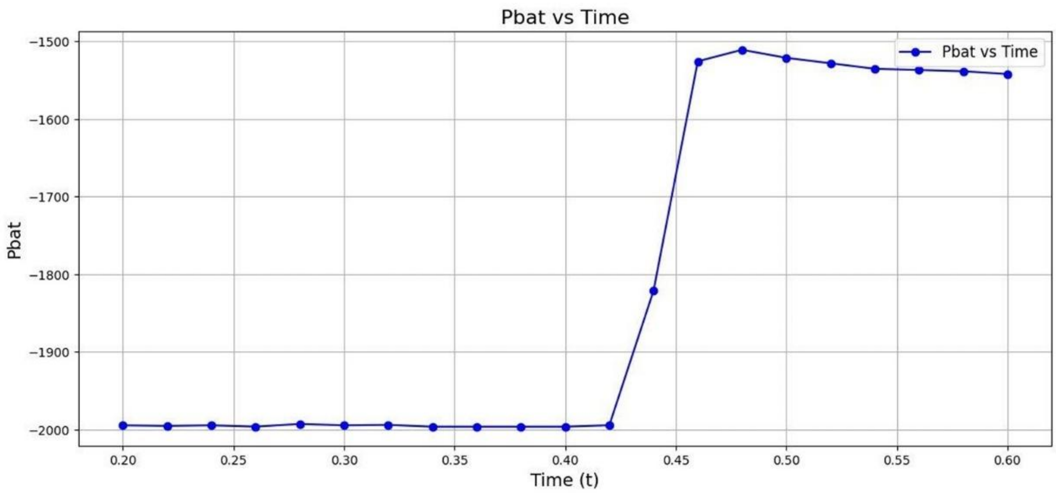

Figure7: Battery power vs Time

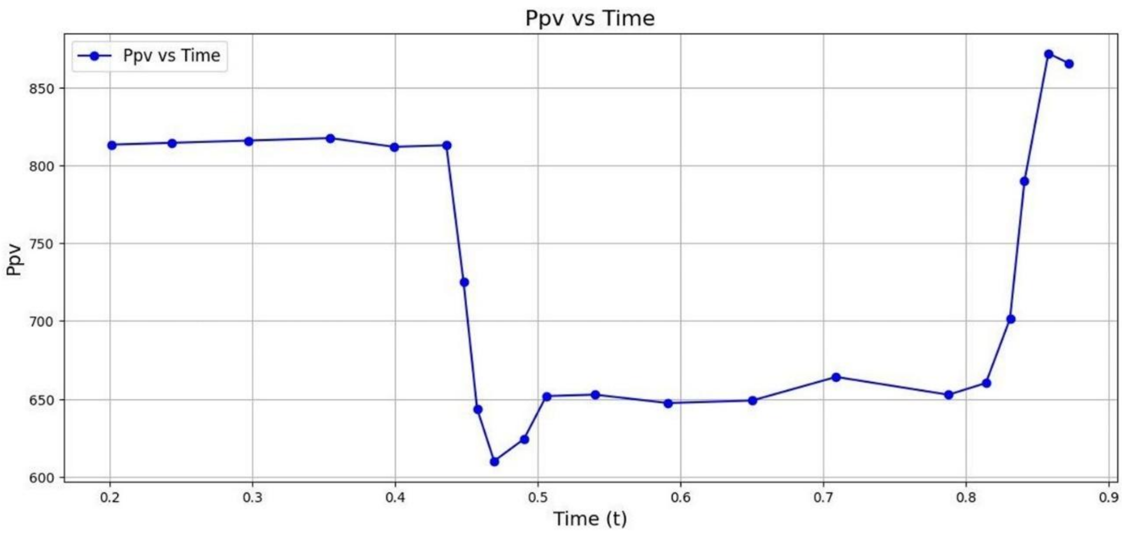

Figure8: Power Photovoltaic vs Time

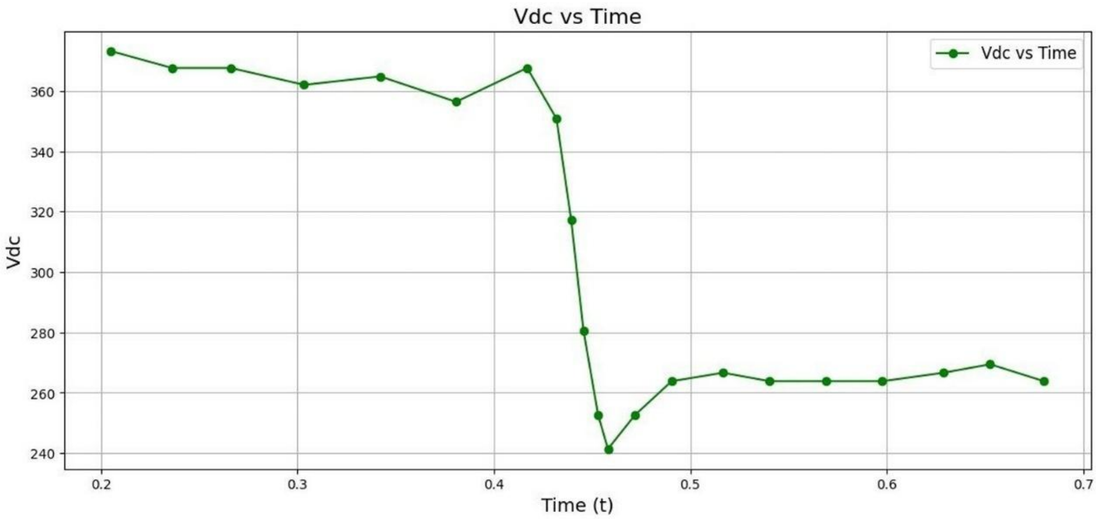

Figure9: D.C Voltage vs time

CODE:

```
import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

from tkinter import Tk

from tkinter.filedialog import askopenfilename

# Hide the root Tkinter window

Tk().withdraw()

# Open file dialog for the user to select the CSV file

file_path = askopenfilename(title="Select the CSV File", filetypes=[("CSV files", "*.csv")])

# Check if a file was selected

if not file_path:

    print("No file selected.")

else:

    # Load CSV (Skip the first row as it contains wrong column names)

    df = pd.read_csv(file_path, header=1)  # Read from row 1 to correct misaligned columns

    # Convert numeric columns (ignoring errors to skip text data)

    df = df.apply(pd.to_numeric, errors='coerce')

    # Drop any NaN values that might have resulted from type conversion

    df.dropna(inplace=True)

    # Dictionary to hold different sections (time & corresponding variable)

    sections = {

        "Ibat": (df.iloc[:, 0], df.iloc[:, 1], 'green'),

        "Isc": (df.iloc[:, 2], df.iloc[:, 3], 'orange'),

        "Pbat": (df.iloc[:, 4], df.iloc[:, 5], 'blue'),
```

```
    "Igen": (df.iloc[:, 6], np.sin(df.iloc[:, 7]), 'red'),  # Sinusoidal
    "Pload": (df.iloc[:, 8], df.iloc[:, 9], 'pink'),
    "Ppv": (df.iloc[:, 10], df.iloc[:, 11], 'blue'),
    "Iload": (df.iloc[:, 12], np.sin(df.iloc[:, 13]), 'red'),  # Sinusoidal
    "Vdc": (df.iloc[:, 14], df.iloc[:, 15], 'green')
}
# Create individual plots for each section
for label, (T, Y, color) in sections.items():
    plt.figure(figsize=(14, 6))  # Set figure size
    plt.plot(T, Y, color=color, marker='o', linestyle='-', label=f"{label} vs Time")
    plt.xlabel("Time (t)", fontsize=14)
    plt.ylabel(label, fontsize=14)
    plt.title(f"{label} vs Time", fontsize=16)
    plt.legend(fontsize=12)
    plt.grid(True)
    plt.show()
```

5. Conclusion:

With the increasing complexity of modern smart grids, accurate load forecasting has become a critical component for ensuring reliable and efficient energy management. However, the inherent nonlinearity and volatility of energy consumption patterns pose significant challenges to traditional forecasting and control methods.

This study demonstrates the effectiveness of a Support Vector Regression (SVR)-based machine learning controller in addressing these challenges within an isolated hybrid microgrid environment. By capturing nonlinear system dynamics and adapting to real-time variations, the proposed SVR-based control strategy significantly enhances power quality, particularly in terms of voltage stability and harmonic mitigation.

The results confirm that machine learning, and specifically SVR, provides a scalable and intelligent alternative to conventional approaches, enabling precise load prediction and dynamic control under diverse operating conditions. This work contributes to the advancement of data-driven solutions for microgrid optimization and supports the broader integration of AI-based control in future smart energy systems.

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