

Artificial Neural Network-Based Adaptive Energy Management System for Solar PV-Powered EV Charging Stations

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Abstract - The increasing penetration of electric vehicles requires charging stations that can coordinate renewable generation, battery storage, grid support, and variable charging demand without compromising DC-link regulation or supply continuity. This paper presents a MATLAB/Simulink model of a solar photovoltaic (PV)-powered EV charging station with standby battery energy storage and a single-phase grid interface. An adaptive neuro-fuzzy inference system (ANFIS) performs maximum power point tracking at the PV converter. At the same time, a five-input artificial neural network (ANN) serves as the supervisory energy-management controller. The ANN uses standby-battery state of charge, PV power, DC-link voltage, standby-battery voltage, and grid current to generate the d-axis grid-current reference. We evaluate two operating scenarios by changing the initial stationary-battery state of charge while applying the same stepwise PV-power reduction. The PV power decreases from approximately 2 kW to 0.2 kW, whereas the 500 V DC link achieves a mean voltage of 499.6284 V and a mean error of 0.0743%. The ANN converges at epoch 878, with a best validation mean squared error of 1.3714×10^{-5} at epoch 872 and an overall regression coefficient of 0.99994. The high-SOC case shows battery discharge and partial grid export, while the low-SOC case shows battery charging and subsequent grid import. In both cases, EV charging is maintained. The results demonstrate the feasibility of combining ANN-based supervisory energy management with ANFIS-based PV tracking for coordinated PV-battery-EV-grid operation.

Key Words: Artificial neural network, adaptive energy management, ANFIS, electric vehicle charging, maximum power point tracking, photovoltaic system, battery energy storage, grid integration.

1. INTRODUCTION

The rapid adoption of electric vehicles (EVs) is changing the electrical characteristics of transportation infrastructure. Charging stations are no longer passive loads; they can become controllable energy hubs that exchange power among photovoltaic (PV) generation, stationary battery energy storage, EV batteries, and the utility grid. Recent studies identify renewable-powered charging, energy storage,

intelligent control, and grid interaction as major research directions for sustainable EV charging infrastructure [1]–[2]. A charging station that incorporates local renewable generation can reduce dependence on grid electricity, but variable solar generation creates a persistent mismatch between available PV power and charging demand.

PV output varies with irradiance and temperature, whereas EV demand depends on vehicle arrival, battery state of charge (SOC), charging limits, and user requirements [1]–[3]. Consequently, a practical PV-powered EV charging station requires coordinated control of multiple power-conversion stages rather than an isolated PV controller. A standby battery can absorb surplus PV energy and compensate for short-term generation deficits. The grid interface can provide additional support when local resources are insufficient and can absorb excess power when generation exceeds local demand. The supervisory controller must therefore recognize the instantaneous operating condition and select an appropriate power-sharing response.

Conventional energy-management strategies can be implemented using deterministic rules, optimization, or classical feedback controllers. These approaches are useful, but the nonlinear interaction among PV generation, storage SOC, converter states, EV demand, and grid exchange makes intelligent supervisory control attractive. ANN-based methods can approximate nonlinear relationships from operating data and generate control references without requiring an explicit analytical representation of every operating condition [4]–[5]. At the PV interface, maximum power point tracking (MPPT) is also essential because the maximum available solar power changes with environmental conditions. Conventional incremental-conductance and perturb-and-observe methods are widely used, while intelligent methods such as ANFIS can learn nonlinear operating relationships [7]–[9].

This study combines these two intelligent-control layers in a common simulation model. ANFIS performs fast PV-side maximum-power tracking, while a five-input ANN acts at the supervisory level and produces the d-axis grid-current reference, Idref. This functional separation is intentional: the ANFIS controller handles local PV extraction, while the ANN

coordinates energy flow among PV generation, the stationary battery, the EV battery, and the grid. The common 500 V DC link electrically couples these subsystems.

The main contributions of the work are: (i) development of a coordinated PV-battery-EV-grid charging-station model in MATLAB/Simulink; (ii) integration of ANFIS-based MPPT with ANN-based supervisory energy management; (iii) use of five measured operating variables SOC of the standby battery, PV power, dc-link voltage, standby-battery voltage, and grid current as ANN inputs; (iv) validation of ANN training using MSE, regression, gradient, damping parameter, and validation checks; and (v) evaluation of high- and low-SOC operating scenarios to demonstrate how storage availability changes grid and battery power-flow decisions.

2. LITERATURE REVIEW AND RESEARCH GAP

EV charging technology has evolved from conventional grid-fed chargers to architectures that combine renewable generation, standby battery storage, bidirectional converters, and intelligent scheduling. A recent review of charging technologies and converter configurations highlights the importance of coordinated interfaces and power-conversion architectures for EV infrastructure [1]. In grid-integrated PV charging stations, the main control challenge is maintaining reliable charging as solar generation and storage conditions vary.

Energy-management strategies for PV-battery charging stations broadly fall into rule-based, optimization-based, and learning-based approaches. Classical strategies can be transparent and easy to implement, but their performance depends on carefully designed operating rules. Optimization approaches can consider multiple objectives, but they may require forecasts, objective functions, and computational resources. Neural-network methods provide a complementary approach by learning nonlinear mappings between measured operating conditions and desired control actions. Recent work has specifically investigated ANN-based energy management for PV-powered EV charging with battery backup and vehicle-to-grid support [4]. Other studies have also examined neural-network-trained energy management and more advanced recurrent architectures [5]–[6].

MPPT is another critical control layer. PV electrical characteristics are nonlinear and depend strongly on irradiance and temperature. ANFIS combines fuzzy inference with neural-network learning and is therefore suitable for approximating nonlinear mappings at the PV interface [8]–[9]. Survey work has also examined ANFIS applications in inverter and power-electronic control [11]. In addition,

recent studies on optimized ANFIS control for EV charging stations demonstrate continued interest in intelligent nonlinear control for renewable-powered charging applications [10].

This paper addresses the research gap of coordinating two distinct intelligent control functions within a single PV-EV charging architecture: ANFIS for local PV maximum-power extraction and ANN for higher-level energy management. The present work further evaluates the effect of standby-battery SOC on the resulting energy-flow pattern using the same PV disturbance sequence. This allows the controller response to be examined not only from the perspective of PV tracking but also from the system level, including battery support, EV charging continuity, grid import/export, and DC-link regulation.

3. SYSTEM ARCHITECTURE AND METHODOLOGY

3.1 System Configuration

The proposed charging station consists of a PV array, a unidirectional PV-side DC-DC boost converter, an ANFIS MPPT controller, a stationary battery connected through a bidirectional DC-DC converter, an EV battery charging interface, a common 500 V DC link, and a single-phase grid-connected inverter with an LCL filter. The DC link serves as the energy hub that coordinates PV generation, standby battery, EV charging demand, and grid exchange.

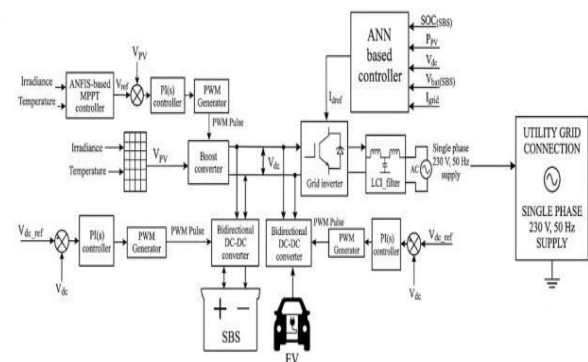


Fig. 1. Proposed PV-powered EV charging station with ANFIS-based MPPT and ANN-based adaptive energy management.

The architecture separates local converter control from supervisory energy management. The PV-side controller adjusts the PV converter operating point to extract available solar power. The standby battery provides short-term buffering: it can charge when surplus PV power is available and discharge when the PV source is insufficient. The grid-

side inverter provides an additional path for power import or export. The ANN receives operating measurements and generates I_{dref} for the grid-side current-control loop.

3.2 Power-Flow Balance

The instantaneous energy balance at the common DC bus is represented by:

$$P_{PV} + P_{Grid} + P_{SB} = P_{EV} + P_{Loss} \quad (1)$$

where P_{PV} is PV power, P_{Grid} is the power exchanged with the utility, P_{SB} is standby-battery power, P_{EV} is EV charging power, and P_{Loss} represents conversion and filter losses. The adopted sign convention defines positive grid power as utility import and negative grid power as export. Therefore, changes in PV production must be compensated by the standby battery, the grid, or a combination of both to keep EV charging demand and DC-link operation within the required range.

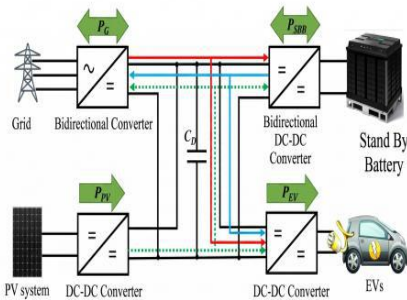


Fig. 2. Power-flow balance and energy exchange among the grid, PV system, stationary battery, DC link, and EV.

3.3 PV Generation and ANFIS-Based MPPT

The PV output power is calculated from measured array voltage and current as:

$$P_{PV} = V_{PV} I_{PV} \quad (2)$$

In the implemented ANFIS controller, irradiance and temperature are used as inputs. The trained nonlinear mapping produces the PV operating reference, which the converter voltage-control and PWM stages then apply. This arrangement reflects the physical dependence of PV characteristics on environmental conditions and avoids treating the MPPT operating point as fixed [8]–[9].

The reported duty-cycle response remains centered around 0.51, with small changes during the imposed irradiance transitions. The controller therefore adapts its converter

command rather than applying a single fixed duty ratio across all operating conditions. The response is consistent with ANFIS's intended role as a nonlinear adaptive controller at the PV interface [11].

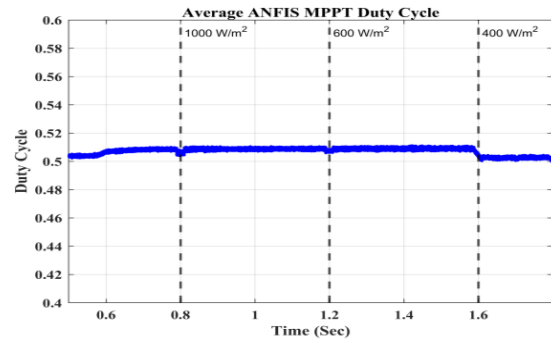


Fig. 3. Average ANFIS MPPT duty cycle under stepwise irradiance conditions.

3.4 Standby-battery and EV Charging Model

The standby battery acts as an energy buffer between PV generation and charging demand. Its normalized SOC is expressed as:

$$SOC(t) = [E_b(t) / E_{b,max}] \times 100\% \quad (3)$$

During discharge, the battery supplies energy to the DC link and its SOC decreases. During charging, power transfer reverses, and the SOC increases. The EV battery is treated as the principal charging load, so its SOC is expected to increase during the simulation. We therefore use two initial stationary-battery SOC conditions to test whether the supervisory EMS changes its energy-flow decision based on storage availability.

3.5 ANN-Based Adaptive Energy Management

The supervisory EMS uses a five-input feedforward ANN to approximate the nonlinear mapping between measured station conditions and the grid-side current-control command. The input vector is:

$$x = [SOC_{SB}, P_{PV}, V_{DC}, V_{SB}, I_{grid}] \quad (4)$$

The hidden-layer transformation and output can be represented as:

$$h = (W1x + b1) \quad (5)$$

$$I_{dref} = (W2h + b2) \quad (6)$$

where x is the input vector, h is the hidden-layer output, I_{dref} is the reference d-axis grid current, W and b are the learned weights and biases, and f and g represent the selected activation functions. The learned parameters are generated during training in MATLAB. The controller is therefore not a fixed rule table; it provides a learned mapping from the charging station's operating state to the grid-side control reference.

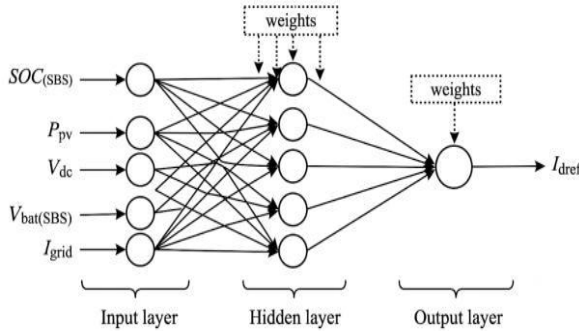


Fig. 4. Five-input ANN structure used for adaptive energy management; the network output is I_{dref} .

3.6 Operating Scenarios and Control Logic

The simulation uses a common PV disturbance sequence in both cases to isolate the effect of standby-battery SOC. In Scenario A, the stationary battery begins at approximately 90% SOC. In Scenario B, the same station begins at approximately 10% SOC. In both cases, PV power is reduced in steps from approximately 2 kW toward 0.2 kW. The supervisory controller responds to the changed energy balance while the EV charging path remains active.

The intended supervisory behavior can be summarized as follows. When PV generation is sufficient, PV power supports the EV load, charges the standby battery, or contributes to grid export. When PV generation falls, a high-SOC stationary battery can discharge, reducing the need for grid import. When the standby battery is at low SOC, it instead charges when energy is available, and the grid becomes increasingly important for maintaining local power balance. This operating logic is not implemented as a simple fixed rule sequence; rather, the ANN learns the control relationship from the training data and produces the grid current reference used by the inverter.

4. ANN TRAINING AND CONTROLLER VALIDATION

The ANN was implemented in MATLAB and trained using the Levenberg-Marquardt algorithm with mean squared error (MSE) as the performance criterion. The available dataset was randomly divided into 70% training, 15%

validation, and 15% testing subsets. Training stopped at epoch 878. The best validation performance was reached at epoch 872, with a validation MSE of 1.3714×10^{-5} . The final reported performance was approximately 1.48×10^{-5} , with a final gradient of 3.76×10^{-4} , damping parameter μ of 1×10^{-8} , and six validation checks at termination.

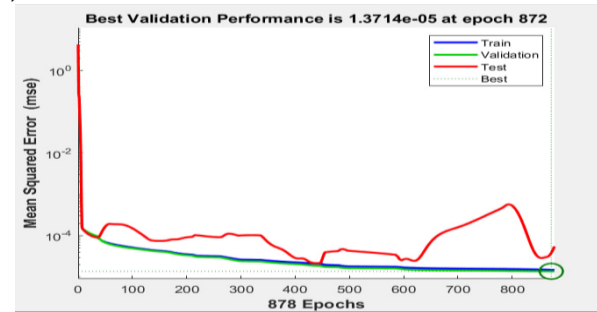


Fig. 5. ANN training, validation, and test performance versus training epoch.

The training curve shows a rapid initial error reduction, followed by convergence to a low-error region. The best validation point occurs before termination, and training ends after the validation stopping criterion is satisfied. This behavior indicates that the network reached a stable, low-error solution without unnecessary training after validation performance stopped improving.

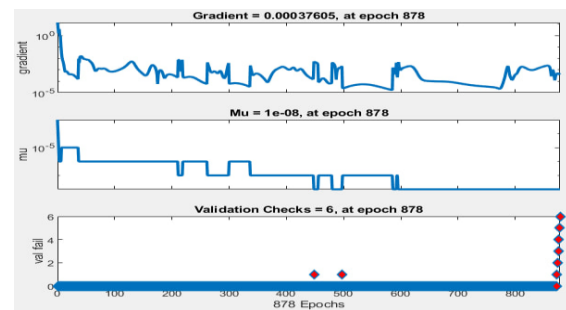


Fig. 6. ANN training state showing gradient, damping parameter μ , and validation checks.

Regression analysis provides an additional measure of the learned mapping. The reported coefficients are 0.99995 for training, 0.99996 for validation, 0.99988 for testing, and 0.99994 for the complete dataset. The data points remain closely distributed around the ideal output-versus-target line, indicating strong agreement between the ANN predictions and the target control values used for supervised learning.

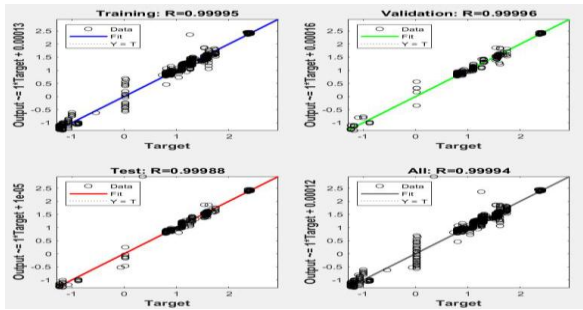


Fig. 7. ANN regression performance for training, validation, test, and combined datasets.

Table 1. ANN training and validation results.

Training quantity	Reported value
Training algorithm	Levenberg–Marquardt
Performance function	Mean squared error (MSE)
Data division	70% / 15% / 15%
Stopping epoch	878
Best validation MSE	1.3714×10^{-5} at epoch 872
Final performance	1.48×10^{-5}
Final gradient	3.76×10^{-4}
Final μ	1×10^{-8}
Validation checks	6
R (training)	0.99995
R (validation)	0.99996
R (test)	0.99988
R (all)	0.99994

5. RESULTS AND DISCUSSION

5.1 Scenario A: High standby-battery SOC

In Scenario A, the standby battery starts at about 90% SOC and decreases to about 85% over the investigated interval. This reduction indicates that the system releases stored energy to support the charging station as PV generation decreases. Under the adopted grid-power sign convention, negative grid power indicates export, and the reported operating sequence shows an export interval of approximately 0.2 kW–0.4 kW. At the same time, the EV battery SOC increases, confirming that charging continues while the EMS coordinates PV generation, storage, and grid exchange.

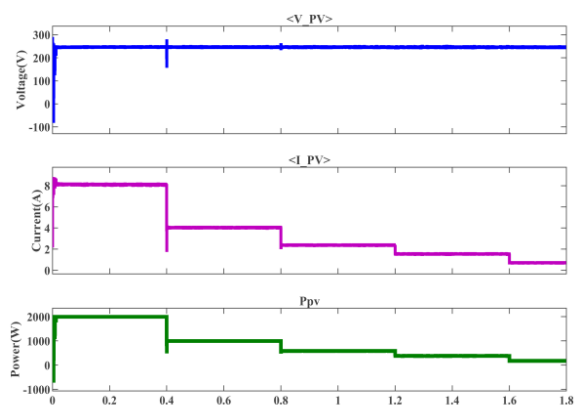


Fig. 8. Scenario A: PV voltage, current, and power response under varying irradiance.

After the initial transient, the PV voltage remains close to its operating level, while the PV current decreases in steps. As a result, PV power decreases from about 2 kW to 1 kW, 0.6 kW, 0.4 kW, and finally around 0.2 kW. This controlled stepwise reduction provides a clear disturbance for assessing both the ANFIS MPPT behavior and the higher-level EMS response.

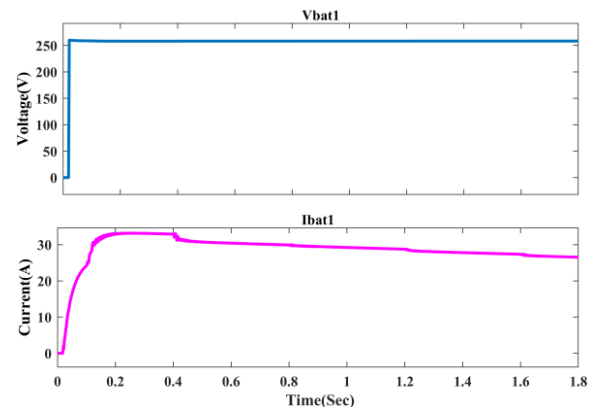


Fig. 9. Scenario A: standby-battery voltage and current response.

The standby-battery voltage quickly settles near 250 V and remains comparatively stable. Its current changes as the PV operating condition changes, showing that the bidirectional converter modifies the battery contribution rather than maintaining a fixed-current operating mode. The EV-battery voltage also settles close to 250 V, while the charging current moves from its initial transient toward a relatively stable operating region.

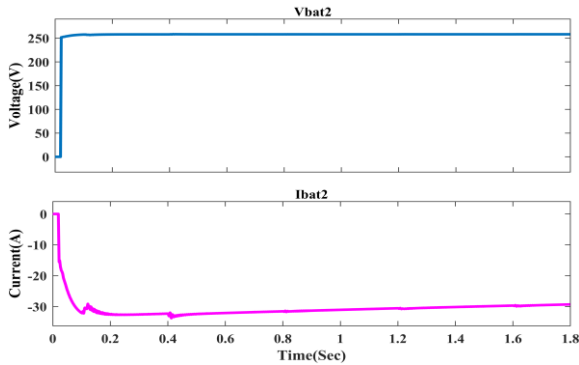


Fig. 10. Scenario A: EV-battery voltage and current response.

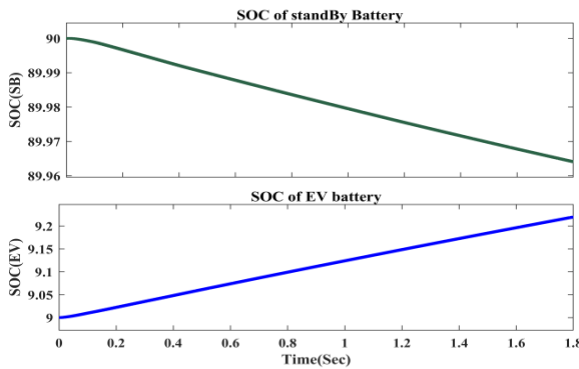


Fig. 11. Scenario A: standby-battery and EV-battery SOC response.

The SOC waveforms directly show the energy-flow direction. The standby battery decreases from approximately 90% toward 85%, while the EV battery SOC increases. Thus, when solar generation falls short, the high-SOC standby battery contributes stored energy while the EV continues to receive charging power.

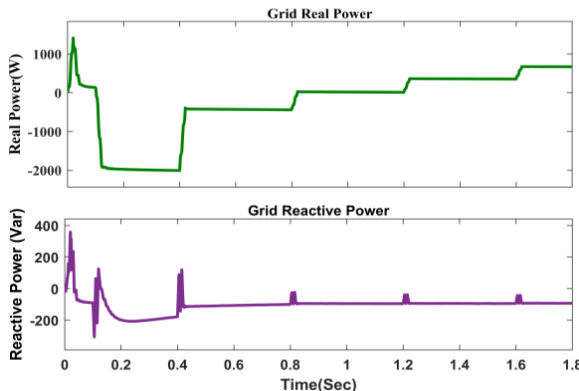


Fig. 12. Scenario A: grid active and reactive power response.

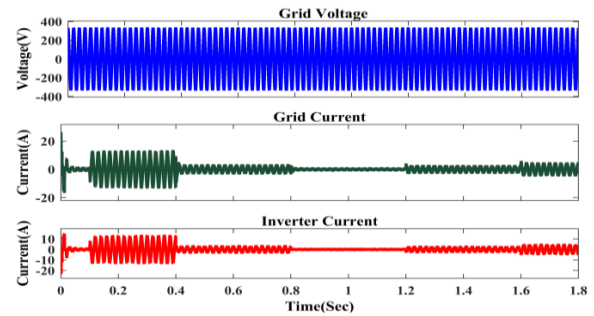


Fig. 13. Scenario A: grid voltage, grid current, and inverter current.

The grid-side response changes with the PV operating transitions. The real-power waveform moves through several levels corresponding to the changing local power balance. In contrast, reactive power shows a short initial transient and smaller disturbances at transition instants, as in Fig. 12 above.

The grid voltage remains periodic, and the grid and inverter currents change amplitude as the required power transfer changes. These responses indicate coordinated grid-interface operation during the imposed PV disturbances, as in Fig. 13 above.

5.2 Scenario B: Low Stationary-Battery SOC

Scenario B uses the same PV operating sequence but begins with a standby-battery SOC of approximately 10%. This case isolates the effect of limited storage availability.

After the initial transient, the PV voltage remains near its operating level, while PV current and power decrease in steps as irradiance declines. Because the standby battery starts at low SOC, the energy-management response differs from Scenario A: the battery SOC increases. At the same time, the grid supplies more power as local generation falls short.

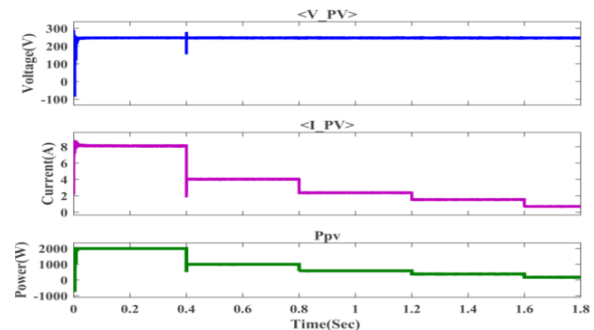


Fig. 14. Scenario B: PV voltage, current, and power response.

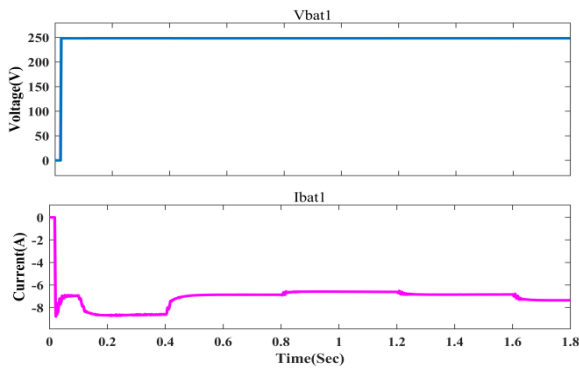


Fig. 15. Scenario B: stationary-battery voltage and current response.

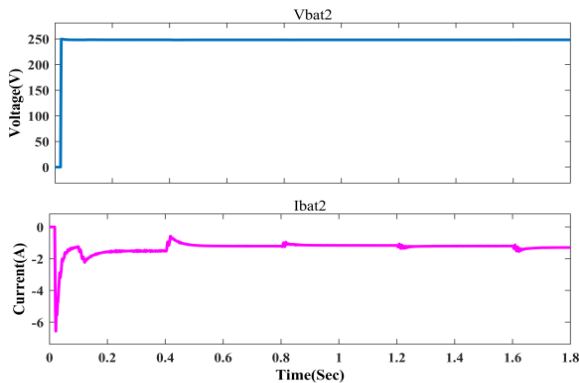


Fig. 16. Scenario B: EV-battery voltage and current response.

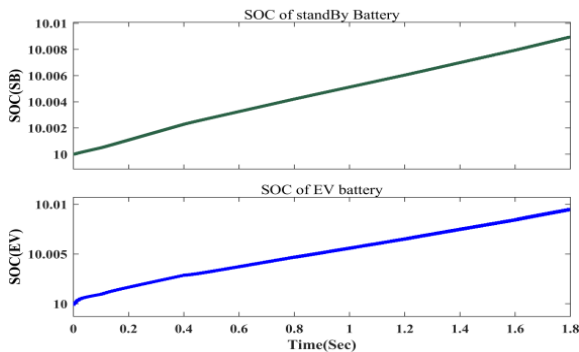


Fig. 17. Scenario B: standby-battery and EV-battery SOC response.

The standby-battery SOC starts near 10% and increases, while the EV-battery SOC also rises from about 9%. The simultaneous increase indicates that the low-SOC operating condition directs available energy toward storage while maintaining EV charging. The result demonstrates why standby-battery SOC is an important supervisory input: the

same PV disturbance does not produce the same power-sharing decision when storage availability changes.

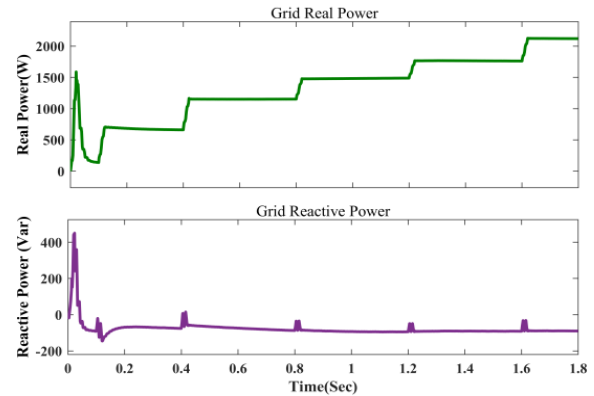


Fig. 18. Scenario B: grid real and reactive power responses.

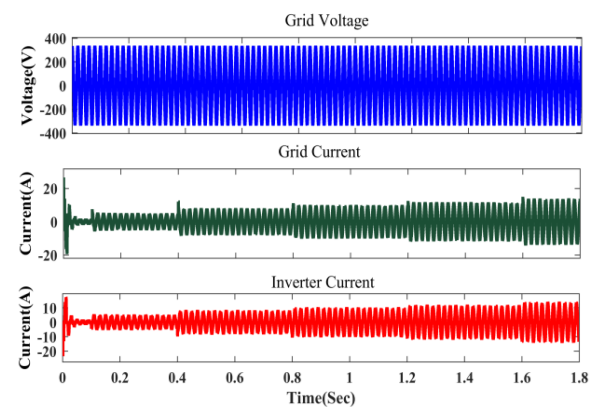


Fig. 19. Scenario B: grid voltage, grid current, and inverter current responses.

The grid real-power response moves through a pronounced negative-power interval, then near zero, and finally positive power. With the adopted sign convention, this corresponds to a transition from grid export toward grid import as the local PV and battery balance changes. Reactive power contains transient excursions at operating transitions before settling close to its operating level. The periodic grid voltage and changing current amplitude show that the grid interface remains active while the station passes through the imposed PV transitions.

5.3 Quantitative Comparison of the Operating Scenarios

Table 2. Comparative performance of the investigated operating scenarios.

Parameter	Scenario A: High SOC	Scenario B: Low SOC
Initial stationary-battery SOC	≈90%	≈10%
PV power variation	2.0 → 0.2 kW	2.0 → 0.2 kW
Stationary-battery behavior	Discharging	Charging
Stationary-battery SOC	≈90% → 85%	≈10% → higher SOC
EV-battery SOC	Increases	Increases
Grid power	Export during part of interval	Export → near zero → import
EV charging	Maintained	Maintained
DC-link behavior	Stable around reference	Stable around reference

The comparison shows that initial standby-battery SOC changes the direction of stationary-battery energy exchange and the corresponding grid contribution. In Scenario A, stored energy supports the station, allowing the battery SOC to fall while grid export occurs for part of the sequence. In Scenario B, the battery begins with limited stored energy and its SOC increases, while the grid transitions toward import as PV power becomes insufficient. The EV battery SOC increases in both scenarios, indicating that the charging objective is maintained.

5.4 ANN Controller Verification

To verify the trained network's transfer into the dynamic Simulink model, we compared the ANN output produced in Simulink with the MATLAB ANN prediction. The two traces closely overlap across the step changes in the control reference, with only small differences around switching and transition instants. This comparison verifies that the trained ANN mapping was transferred consistently into the simulated controller implementation.

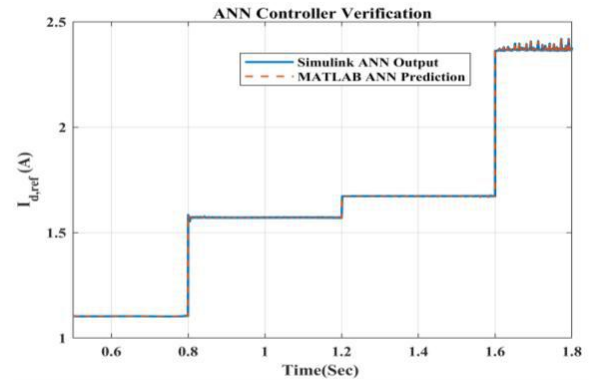


Fig. 20. ANN controller verification: Simulink output versus MATLAB ANN prediction.

5.5 DC-Link Voltage and Grid-Side Dynamic Response

The DC-link waveform provides the clearest system-level measure of coordinated converter operation. The mean voltage is 499.6284 V against the 500-V reference, giving a mean error of 0.3716 V or 0.0743%. The maximum and minimum values are 514.2536 V and 485.0219 V, respectively, giving a maximum absolute deviation of 14.9781 V (2.9956%). The small mean error together with bounded transient excursions indicates that the DC bus remains close to its reference. At the same time, the PV, battery, EV, and grid-side converters change operating conditions.

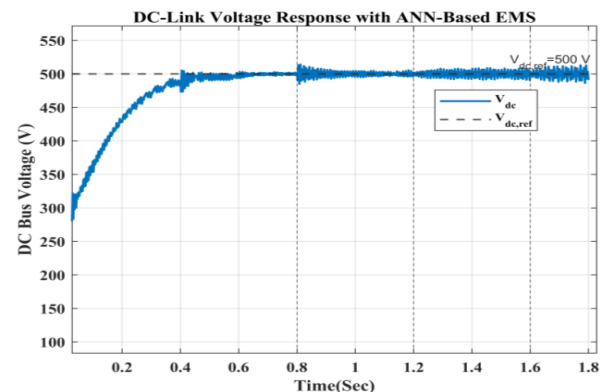


Fig. 21. Quantitative DC-link voltage response of the integrated charging station.

6. DISCUSSION

The simulation results indicate that the proposed two-layer intelligent control structure performs two complementary functions. First, the ANFIS controller adapts the PV converter command to changes in irradiance and temperature, allowing the PV source to operate near its available power

point. Second, the ANN supervisory controller uses the measured station state to determine the grid-side current reference. The two layers therefore address different time scales and control objectives: local PV extraction and system-level power coordination.

The scenario comparison also demonstrates the importance of including stationary-battery SOC as an ANN input. When the battery starts near 90% SOC, it can discharge as PV generation falls. When it starts near 10% SOC, it instead charges, and the grid provides increasing support. The controller consequently responds not only to PV power but also to storage availability.

The DC-link result further supports the integrated system's coordinated operation. A mean voltage error of 0.0743% is small relative to the 500 V reference, although the transient range shows the system is not perfectly disturbance-free. The present study focuses on the demonstrated MATLAB/Simulink response and does not claim experimental validation, long-term battery aging analysis, or a complete power-quality assessment.

7. LIMITATIONS AND FUTURE WORK

The present work is limited to MATLAB/Simulink simulation. Experimental implementation and hardware-in-the-loop validation are therefore required before practical deployment. Future work should include real-time controller execution analysis, systematic comparison with conventional MPPT and EMS methods, battery aging and thermal considerations, a wider range of EV charging profiles, and detailed assessment of power quality and grid-code requirements. Further studies can also investigate larger and more diverse training datasets, online adaptation, forecast-based supervisory control, and the interaction of the charging station with multiple EVs and multiple storage units.

8. CONCLUSION

This paper presents a MATLAB/Simulink implementation of a neural network-based adaptive energy management system for a solar PV-powered EV charging station with stationary battery storage that connects to the grid. ANFIS was used at the PV interface to perform MPPT. A five-input ANN was trained to act as the controller and to produce the d-axis grid current reference. The ANN inputs were stationary-battery SOC, PV power, dc-link voltage, stationary-battery voltage, and grid current.

The PV operating sequence lowered the power from about 2 kW to 0.2 kW. Even with these changes, the 500 V DC link

stayed close to the target with a mean value of 499.6284 V and a mean error of only 0.0743 %. The ANN reached a validation mean squared error of 1.3714×10^{-5} at epoch 872 and stopped training at epoch 878. The regression coefficients were 0.99995 for training, 0.99996 for validation, 0.99988 for testing and 0.99994 for all data combined. A comparison between MATLAB and Simulink also showed that the network prediction matched the implemented controller output well.

The two operating scenarios created energy flow patterns. In the scenario when the stationary battery was at a high SOC, the battery discharged from about 90 % to 85%, and the station exported power to the grid during part of the sequence. In the scenario where the stationary battery was at a low SOC, the battery SOC rose from about 10 %, and the station had to import power from the grid as PV power fell. In both cases the EV battery SOC. The EV charging continued. Overall, these results show that ANFIS-based PV tracking and ANN-based energy management can coordinate PV, battery, EV, and grid operation under the simulated conditions.

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