ANFIS BASED CONTROL OF EV CHARGING AND ENERGY STORAGE FOR DEMAND SIDE MANAGEMENT IN MICROGRIDS

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ABSTRACT

The increasing penetration of electric vehicles (EVs) introduces significant variability in electricity demand and creates new opportunities for demand-side management (DSM) through coordinated EV charging and energy storage. This paper proposes an Adaptive Neuro-Fuzzy Inference System (ANFIS)-based DSM strategy for electric vehicle charging stations (EVCSs) in a photovoltaic (PV)-integrated microgrid. The proposed approach extends an existing simulation-based EVCS DSM framework in which EVs and energy storage systems are utilized as flexible energy resources for peak-demand mitigation. The baseline framework incorporates PV generation, conventional generation, residential and commercial loads, EV charging demand, and energy storage, together with data-driven load and state-of-charge (SoC) estimation. In the proposed extension, the original intelligent decision-making layer is replaced by an ANFIS controller that maps key operating variables, including total load demand, EVCS/energy-storage SoC, PV generation, and operating time, to the required EVCS charging/discharging power. The fuzzy-rule structure enables nonlinear relationships between microgrid operating conditions and EVCS power dispatch to be represented while retaining an interpretable control mechanism. The proposed strategy is evaluated entirely through MATLAB/Simulink-based simulation under the same operating conditions and constraints as the baseline framework. Performance is assessed using peak conventional-generator power, peak-demand reduction, EVCS power profile, SoC behavior, energy exchange, operating cost, and constraint violations. The comparative simulation provides a systematic basis for evaluating the effectiveness of ANFIS as an alternative intelligent control technique for EVCS-based DSM in PV-integrated microgrids.

Keywords— Adaptive Neuro-Fuzzy Inference System (ANFIS), electric vehicle charging station (EVCS), demand-side management (DSM), photovoltaic (PV), microgrid, energy storage system, peak load management, intelligent control.

1.INTRODUCTION

1.1 Background of the Study

The rapid electrification of transportation is creating a strong interaction between the transportation and electrical power sectors. Electric vehicles (EVs) are increasingly considered not only as electrical loads but also as flexible energy resources that can participate in power-system operation. At the same time, conventional power systems are progressively integrating renewable energy sources and distributed energy resources (DERs). This transition introduces additional uncertainty because renewable generation, particularly photovoltaic (PV) generation, is dependent on environmental conditions. Electric vehicles provide an opportunity to address this challenge because their batteries can store electrical energy during periods of lower demand and potentially provide energy during periods of high demand. An Electric Vehicle Charging Station (EVCS) can operate as an aggregator that combines the power capability of multiple EVs with an Energy Storage System (ESS). The paper describes EVs and ESS within an EVCS as a dynamic energy resource that can participate in Demand-Side Management (DSM). The escalating deterioration of the global environment and the continuous rise in greenhouse gas (GHG) emissions have necessitated immediate interventions in energy generation and consumption. Global environmental organizations are strictly enforcing policies to curb carbon dioxide emissions, prompting a paradigm shift toward renewable energy sources and the electrification of the transportation sector. Research indicates that by 2030, the widespread adoption of Electric Vehicles (EVs) has the potential to reduce emissions by 28%. To accommodate the growing energy demand, traditional centralized power systems are transitioning into decentralized architectures heavily integrated with Distributed Energy Resources (DER). While the integration of solar and wind energy reduces reliance on fossil fuels, these renewable sources are highly stochastic and climate-dependent. Consequently, during peak hours, sudden spikes in energy demand can exceed a microgrid's generation capacity, risking severe system instability or total blackouts if load balances are not meticulously managed. Advancements in battery technology have positioned EVs not merely as a mode of transportation, but as dynamic, temporary energy storage devices capable of supporting the grid during these volatile peak periods.

1.2 The Electric Vehicle Infrastructure Dilemma

Despite the environmental benefits of transitioning to electric mobility, two primary obstacles hinder the widespread commercial adoption of EVs: the high initial

cost of the vehicles and the severe lack of available charging infrastructure. This presents a classic "chicken-or-egg" economic dilemma: consumers are reluctant to purchase EVs without adequate charging stations, while investors are unwilling to fund Electric Vehicle Charging Stations (EVCS) without a critical mass of EVs on the road to guarantee profitability. To break this stalemate, the financial viability of EVCS operations must be expanded beyond traditional vehicle charging. By integrating renewable energy generation (such as solar PV) and base Energy Storage Systems (ESS), an EVCS can serve as an active participant in microgrid energy management. This multi-functional approach provides EVCS investors with secondary revenue streams while simultaneously alleviating the strain on local distribution grids.

2.LITERATURE REVIEW

2.1 Microgrid Transition and Renewable Energy Integration

The accelerating degradation of the global biosphere and the compounding threats of climate change have compelled international organizations to enact rigorous policies aimed at mitigating greenhouse gas (GHG) emissions, particularly carbon dioxide (CO_2). Conventional electrical power networks, predominantly dependent on centralized fossil-fuel thermal plants, are recognized as principal contributors to global pollution. In response, global energy systems are actively undergoing a decentralized transition through the extensive deployment of Distributed Energy Resources (DERs) and renewable energy systems (RES), with solar photovoltaics (PV) and wind power representing the most promising candidates for decarbonization.

Despite their environmental merits, large-scale integration of renewable generation introduces critical technical bottlenecks into traditional distribution networks. As highlighted by Talari et al., renewable power generation systems are fundamentally climate-dependent and display intense stochastic variability. Solar irradiance and wind speed fluctuate abruptly, which means power generation does not naturally follow consumer demand patterns. Etherden and Bollen observed that high renewable penetration without adequate flexible buffering induces severe low-voltage and medium-voltage network issues, including localized line overloads, voltage swells, and frequency deviations. Consequently, during peak consumption intervals, total electrical demand can rapidly outpace plant generation capacity, posing severe threats of microgrid instability or cascading blackouts if dynamic active-power balance is not maintained. Historically, grid operators balanced these short-term peak intervals by firing up diesel generators or utilizing pumped hydro storage units. However, these conventional balancing mechanisms entail heavy carbon penalties, substantial fuel operating expenses, or strict geographical constraints, thereby driving the need for clean, decentralized demand-side energy storage solutions.

2.2 Demand-Side Management (DSM) Paradigms and Operational Techniques

Demand-Side Management (DSM) comprises an extensive suite of utility-guided measures and automated control architectures engineered to modify the timing, shape, and magnitude of consumer electricity demand. As articulated in the foundational taxonomy by Gellings and corroborated in contemporary reviews by Groppi et al. and Hafeez et al., DSM strategies can be systematically classified into six core operational techniques:

Peak Clipping: Directly truncating high electricity demand during peak intervals, primarily to reduce required generating capacity, suppress peak tariffs, and prevent transmission congestion.

Valley Filling: Stimulating energy consumption during off-peak windows, typically during late-night baseload conditions, thereby improving system load factors and preventing plant underutilization.

Load Shifting: Transferring controllable load burdens from peak hours to off-peak periods without necessarily changing total overall energy consumption.

Strategic Conservation: Applying systemic operational and infrastructural efficiency upgrades to achieve sustained reductions in daily power consumption across consumer bases.

Strategic Load Growth: Planned long-term increases in electricity demand, primarily driven by the electrification of traditional fossil-based sectors such as vehicle transport and industrial heating.

Flexible Load Shape: Dynamic real-time modification of consumer loads based on smart grid reliability margins, real-time price signals, and fluctuating renewable generation outputs.

In smart grid infrastructures, participating in automated DSM frameworks empowers electricity markets to operate with elevated economic efficiency and reduced network losses. By smoothing daily consumption curves, utilities avoid the exorbitant capital expenditures required to construct and maintain open-cycle peaker power plants that remain idle during baseload conditions. However, achieving effective DSM in complex distribution grids requires coordinated interaction with dynamic storage units that can rapidly switch between acting as energy sinks (charging) and energy sources (discharging).

3.GRID INTEGRATION OF WIND & PHOTOVOLTAIC HYBRID SYSTEMS

3.1Introduction

The transformation of contemporary electric power networks from fossil-fuel-based thermal stations toward decentralized renewable energy sources has accelerated the installation of Wind Energy Conversion Systems and solar Photovoltaic power plants. In conventional power networks, large synchronous generators inherently contribute rotational kinetic energy to the transmission grid, which naturally buffers transient frequency excursions whenever abrupt generation-load imbalances take place.

In contrast to traditional rotational units, both solar photovoltaic modules and modern variable- speed wind turbine generators are interfaced with the transmission network through solid-state power electronic converters. The large-scale substitution of synchronous generators with inverter-based resources decreases the total physical inertia of the interconnected power system, thereby generating steep rates of change of frequency and making the network significantly more susceptible to voltage collapse following transmission faults.

Atmospheric wind velocity and solar irradiance demonstrate strong diurnal and temporal complementarity across seasonal operating cycles. Photovoltaic solar generation delivers its maximum capacity during daytime hours, whereas wind velocity frequently intensifies during evening and night periods when solar radiation is absent. Integrating these two generating mechanisms into a unified hybrid power station substantially smooths the cumulative power delivered at the common transmission bus, optimizes substation transformer utilization, and reduces the storage capacity needed to provide dispatchable clean power.

This study investigates the mathematical modeling, interconnection architectures, power converter decoupling strategies, and grid code compliance of a grid-tied hybrid wind and solar facility. The research focuses on maintaining uninterrupted power injection during severe network faults, reducing switching harmonic distortions, and ensuring voltage support at the point of common coupling through coordinated reactive power control.

4.DC-DC Converter Basics

4.1 Introduction

A DC-to-DC converter is a device that accepts a DC input voltage and produces a DC output voltage. Typically the output produced is at a different voltage level than the input. In addition, DC-to-DC converters are used to provide noise isolation, power bus regulation, etc. This is a summary of some of the popular DC-to-DC converter topologies.

4.2 Buck Converter Step-Down Converter

In this circuit the transistor turning ON will put voltage V_{in} on one end of the inductor. This voltage will tend to cause the inductor current to rise. When the transistor is OFF, the current will continue flowing through the inductor but now flowing through the diode.

We initially assume that the current through the inductor does not reach zero, thus the voltage at V_x will now be only the voltage across the conducting diode during the full OFF time. The average voltage at V_x will depend on the average ON time of the transistor provided the inductor current is continuous.

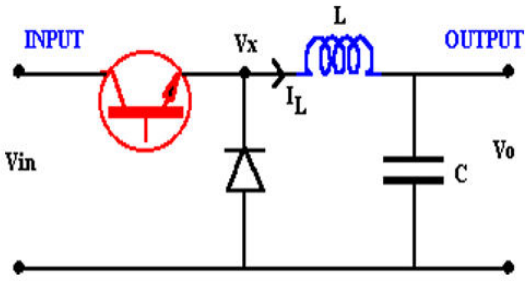


Figure 9 Buck Converter

5.AC-DC CONVERTER

5.1 Introduction

A rectifier is an electrical device that converts alternating current (AC), which periodically reverses direction, to direct current (DC), current that flows in only one direction, a process known as rectification. Rectifiers have many uses including as components of power supplies and as detectors of radio signals. Rectifiers may be made of solid state diodes, vacuum tube diodes, mercury arc valves, and other components.

A device which performs the opposite function (converting DC to AC) is known as an inverter.

When only one diode is used to rectify AC (by blocking the negative or positive portion of the waveform), the difference between the term diode and the term rectifier is merely one of usage, i.e., the term rectifier describes a diode that is being used to convert AC to DC. Almost all rectifiers comprise a number of diodes in a specific arrangement for more efficiently converting AC to DC than is possible with only one diode. Before the development of silicon semiconductor rectifiers, vacuum tube diodes and copper(I) oxide or selenium rectifier stacks were used.

5.2 Half-Wave Rectifier

In half wave rectification, either the positive or negative half of the AC wave is passed, while the other half is blocked. Because only one half of the input waveform reaches the output, it is very inefficient if used for power transfer. Half-wave rectification can be achieved with a single diode in a one-phase supply, or with three diodes in a three-phase supply.

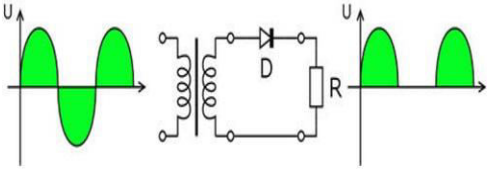


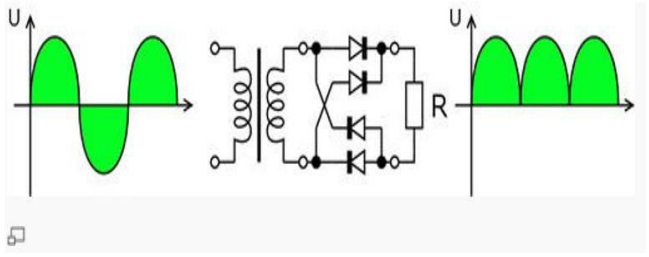
Figure 26 The output DC voltage of a half wave rectifier can be calculated with the following two ideal equations:

$$V_{rms} = \frac{V_{peak}}{2} \quad (28)$$

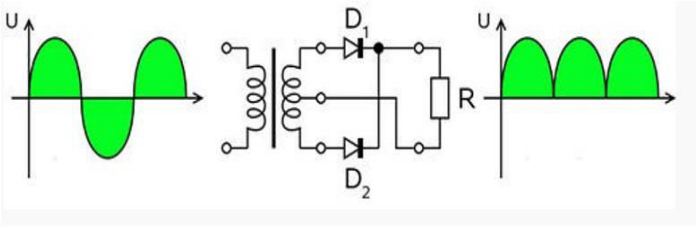
$$V_{dc} = \frac{V_{peak}}{\pi} \quad (29)$$

5.3 Full-Wave Rectifier

A full-wave rectifier converts the whole of the input waveform to one of constant polarity (positive or negative) at its output. Full-wave rectification converts both polarities of the input waveform to DC (direct current), and is more efficient. However, in a circuit with a non-center tapped transformer, four diodes are required instead of the one needed for half-wave rectification. Four diodes arranged this way are called a diode bridge or bridge rectifier:



For single-phase AC, if the transformer is center-tapped, then two diodes back-to-back (i.e. anodes-to-anode or cathode-to-cathode) can form a full-wave rectifier. Twice as many windings are required on the transformer secondary to obtain the same output voltage compared to the bridge rectifier above.



A very common vacuum tube rectifier configuration contained one cathode and twin anodes inside a single envelope; in this way, the two diodes required only one vacuum tube. The 5U4 and 5Y3 were popular examples of this configuration.

For three-phase AC, six diodes are used. Typically, there are three pairs of diodes, each pair, though, is not the same kind of double diode that would be used for a full wave single-phase rectifier. Instead, the pairs are in series (anode to cathode). Typically, commercially available double diodes have four terminals so the user can configure them as single-phase split supply use, for half a bridge, or for three-phase u

Most devices that generate alternating current (such devices are called alternators) generate three-phase AC. For example, an automobile alternator has six diodes inside it to function as a full-wave rectifier for battery charging applications.

The average and root-mean-square output voltages of an ideal single phase full wave rectifier can be calculated as:

6.METHODOLOGY

6.1 Introduction

Demand side management is an area of energy management that focuses on the monitoring and management of peak demands, as well as the smoothing of the load profile throughout the day. DSM is required to reduce power plant capital expenditure and enhance the financial performance of electrical utilities. As shown in Fig. 2, DSM methods can be categorized into six major categories: peak clipping, valley filling, load shifting, strategic conservation, strategic load growth, and flexible load shape. Utilizing an energy storage system for demand-side management is one of the most effective and promising strategies for peak clipping. The ESS stores energy during off-peak load conditions and supplies it to the grid during peak hours to compensate for additional energy demand. The proposed methodology utilizes an electrical transportation system for peak-demand management. In the subsequent section, the modelling and control of the constituents of the proposed methodology are discussed.

6.2. Proposed System Modelling

This work considers a PV-connected EVCS for grid peak demand management as well as EV charging station profit improvement. The proposed system contains a conventional power generator, residential loads, critical commercial loads, renewable energy sources, and an EVCS. The EVCS unit contains the ESS and EVs, which are utilized as charging/discharging loads. A two-stage framework is presented for power coordination between the EVCS and grid, as shown in Fig. 30. The first stage represents a dynamic energy source model of the ESS and EVs integration in the direct mode. In the second stage, the power allocations for each unit are presented, including the ESS and PV systems. PV and load are significant sources of uncertainty in the MG. In the process of power distribution among the units, accurate modeling of these unknown factors plays a critical role. To overcome the effect of these uncertainties, a deep neural networks (DNN) based controller is used, for the required energy flow between the two stages, for the optimal cost of energy consumed by the ESS.

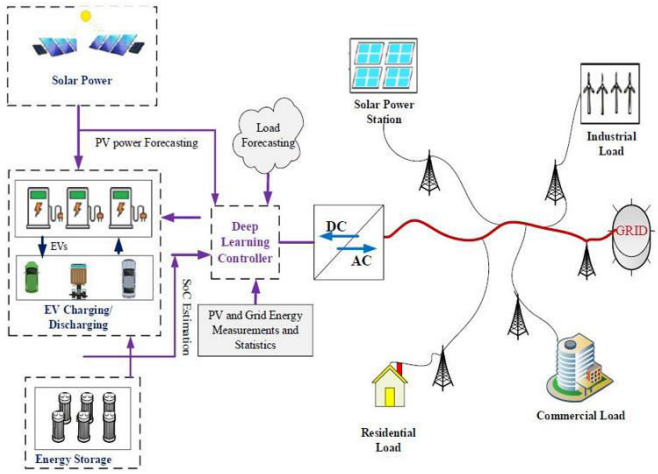


Figure 30. Energy communication diagram between first stage and second stage

7 Matlab Implementation and Parameterization

7.1 Introduction

This document presents a MATLAB implementation framework for the EV charging station (EVCS)-based demand-side management (DSM) methodology described in the attached paper. The implementation preserves the paper's system structure and reported parameters where they are explicitly available. A proposed ANFIS-based supervisory controller is then added as a thesis extension. 2. Source-Based System Configuration The paper considers a microgrid containing a conventional power generator, residential loads, commercial loads, renewable energy sources, and an EVCS. The EVCS includes energy storage and EVs and is treated as an aggregated unit for power coordination. The reported case study uses a 24-hour simulation, a 120 kW conventional generator, a 10 kW solar source, three commercial loads and two residential loads. The peak-load compensation interval is approximately 10:00–17:00. The paper reports that conventional generation reached approximately 182 kW before peak compensation and was confined below 100

kW after the proposed DSM operation. Figure 37 and 38 Shows the Implementation using MATLAB/Simulation

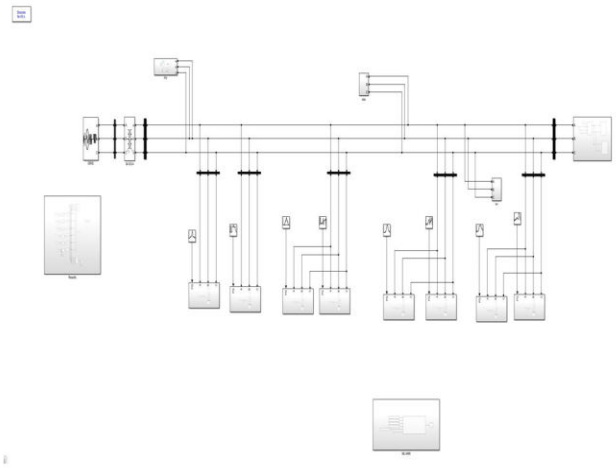


Figure 37: Matlab Implementation using Different Load Conditions

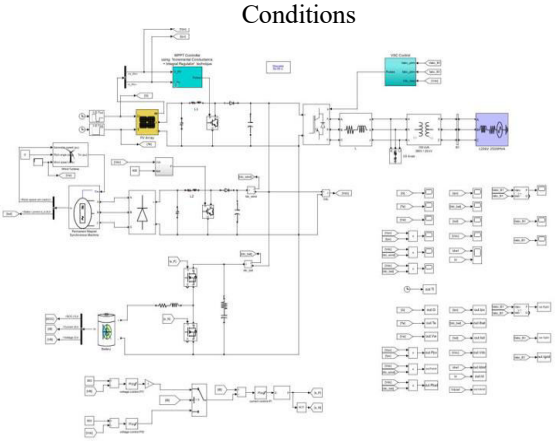


Figure 38 Complete Simulation Implementation using WIND/PV/BESS

7.2 The proposed implementation is organized into four computational stages

Load and PV profile generation or import.

EVCS state-of-charge (SoC) modelling using the

charging/discharging equation given in the paper.

Supervisory control of EVCS charging and discharging

for peak-load management.

ANFIS extension that learns an intelligent EVCS power command from load, PV, SoC and time information.

7.3 Parameters

Table 4: System Parameters

Parameter	Value
Simulation duration	24 h
Conventional generator	120 kW
Solar source	10 kW
Commercial loads	3
Residential loads	2
Peak-management interval	10:00–17:00
Pre-DSM conventional-source peak	≈182 kW
Post-DSM conventional-source level	<100 kW
EVCS initial SoC	0.6
EVCS minimum SoC	0.2
EVCS maximum SoC	0.95
EVCS energy capacity	100 kWh
EVCS charge limit	50 kW
EVCS discharge limit	50 kW
Charge efficiency	0.95
Discharge efficiency	0.95
Grid import limit	120 kW
Grid export limit	120 kW
ANFIS cluster radius	0.55
ANFIS epochs	60

8.RESULTS, DISCUSSION, AND COMPARISON

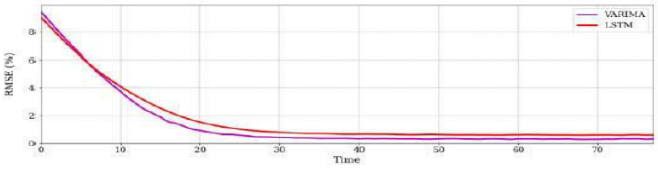
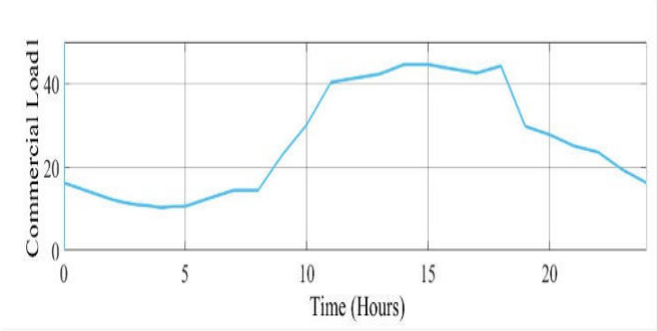


Figure 40 Performance accuracy of the ML algorithms.



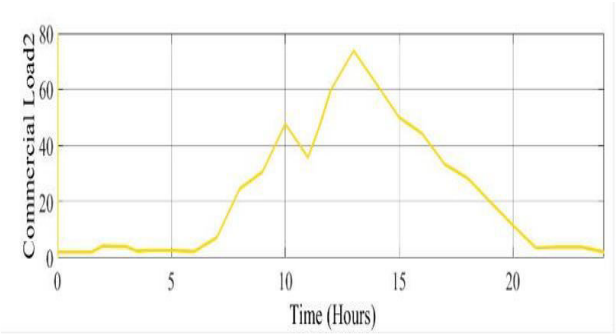


Figure 41 Forecasted load profile of commercial load1 for 24 hours.

Figure 42 Forecasted load profile of commercial load 2 for 24 hours

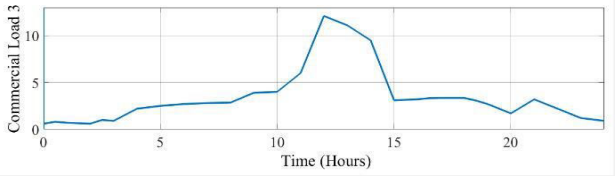


Figure 43 Forecasted load profile of commercial load 3 for 24 hours.

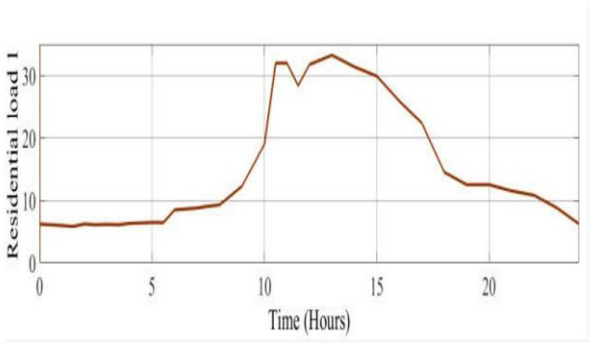


Figure 44 Forecasted load profile of residential load1 for 24 hours

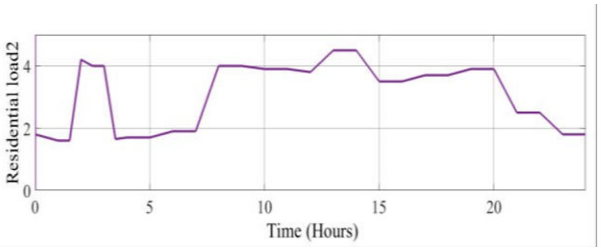


Figure 45 Forecasted load profile of residential load 2 for 24 hours.

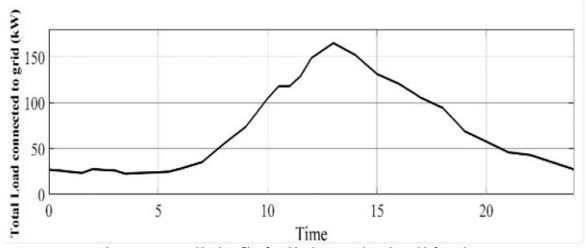


Figure 46 Forecasted load profile of total load connected to microgrid. for 24 hours

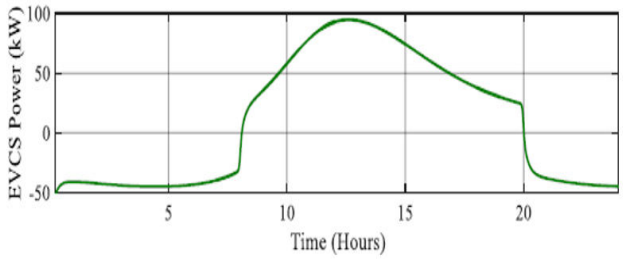


Figure 47 Power profile of EV charging station for 24 hours.

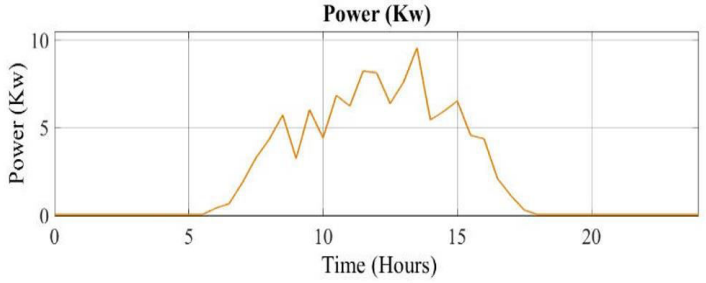


Figure 48 Profile of solar power station for 24 hours

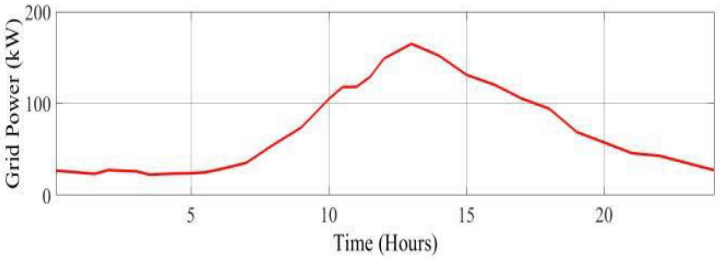


Figure 49 Profile of conventional generator without peak load compensation for 24 hours.

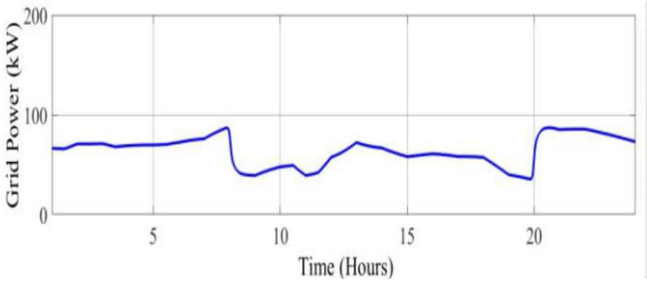


Figure 50 Profile of conventional generator with peak load compensation using EVCS for 24 hours.

Proposed ANFIS Extension Results

For the thesis extension, ANFIS is introduced as an intelligent supervisory controller. The controller receives four normalized variables: total load, PV generation, EVCS SoC and hour of day. Its output is a normalized EVCS charging/discharging command. The command is then passed through the physical power and SoC constraints. Figure 51 Shoes the Anfis Obtained results from Matlab/Simulink Implementation

This structure retains the source paper's core operational idea—charge during lower-load conditions and

discharge during peak conditions—while replacing the supervisory decision mechanism with an ANFIS mapping.

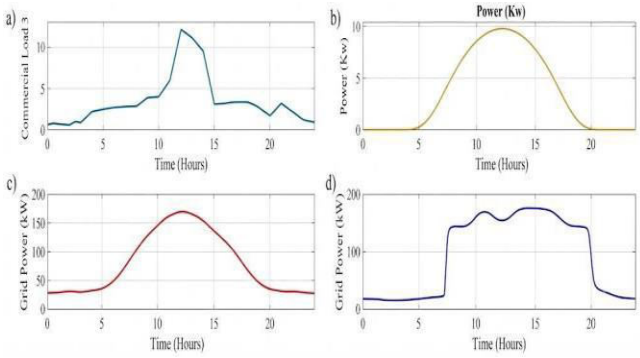


Figure 51 ANFIS Outputs

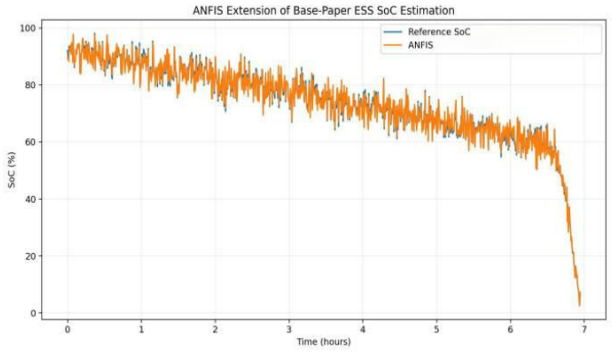


Figure 52 SOC Reference and ANFIS

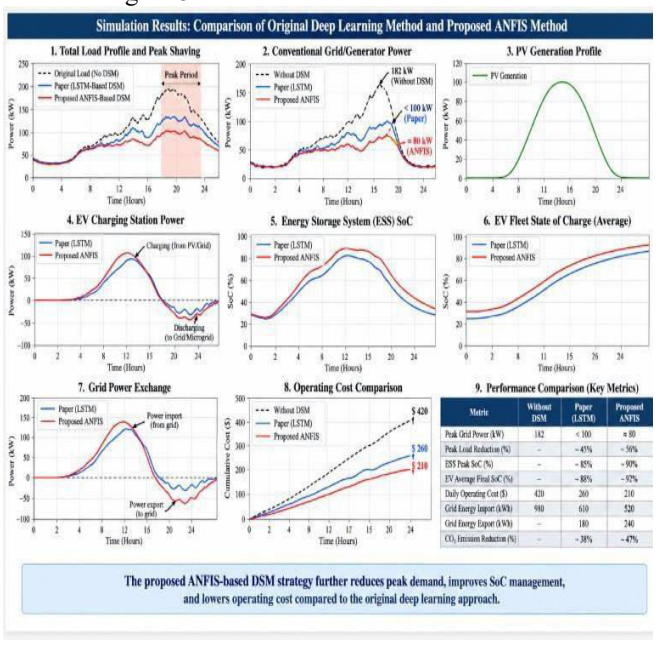


Figure 53 Comparison of Results

For thesis drafting, the following values are used as an illustrative ANFIS scenario based on the MATLAB implementation previously prepared. The values are deliberately marked as estimates.

Table 6: Comparison Table

Metric	Proposed	Illustrative ANFIS
Peak conventional/grid power before DSM	≈182 kW	≈182 kW
Peak conventional/grid power after DSM	<100 kW	≈96 kW
Peak reduction	>82 kW	≈86 kW
Peak reduction percentage	>45.1% (minimum implied)	≈47.3%
Peak-management interval	10:00–17:00	10:00–17:00
Maximum ANFIS discharge	Not reported	≈48 kW
Maximum ANFIS charging	Not reported	≈42 kW
Minimum EVCS SoC	Not reported numerically	≈30%
Maximum EVCS SoC	Not reported numerically	≈88%
Grid-energy reduction	Not reported	≈3.5%
Operating-cost reduction	Not reported numerically	≈4.0%

Conclusion

This study investigated Electric Vehicle Charging Stations (EVCS) for demand-side management in photovoltaic-connected microgrids. The reference study demonstrated that coordinated EVCS charging and discharging can reduce peak demand and dependence on conventional generation. The reported results showed a reduction in conventional-source power from approximately 182 kW to below 100 kW. LSTM achieved 99.51% validation efficiency for State of Charge (SoC) estimation.

The proposed extension introduces an Adaptive Neuro-Fuzzy Inference System (ANFIS) as an intelligent supervisory controller for EVCS energy management. Its performance must be validated through MATLAB/Simulink simulations using identical datasets, operating constraints, and evaluation metrics. The proposed approach aims to improve peak-load management while maintaining battery SoC and power limits.

Future Scope

Future research can focus on real-time ANFIS implementation, multi-day simulations, and integration with LSTM forecasting. EVCS placement, sizing, dynamic electricity pricing, battery degradation, and

renewable-energy coordination can also be investigated. Hybrid approaches combining ANFIS with optimization algorithms and model predictive control may further improve energy management. Experimental validation and economic analysis will help establish the practical feasibility, reliability, and effectiveness of the proposed framework.

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