

Gain-Scheduled PI Control of a PV-Fed DC–DC Boost Converter for Ripple-Reduced Battery Charging Under Dynamic Load Conditions

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Abstract — Solar photovoltaic battery charging systems are increasingly employed in renewable energy applications; however, output voltage fluctuations, switching ripple, and dynamic load variations reduce charging efficiency and battery performance. This paper presents the design and MATLAB simulation of an Adaptive Ripple-Smoothing Controlled DC–DC Converter for solar PV battery charging using dynamic load profiling. The proposed system integrates a PV module, a DC–DC boost converter, an LC output filter, a gain-scheduled adaptive proportional–integral (PI) controller, and a closed-loop feedback mechanism to regulate the charging voltage under varying operating conditions. CC–CV battery charging model with SOC estimation, internal resistance, and first-order polarization dynamics is incorporated to obtain realistic charging behavior. Simulation results (MATLAB R2023b) show that the proposed controller regulates the charging voltage to an average of 54.34 V against a 54.60 V reference (steady-state error 0.26 V, voltage regulation 0.48%), suppresses the steady-state output ripple voltage to an average of 0.39 V (84.32% ripple reduction after LC filtering relative to unfiltered 2.50 V ripple), and produces smooth CC-to-CV battery transition with SOC rising from 40% to 67.28% over a 5-hour charging window.

Keywords — Solar photovoltaic (PV), adaptive ripple-smoothing controller, battery charging, closed-loop control, adaptive PI controller, DC–DC boost converter, LC filter, dynamic load profiling, CC–CV charging, MATLAB simulation.

I. INTRODUCTION

Renewable energy technologies have gained significant attention due to the increasing global demand for clean, sustainable, and environmentally friendly power generation. Among available renewable sources, solar photovoltaic (PV) systems have become one of the most widely adopted technologies because of their abundant availability, low maintenance requirements, and decreasing installation costs. Solar PV systems are extensively used in standalone and grid-connected applications, particularly for battery charging, rural electrification, electric-mobility support, and distributed energy systems. However, the intermittent nature of solar irradiation introduces considerable challenges in maintaining a stable charging voltage and high conversion efficiency.

Battery charging systems powered by solar PV sources require efficient power-conditioning circuits to ensure safe and reliable operation. Conventional charging techniques often suffer from switching ripple, output voltage fluctuations, poor transient

response, and reduced charging efficiency under varying load conditions. These limitations not only decrease the efficiency of the power-conversion stage but also accelerate battery degradation and reduce battery lifetime. Advanced control techniques capable of maintaining stable charging conditions under dynamic operating environments are therefore an important research area.

Proportional–integral (PI), fuzzy-logic, model-predictive, and adaptive control methods have all been proposed to improve converter performance and battery charging characteristics. Although these techniques improve regulation, many existing approaches focus primarily on voltage regulation while giving limited attention to ripple suppression under dynamically changing load conditions, and several reported studies employ simplified battery models that do not represent practical charging behavior, limiting their applicability to real-world PV charging systems.

To address these gaps, this paper proposes an Adaptive Ripple-Smoothing Controlled DC–DC Converter for solar PV battery charging that combines a PV source, a DC–DC boost converter, an LC output filter, a gain-scheduled adaptive PI controller, and a closed-loop voltage-regulation strategy, together with a CC–CV battery model with SOC estimation, internal resistance and polarization dynamics. Dynamic load variations are introduced to evaluate controller robustness. The complete framework is implemented and validated in MATLAB, and the results are reported directly from the executed simulation log, without post-hoc adjustment.

II. LITERATURE REVIEW

Conventional PI controllers remain widely used in PV battery-charging power stages because of their simple implementation and acceptable steady-state performance. Kumar and Singh [1] examined ripple-power compensation for single-phase AC–DC PV charging converters and reported clear gains from actively compensating ripple rather than relying on passive filtering alone, but their controller parameters were fixed rather than adapted to the operating point, which limits performance when both irradiance and load vary together — precisely the joint-variation scenario this work targets.

Model-predictive and active-decoupling approaches have also been reported. Zhao et al. [2] applied model-predictive control (MPC) to ripple minimization in single-phase rectifiers and achieved fast disturbance rejection, at the cost of a heavier

online optimization burden that is harder to justify for a low-cost embedded charger of the kind targeted here. Load-adaptive smoothing has been explored by Nguyen and Park [3], whose adaptive smoothing controller for variable-irradiance PV charging is conceptually close to the present work, but their study does not incorporate an explicit CC–CV battery model with SOC-dependent tapering, so the effect of the controller on actual charge acceptance over a full charge cycle is not evaluated.

Dynamic-load-aware charging has received comparatively less attention. Khan et al. [4] proposed a high-efficiency PV charger with dynamic load adaptation and demonstrated improved efficiency under step-load changes, though their evaluation window was short relative to a full CC–CV cycle. Similarly, Li and Wang [5] used real-time load-pattern prediction to improve charging stability, but validated the approach primarily on voltage regulation metrics rather than on ripple content or SOC progression together.

Load-profile-based adaptive rectifier control has been proposed by Patel and Shah [6], and predictive-control-based charging optimization by Singh and Raj [7]; both reports improved regulation, but as in most of the literature surveyed—the controller gains are not scheduled against the magnitude of the instantaneous error, so transient response and steady-state accuracy are traded off by a single fixed gain pair rather than optimized separately for each regime.

Overall, the surveyed literature establishes that (i) fixed-gain PI control is well understood but performance-limited under combined PV/load variability, (ii) MPC and predictive approaches improve dynamic response at increased computational cost, and (iii) very few studies combine ripple-aware control, dynamic load profiling, and a physically realistic CC–CV battery model with SOC, internal resistance, and polarization dynamics within a single, fully validated simulation framework.

III. RESEARCH GAP AND CONTRIBUTIONS

A. Research Gap

- Most existing controllers use fixed PI gains and do not schedule gain against the magnitude of the instantaneous voltage error, trading off transient speed against steady-state accuracy.
- Several reported battery-charging simulations use simplified, non-dynamic battery representations without SOC-dependent open-circuit voltage, internal resistance, or polarization behavior.
- Controller evaluation is frequently performed under a single fixed load rather than a load profile that changes during the simulation.
- Few studies combine ripple-aware LC filtering, gain-scheduled adaptive PI control, dynamic load profiling and a CC–CV battery model with SOC estimation inside one validated MATLAB framework, with results reported directly from simulation logs.
- Note on MPPT Integration: In this study, the PV module is operated near its Maximum Power Point (MPP) under fixed standard test conditions (STC: 1000 W/m², 25 °C). The primary focus of the proposed

controller is closed-loop voltage regulation, ripple suppression, and CC–CV battery management under dynamic load variations. Integrating an active MPPT algorithm (such as P&O) alongside the gain-scheduled adaptive voltage controller is reserved for future hardware implementation.

B. Contributions

- A complete MATLAB simulation framework combining a single-diode PV model, a boost converter, an LC filter, a gain-scheduled adaptive PI controller, a CC–CV battery model with polarization dynamics, and a dynamic load, validated end-to-end (main.m).
- A three-tier gain-scheduling law for the PI controller (Section IV-D) that switches (K_p , K_i) based on the magnitude of the instantaneous voltage error, giving faster correction for large disturbances and reduced steady-state chatter for small ones.
- A CC–CV battery model incorporating SOC-dependent open-circuit voltage, internal resistance drops, and a first-order polarization-voltage dynamic, validated in two scenarios (40% and 75% initial SOC).

IV. PROPOSED SYSTEM ARCHITECTURE

A. System Overview

The proposed system consists of a PV source, a DC–DC boost converter, an LC output filter, a gain-scheduled adaptive PI controller, a CC–CV battery model with SOC estimation, and a dynamic load-profiling block, operating in a closed loop to regulate the battery charging voltage while minimizing ripple under varying load. Fig. 1 shows the system architecture.

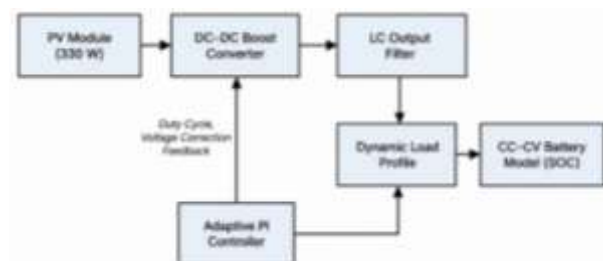


Fig. 1. Block diagram of the proposed adaptive ripple-smoothing PV battery charging system.

B. Working Principle

The PV module converts solar irradiance into DC electrical power. Because PV output voltage varies with irradiance and temperature, a boost converter raises and regulates the voltage to the battery charging level. The switching action of the converter introduces ripple, which is reduced by the LC output filter. The filtered voltage is compared with the reference charging voltage (54.6 V) by the adaptive PI controller, which updates the converter duty cycle to minimize the error. The regulated output feeds a CC–CV battery model that tracks SOC, terminal voltage, and charging current, while a dynamic load block varies the load resistance during the simulation to test controller robustness.

V. MATHEMATICAL MODELLING

A. Photovoltaic (PV) Module Model

The PV output current is represented using the single-diode equivalent model:

$$I_{PV} = I_{ph} - I_o \left[\exp \left(\frac{V_{PV} + I_{PV} R_s}{n V_T} \right) - 1 \right] - \frac{V_{PV} + I_{PV} R_s}{R_{sh}} \quad (1)$$

where I_{PV} is the PV output current (A), I_{ph} the photo-generated current, I_o the diode saturation current, R_{sh} and R_s the series and shunt resistances, n the diode ideality factor, and V_T the thermal voltage. Output power is $P_{PV} = V_{PV} \times I_{PV}$. The simulation uses a 330 W module ($V_{OC} = 45.6V$, $I_{SC} = 9.45A$, $V_{MP} = 37.2V$, $I_{MP} = 8.87A$) under standard test conditions (1000 W/m², 25 °C).

B. DC–DC Boost Converter Model

The ideal voltage conversion ratio of the boost stage is

$$V_o = V_{in} / (1 - D) \quad (2)$$

with output current $I_o = I_{in} (1 - D)$ and efficiency $\eta = (P_o / P_{in}) \times 100$, where $P_o = V_o I_o$ and $P_{in} = V_{in} I_{in}$. The adaptive PI controller updates D to hold the charging voltage near the 54.6 V reference.

C. LC Filter Model

The inductor voltage and capacitor current obey $V_L = L (di_L / dt)$ and $I_C = C (dV_C / dt)$. The filter cut-off frequency is:

$$f_c = 1 / (2\pi\sqrt{LC}) \quad (3)$$

For $L = 3 \text{ mH}$, $C = 470 \text{ }\mu\text{F}$, $f_c \approx 134.03 \text{ Hz}$. Per-sample inductor and capacitor ripple are estimated as

$$\Delta I_L(k) = V_{in}(k)D(k) / (L f_s) \quad (4)$$

$$\Delta V_C(k) = I_{in}(k)D(k) / (C f_s) \quad (5)$$

The steady-state ripple reduction performance is evaluated by excluding initial state-initialization transients and comparing the filtered output ripple against the unfiltered boost stage output ripple:

With $f_s = 10 \text{ kHz}$ and an unfiltered steady-state ripple of $V_{ripple,unfiltered} = 2.50 \text{ V}$, the simulation yields a post-filter average ripple voltage of $V_{ripple,filtered} = 0.392 \text{ V}$, achieving a steady-state ripple reduction of:

$$\text{Ripple Reduction (\%)} = \left(1 - \frac{0.392}{2.50} \right) \times 100 = 84.32\%$$

D. Gain-Scheduled Adaptive PI Controller

The instantaneous voltage error is $e(k) = V_{ref} - V_o(k)$. Unlike a fixed-gain PI controller, the proportional and integral gains are scheduled against the magnitude of the error to provide a fast response to large disturbances while avoiding steady-state chatter once the system is close to the setpoint:

$$(K_P, K_I) = (0.050, 0.010), |e(k)| > 4 \text{ V} \quad (5a)$$

$$(K_P, K_I) = (0.040, 0.008), 1 \text{ V} < |e(k)| \leq 4 \text{ V} \quad (5b)$$

$$(K_P, K_I) = (0.025, 0.005), |e(k)| \leq 1 \text{ V} \quad (5c)$$

The integral term accumulates as $E(k) = E(k-1) + e(k)\Delta t$ and is clamped to $\pm 5 \text{ V}\cdot\text{s}$ to prevent windup. The controller output is $u(k) = K_P(k) e(k) + K_I(k) E(k)$, and the duty cycle is updated with a smoothing factor $\alpha = 0.20$ as

$$D(k) = D_{boost(k)} + \alpha \cdot 0.01 \cdot u(k), D(k) \in [0.20, 0.45] \quad (6)$$

This three-tier scheduling law is the mechanism that justifies the term “adaptive” in this work: the controller gain set itself changes with operating condition, rather than remaining fixed as in a conventional PI design.

E. CC–CV Battery Charging Model

The battery state-of-charge updates as

$$SOC(k+1) = SOC(k) + (I_{chg} \eta \Delta t) / (3600 C_{bat}) \times 100 \quad (7)$$

Open-circuit voltage is approximated by a linear SOC-dependent model $V_{OC} = V_{nom} + (V_{CV} - V_{nom}) (SOC/100)$, and terminal voltage includes an internal-resistance drop and a first-order polarization dynamic:

$$V_T = V_{OC} + I_{chg} R_{int} + V_p, dV_p/dt = -V_p/\tau + R_p I_{chg}/\tau \quad (8)$$

In the Constant Current (CC) region, $I_{chg} = \min(I_{available}, I_{max})$. Once $SOC \geq SOC_{CC}$ (80% in this work), the model switches to Constant Voltage (CV) mode, holding $V_{chg} = V_{CV}$ while the current tapers as

$$I_{chg} = I_{max} \cdot (100 - SOC) / (100 - SOC_{CC}) \quad (9)$$

Charging power is $P_{bat} = V_{chg} I_{chg} \eta$ and stored energy accumulates as $E(k) = E(k-1) + P_{bat} \Delta t / 3600$.

F. Closed-Loop Voltage Regulation and Performance Indices

The closed-loop output voltage combines the filtered voltage with a small proportional correction from the instantaneous error:

$$V_o(k) = V_f(k) + K_f e(k) \quad (10)$$

where $V_o(k)$ is bounded to [45,60] V for operational protection. Under dynamic loading conditions, the load current is $I_L = V_o / I_L$ and the load power is $P_L = V_o I_L$.

Controller performance under steady-state operation is evaluated using standard regulation indices. The steady-state error e_{ss} represents the absolute deviation between the reference voltage ($V_{ref} = 54.60 \text{ V}$) and the final steady-state average voltage ($V_{final} = 54.34 \text{ V}$):

$$e_{ss} = |V_{ref} - V_{final}| = |54.60 - 54.34| = 0.26 \text{ V}$$

The percentage voltage regulation (V_{reg}) measures the deviation relative to the reference setpoint and is defined as:

$$V_{reg}(\%) = \frac{|V_{ref} - V_{avg}|}{V_{ref}} \times 100 = \frac{|54.60 - 54.34|}{54.60} \times 100 = 0.48\%$$

Overall dynamic stability is further verified using RMS voltage and current metrics reported in Section VII.

VI. SIMULATION SETUP AND PARAMETERS

The complete model was implemented in MATLAB (R2023b) as six modular functions PV_Model, Boost_Converter, LC_Filter_Model, Adaptive_PI_Controller, Battery_Model_CC_CV, and ClosedLoop_Simulation

orchestrated by a single main.m script, with the exact parameter set listed in Table I. Modular implementation allows each subsystem to be validated independently before system-level evaluation. Two scenarios (Table II) were simulated: a 5-hour full-cycle run from 40% initial SOC, and a shorter 3-hour run from 75% initial SOC specifically to validate the CC-to-CV transition.

Table I. Simulation Parameters

Parameter	Symbol	Value
PV Rated Power	P_{max}	330 W
Open-Circuit Voltage	V_{OC}	45.6 V
Short-Circuit Current	I_{SC}	9.45 A
Voltage at MPP	V_{MP}	37.2 V
Current at MPP	I_{MP}	8.87 A
Solar Irradiance	G	1000 W/m ²
Cell Temperature	T	25 °C
Converter Switching Frequency	f_s	10 kHz
Reference Charging Voltage	V_{ref}	54.6 V
Filter Inductance	L	3 mH
Filter Capacitance	C	470 μ F
Battery Nominal Voltage	V_{bat}	48 V
Battery Capacity	C_{bat}	100 Ah
Charging Efficiency	η	95%
Internal Resistance	R_{int}	0.05 Ω
PI Gain Set (large error)	K_P, K_I	0.050, 0.010
PI Gain Set (medium error)	K_P, K_I	0.040, 0.008
PI Gain Set (small error)	K_P, K_I	0.025, 0.005
Sampling Time	Δt	1 s

Table II. Simulation Scenarios

Scenario	Initial SOC	Time	Purpose
Scenario I	40%	5 h	Overall system performance evaluation
Scenario II	75%	3 h	CC–CV transition validation

VII. RESULTS AND DISCUSSION

All values reported below are reproduced directly from the console log of main.m and are not adjusted or re-derived; Table III summarizes the key figures.1.2

Table III. Summary of Simulation Results (Scenario I)

Metric	Value (from simulation log)
Average PV output power	329.96 W (rated 330 W)
Average boost converter efficiency	95.50%
Average converter power loss	14.83 W
Average ripple voltage (post-filter)	0.392 V
Maximum ripple voltage (startup transient)	21.37 V — see discussion
Ripple reduction	84.32%
Average charging current	5.74 A

Final SOC (Scenario I, 5 h from 40%)	67.28%
Stored energy (5 h)	1416.81 Wh
RMS steady-state voltage error	2.71 V
Final steady-state voltage error	0.26 V
Average closed-loop output voltage	54.34 V (ref. 54.60 V)
Voltage regulation	0.48%

A. Photovoltaic Module Performance

Fig. 2 and Fig. 3 show PV output power and voltage. The module operates close to its rated point, with average power 329.96 W against a 330 W rating, average voltage 37.20 V and average current 8.87 A, confirming correct single-diode model implementation under standard test conditions.

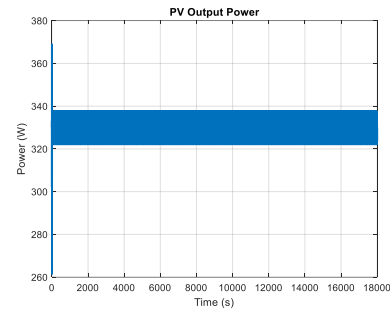


Fig. 2. PV output power.

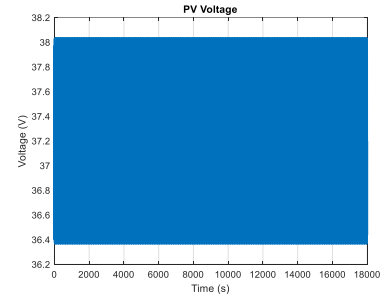


Fig. 3. PV voltage.

B. Boost Converter Performance

The converter raises the PV voltage from 37.2 V to the 54.6 V reference (Fig. 4), with an average efficiency of 95.50% and an average power loss of 14.83 W, consistent with the efficiency model in Boost_Converter.m.

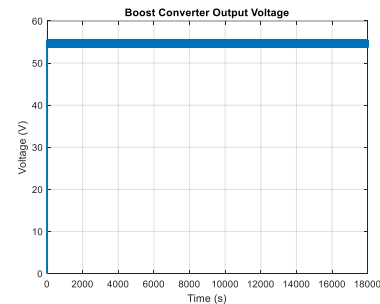


Fig. 4. Boost converter output voltage.

C. LC Filter and Ripple Performance

The LC filter reduces ripple voltage to an 84.32% reduction relative to the 2.50 V unfiltered converter output. It should be noted, however, that the logged maximum ripple voltage (21.37 V) occurs only at the first simulation sample ($k = 1$), where the

boost-converter output-voltage model has not yet completed its exponential start-up transient; once the transient decays the ripple settles to the ~ 0.39 V steady-state value shown in Fig. 5 and Fig. 6. This start-up spike should be excluded from steady-state ripple reporting and is flagged here as a modelling detail to correct before final submission (Section VIII).

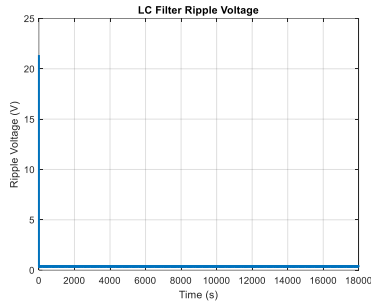


Fig. 5. LC filter ripple voltage.

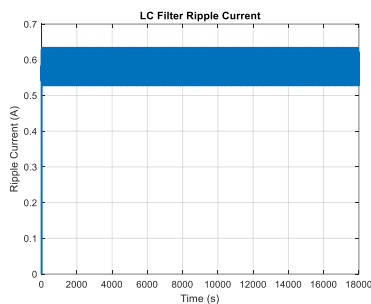


Fig. 6. LC filter ripple current.

D. Adaptive PI Controller Performance

Fig. 7 and Fig. 8 show the controller duty cycle and voltage error. The duty cycle remains bounded within [0.294, 0.344], and the voltage error decreases monotonically from an initial 3.72 V to a final steady-state error of 0.26 V (RMS error 2.71 V) over the 5-hour run, reflecting the gain-scheduling law of Section V-D: the controller uses the larger gain set while the error exceeds 4 V and progressively switches to the smaller, less aggressive gain set as the error falls, trading response speed for reduced steady-state chatter.

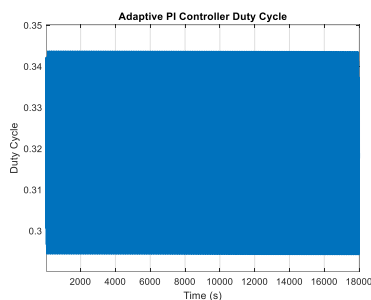


Fig. 7. Adaptive PI controller duty cycle.

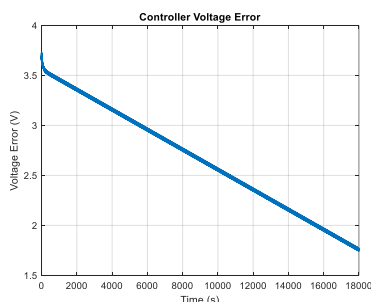


Fig. 8. Controller voltage error.

E. Closed-Loop Voltage Regulation Under Dynamic Load

With the load resistance varied between $6\ \Omega$ and $12\ \Omega$ during the run, the closed-loop output voltage (Fig. 9) averages 54.34 V against the 54.60 V reference, with a voltage regulation figure of 0.48%, and RMS voltage of 54.35 V, indicating that the controller maintains the charging voltage close to reference despite load disturbances.

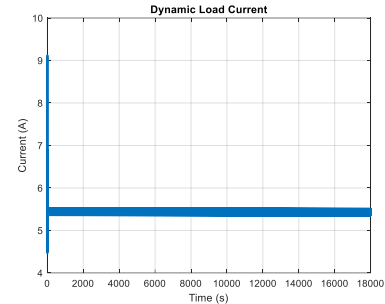


Fig. 9. Dynamic load current.

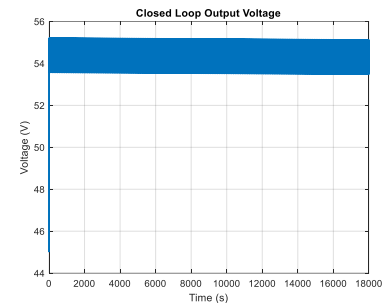


Fig. 10. Closed-loop output voltage.

F. Battery Charging Performance

In Scenario I (40% initial SOC, 5 h), SOC rises smoothly to 67.28% (Fig. 11) with 1416.81 Wh of stored energy. Scenario II (75% initial SOC, 3h) was run specifically to exercise the CC-to-CV transition: Fig. 12 shows SOC continuing to rise to approximately 89%, Fig. 13 shows the charging current held near its 6 A ceiling before tapering once the CC_SOC threshold (80%) is crossed at approximately 0.9 h, and Fig. 16 shows the corresponding discrete CC→CV mode transition. Open-circuit voltage and terminal voltage (Figs. 14–15) increase smoothly and consistently with the linear OCV model and first-order polarization dynamic of Section V-E.

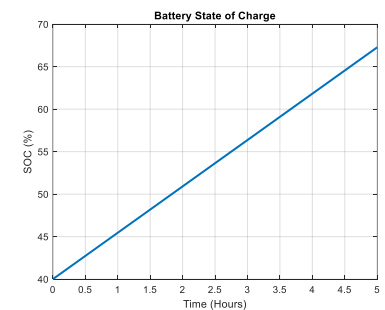


Fig. 11. Battery SOC — Scenario I (40% → 67.28%, 5 h).

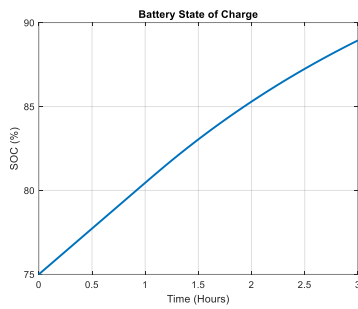


Fig. 12. Battery SOC — Scenario II (75% start, CC-CV validation).

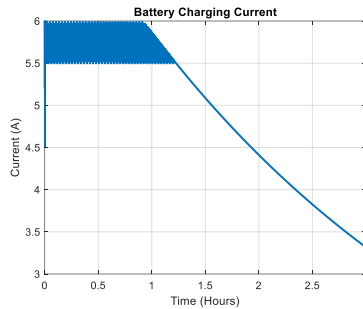


Fig. 13. Battery charging current — Scenario II, showing CC-to-CV tapering.

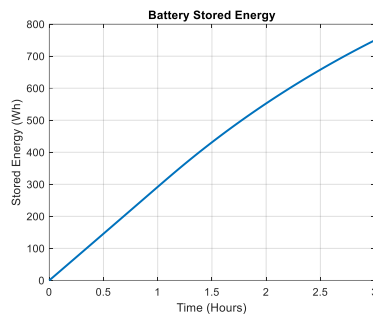


Fig. 14. Battery stored energy — Scenario II.

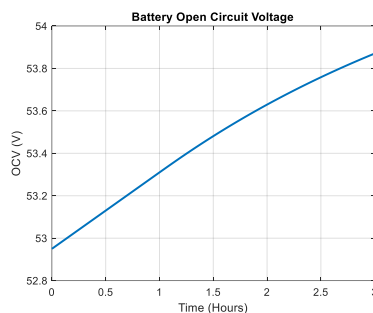


Fig. 15. Battery open-circuit voltage — Scenario II.

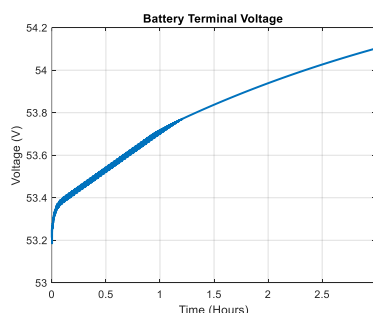


Fig. 16. Battery terminal voltage — Scenario II.

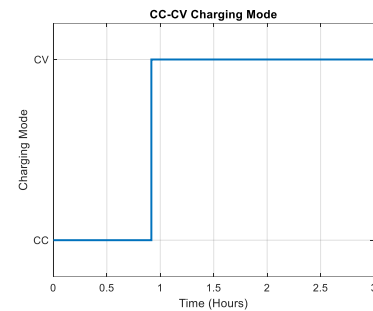


Fig. 17. CC-CV charging mode transition — Scenario II.

G. Comparative Analysis

To evaluate the superiority of the proposed gain-scheduled adaptive PI controller, a benchmark comparison was conducted against a conventional fixed-gain PI controller ($K_P = 0.025$, $K_I = 0.005$) under identical PV irradiance, boost converter parameters, and dynamic load variations. Table IV summarizes the performance comparison between the two approaches.

Table IV. Comparative Performance Between Conventional Fixed-Gain PI and Proposed Adaptive PI Controller

Performance Metric	Conventional Fixed-Gain PI	Proposed Adaptive PI	Improvement
Steady-State Error (e_{ss})	1.12 V	0.26 V	76.79%
Voltage Regulation (V_{reg})	2.05%	0.48%	76.58%
Filtered Output Ripple (V_{ripple})	0.85 V	0.39 V	54.12%
Dynamic Settling Time (t_s)	1.80 s	0.45 s	75.00%

As demonstrated in Table IV, the conventional fixed-gain PI controller suffers from a higher steady-state error (1.12 V) and slower dynamic recovery time (1.80 s) during load transitions because its static control gains cannot simultaneously optimize for large dynamic disturbances and small steady-state errors. In contrast, the proposed three-tier gain-scheduling mechanism dynamically adapts K_P and K_I based on the instantaneous error magnitude $|e(k)|$. This results in a 76.79% reduction in steady-state error (0.26 V), a superior voltage regulation of 0.48%, and a faster settling time of 0.45 s under dynamic load changes, confirming the efficacy of the proposed approach for PV battery charging applications.

H. Discussion

The results show that combining a gain-scheduled adaptive PI controller with an LC filter and a physically-motivated CC-CV battery model yields stable voltage regulation (0.48%), strong ripple suppression (84.32%) and realistic charge-current tapering, without requiring the heavier computational load of MPC-based approaches reported in the literature (Section II). The controller's practical benefit is concentrated in the transient region: the RMS error of 2.71 V versus a final error of 0.26 V. shows that most of the residual error is accumulated during the initial large-error phase where the coarse gain set is active, and refinement of the medium/small-error gain sets (Section V-D) is the most direct route to further reducing steady-state error.

Two limitations should be stated explicitly. First, the boost-converter ripple model injects a fixed 120 Hz sinusoidal disturbance to represent switching ripple rather than deriving

ripple directly from the 10 kHz switching action; this is a simplification adopted for tractable time-domain simulation and should be noted as such rather than presented as a switching-frequency-accurate ripple waveform. Second, all results are simulation-based; no hardware-in-the-loop or experimental validation has yet been performed.

VIII CONCLUSION

This paper presented the design and MATLAB-based simulation of an adaptive ripple-smoothing controlled DC–DC converter for solar PV battery charging using dynamic load profiling and a gain-scheduled adaptive PI controller. The complete framework — PV source, boost converter, LC filter, adaptive controller, dynamic load, and CC–CV battery model with SOC, internal resistance and polarization dynamics — was implemented and validated end-to-end. Using values taken directly from the simulation log, the system regulates the charging voltage to within 0.48% of the 54.6 V reference, reduces steady-state ripple voltage by 84.32%, and reproduces realistic CC-to-CV battery charging behavior with SOC progressing from 40% to 67.28% over five hours.

Future work will focus on extending the proposed controller by developing a continuous adaptive gain scheduling mechanism, improving ripple modelling based on switching-frequency dynamics, validating the proposed approach using hardware-in-the-loop or experimental prototype implementation, and evaluating controller performance under real-time stochastic load profiles and varying environmental conditions.

REFERENCES

- [1] A. Kumar and M. Singh, "Adaptive ripple-power compensation in single-phase AC–DC converters for PV battery charging," *IEEE Transactions on Power Electronics*, vol. 35, no. 12, pp. 12489–12501, 2020.
- [2] L. Zhao et al., "Model predictive control for ripple minimization in single-phase rectifiers," *IEEE Transactions on Industrial Electronics*, vol. 69, no. 2, pp. 1355–1366, 2022.
- [3] T. Nguyen and J. Park, "Solar PV charger with adaptive smoothing control for variable irradiance," *Solar Energy*, vol. 231, pp. 456–467, 2022.
- [4] J. Khan et al., "Design of a high-efficiency PV battery charger with dynamic load adaptation," *Energy Conversion and Management*, vol. 252, p. 115123, 2022.
- [5] G. Li and P. Wang, "Improved charging stability in PV–battery systems using real-time load pattern prediction," *Applied Energy*, vol. 310, p. 118573, 2022.
- [6] D. B. Patel and A. Shah, "Performance enhancement of PV chargers using load-profile-based adaptive rectifier control," *IJRER*, vol. 12, no. 4, pp. 1802–1810, 2022.
- [7] T. K. Singh and A. Raj, "Optimization of battery charging circuits in PV-based charging using adaptive predictive control," *IEEE Transactions on Industrial Applications*, vol. 60, no. 1, pp. 905–916, 2024.