

Adaptive Sliding Mode Control with a Nonlinear Sliding Surface for DC-Bus Voltage Regulation in a Renewable-Energy-Based DC Microgrid

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Abstract—This study proposes an adaptive sliding mode control (ASMC) scheme incorporating a nonlinear sliding surface (NSS), denoted ASMC-NSS, for direct-current (DC)-bus voltage regulation in a renewable-energy-based DC microgrid. ASMC augments conventional sliding mode control (CSMC) through channel-wise switching-gain scheduling based on the integral absolute error (IAE), while the NSS introduces bounded, state-dependent scaling of the current-tracking surface. The gain schedule adjusts the switching authority as the accumulated tracking error crosses prescribed thresholds, whereas the NSS shapes the reaching dynamics to improve transient tracking and suppress overshoot. The controller is applied to a system integrating a wind turbine, a photovoltaic (PV) array, and battery energy storage. MATLAB/Simulink comparisons with CSMC and ASMC without the NSS show that ASMC-NSS reduces the current-tracking IAE by 90.5% and 87.3%, respectively, and achieves a current settling time of 0.054 s. It maintains the 500 V DC bus with a maximum overshoot of 0.28 V and a 0.02 s recovery time to the ± 0.5 V band. Lyapunov analysis establishes asymptotic stability of the ideal inner current loops and uniform ultimate boundedness under bounded matched uncertainties.

Keywords—Adaptive Sliding Mode Control; Battery; DC Microgrid; Nonlinear Sliding Surface; Photovoltaic; Wind Turbine

I. INTRODUCTION

The installed capacity of renewable power generation—particularly photovoltaic (PV) and wind energy—continues to grow annually [1]. This upward trend has driven extensive research aimed at advancing renewable energy technologies, including improvements in power converter systems [2]–[4]. However, developing reliable power converters remains challenging due to the intermittent nature of these energy sources. PV systems cannot generate electricity at night because they depend on solar irradiance within the visible spectrum, while wind energy output is inherently unstable due to fluctuating wind speeds. To address these limitations, battery energy storage systems can be employed to supply power when PV and wind generation are insufficient to meet demand [5]. Moreover, batteries can store excess energy produced during periods of high generation, thereby improving overall system efficiency and reliability [6].

Prior research on microgrid regulation spans optimized classical and intelligent control architectures. A two-degree-of-freedom proportional–integral–derivative (PID) controller tuned through a hybrid dragonfly and pattern-search algorithm has been developed for multi-microgrid load-frequency regulation and evaluated against conventional proportional–integral (PI) and PID controllers [7]. In parallel, an online-trained neural-network architecture has been applied to a grid-connected hybrid AC/DC microgrid to coordinate renewable-source maximum-power-point tracking (MPPT) and grid power exchange under multiple MATLAB/Simulink test conditions [8].

Hybrid converter-control structures extend this line of work to power-flow coordination and DC-bus regulation. One configuration interconnects AC and DC microgrids through a modified unified interphase power controller, assigning fuzzy control to the line power converters and nonlinear-disturbance-observer-based multiple-surface sliding mode control (SMC) to the bus power converter [9]. A complementary approach employs a nonlinear-disturbance-observer-based DC-bus controller that avoids remote load and source-power measurements while suppressing transient voltage fluctuations in a hybrid AC/DC microgrid [10].

Predictive and finite-time nonlinear schemes further broaden the available design space. Model-predictive current-and-power control for the battery converter has been coordinated with model-predictive voltage-and-power control for the AC/DC interlinking converter, thereby smoothing renewable-power fluctuations while regulating the DC bus and grid power exchange [11]. Integral-terminal and fast-integral-terminal SMC have likewise been formulated for a hybrid AC/DC microgrid with renewable generation and hybrid energy storage; the centralized design regulates the AC- and DC-bus voltages in grid-connected and islanded operation and is supported by Lyapunov analysis and real-time hardware-in-the-loop validation [12].

Recent studies have extended sliding-mode-based control for converter-dominated microgrids through robust adaptive compensation of multiple disturbances [13], observerless backstepping disturbance rejection [14], event-triggered

distributed control under imperfect sources [15], and adaptive fixed-time terminal control [16]. At the converter level, adaptive SMC has been applied to a boost converter supplying an unknown constant-power load [17], while an exact-feedback-linearization-based adaptive second-order SMC has been developed for DC–DC boost converters [18]. Complementary developments in reaching-law design and sliding-surface analysis are reported in [19]–[21]. Within DC-microgrid applications, nonlinear optimal trajectory-tracking control has been combined with a super-twisting algorithm to strengthen DC-bus voltage regulation under disturbances [22]. Collectively, these studies motivate a closer examination of adaptive and higher-order SMC structures for coordinated DC-bus regulation in converter-dominated microgrids.

Among adaptive higher-order approaches, one design applies second-order sliding-mode control in both grid-connected and islanded operation and introduces a third-order algorithm for islanded operation to improve chattering attenuation; its stability properties are established through formal analysis [23].

At the supervisory-control level, a decentralized hierarchical framework combines sliding-mode and fractional-order control elements to regulate power, voltage, current, and frequency in a wind/PV/fuel-cell microgrid subject to unbalanced and nonlinear loads; validation is conducted using offline MATLAB/Simulink simulations and an OPAL-RT real-time digital simulator [24]. By contrast, an islanded DC-bus regulation strategy integrates an adaptive observer, sliding-mode control, and fixed-frequency pulse width modulation (PWM) to address source, load, and parameter variations [25].

From a finite-time robustness perspective, second- and third-order sliding-mode controllers have been developed for a different microgrid architecture, with formal finite-time convergence established for the resulting closed loop [26]. Beyond higher-order SMC, an interfacing-converter study compares model predictive control (MPC), SMC, and PI control within its own plant model [27], whereas a grid-connected PV strategy combines reinforcement-learning-based MPPT with SMC current injection and benchmarks it against fuzzy-logic and incremental-conductance SMC [28]. These studies provide useful methodological benchmarks; however, their plant structures, control objectives, and test conditions differ from those adopted here.

This literature demonstrates the value of adaptive, higher-order, predictive, and learning-assisted control strategies. Nevertheless, three gaps remain relative to the present control objective: the reviewed methods do not jointly combine a bounded state-dependent sliding coefficient with an integral absolute error (IAE)-based gain schedule; they do not use nested baselines on the same plant to isolate the individual contributions of adaptive gain scheduling and the nonlinear sliding surface (NSS); and their stability derivations do not explicitly account for the sign change in the bidirectional battery-converter input coefficient. Table 1 summarizes this literature positioning.

Accordingly, the novelty of this study lies in the technically coordinated integration of the proposed components rather than in claiming that each component is independently new. The proposed ASMC-NSS framework

combines a normalized nonlinear progress function that maintains a positive and bounded sliding coefficient, channel-wise IAE-based gain scheduling, a saturation boundary layer, and explicit sign-consistent control laws for the wind, PV, and bidirectional-battery converters within a unified averaged DC-microgrid model. This integration is further supported by a common Lyapunov analysis and nested identical-plant comparisons.

Table 1. Comparison of related control approaches and the positioning of ASMC-NSS

Approach	Main feature	Limitation or relevance to this study
Adaptive HOSMC [23]	Second-/third-order sliding algorithms with adaptive gains	Attenuates chattering but requires a higher-order implementation; it does not use the bounded NSS developed in this study
Decentralized SMC [24]	Hierarchical sliding-mode and fractional-order control for a wind/PV/fuel-cell microgrid under unbalanced and nonlinear loads	Addresses AC-side power, voltage, current, and frequency regulation rather than the bounded DC-converter current-loop NSS examined in this study
Observer-based ASMC [25]	Adaptive observation and fixed-frequency PWM for islanded DC-bus regulation	Uses a different bus-voltage control architecture and does not include the bounded NSS or nested current-loop baselines
Robust HOSMC [26]	Finite-time higher-order design for grid-connected and islanded modes	Provides strong robustness at greater algorithmic complexity and addresses a different controller architecture
MPC/SMC/PI study [27]	Compares predictive, sliding-mode, and linear control	Uses a different plant and objective; its published values are not an identical-condition benchmark for the present converters
RL-SMC [28]	Learning-assisted SMC for PV grid integration	Targets grid-connected PV MPPT and current injection and requires training/data choices; it is not an identical-plant benchmark for the present DC microgrid
Proposed ASMC-NSS	IAE-scheduled gain, bounded NSS, saturation layer, and Lyapunov analysis	Designed as a low-order averaged current-loop controller for a wind/PV/battery DC microgrid

Within this architecture, the NSS reshapes the current-tracking surface, while the IAE schedule adjusts the switching authority as the accumulated error crosses prescribed thresholds. Their incremental effects are isolated through the nested CSMC, ASMC, and ASMC-NSS baselines under identical plant, load, and generation conditions.

The controller is applied to an islanded renewable-energy-based DC microgrid that integrates PV and wind-turbine sources with battery storage, as illustrated in Fig. 1. Its performance is evaluated through matched MATLAB/Simulink simulations, while robustness is addressed analytically and within the explicitly stated operating-condition scope.

The main contributions of this study are summarized as follows:

- Development of a unified ASMC-NSS current-loop architecture for the wind-turbine, PV, and bidirectional-battery converters of an islanded DC microgrid.

- Formulation of a normalized and bounded NSS that preserves the equivalence $S_i = 0 \Leftrightarrow n_i = 0$, together with explicit equivalent and complete control laws for the three converter channels.
- Development of channel-wise IAE-based gain scheduling that increases the switching authority when the accumulated tracking error exceeds predefined thresholds.
- Incorporation of a saturation boundary layer to attenuate discontinuous switching in the averaged current response.
- Establishment of a common Lyapunov stability analysis that explicitly accounts for the negative battery-channel input coefficient, followed by quantitative identical-plant comparisons of current tracking and 500-V DC-bus regulation using CSMC, ASMC, and ASMC-NSS.

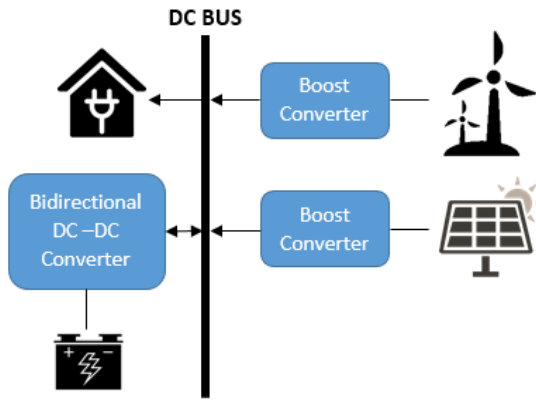


Fig. 1. Configuration of the DC microgrid

II. MODELING OF THE DC MICROGRID

In the proposed configuration, wind and solar sources are coupled to a common DC bus through boost converters, while a battery is connected through a bidirectional converter. The model captures the dynamic behavior of each subsystem and expresses the complete microgrid in state-space form, thereby providing a structured basis for the controller design.

A. Modeling Assumptions

The analysis uses continuous-time averaged converter models operating in continuous-conduction mode. The DC bus is assumed to remain positive, and the wind, PV, and battery current references are bounded and piecewise differentiable. Throughout the controller derivation and the reported averaged-model simulations, $u_i \in \mathbb{R}$ denotes the unconstrained equivalent continuous control input of the ideal averaged model rather than the physical PWM duty ratio; no $[0, 1]$ clipping is imposed on u_i in the ideal stability derivation. Practical PWM mapping and actuator saturation are outside the present averaged-model scope. If imposed in a physical implementation, their matched residual is included in $di(t)$ in (52) and must satisfy the robustness condition in (62). Converter conduction losses are represented by the series resistances R_w , R_{pv} , and R_{bat} ; device-level PWM ripple, semiconductor switching loss, dead time, communication delay, and battery ageing are not explicitly modeled.

B. Dynamic Modeling of the Wind-Turbine System

A wind turbine converts mechanical motion into electrical energy. The dynamic behavior of the wind turbine is derived from the kinetic energy formulation, as expressed in (1) [33].

$$P_w = \frac{1}{2} \rho A v_w^3 C_p \quad (1)$$

where P_w is the mechanical power (W), A is the rotor swept area (m^2), ρ is the air density (kg/m^3), v_w is the wind speed (m/s), and C_p is the turbine power coefficient, expressed as a function of the tip-speed ratio λ . The tip-speed ratio is

$$\lambda = \frac{\omega_w r}{v_w} \quad (2)$$

where ω_w is the rotor angular velocity (rad/s) and r is the rotor radius (m). Substituting $v_w = \omega_w r / \lambda$ from (2) into (1) gives,

$$P_w = \frac{1}{2} \rho A r^3 \frac{\omega_w^3}{\lambda^3} C_p \quad (3)$$

As shown in Fig. 2, the wind turbine drives a permanent-magnet synchronous generator (PMSG), whose output is rectified and delivered to the common DC bus through a boost converter comprising the input resistance and inductance, the controlled switch, the diode, and the DC-link capacitor. The supervisory logic selects either MPPT, which provides an optimal-torque-based reference, or off-MPPT operation, while the SMC generates the converter control action. This arrangement controls the wind-side current and the corresponding power transferred to the DC bus.

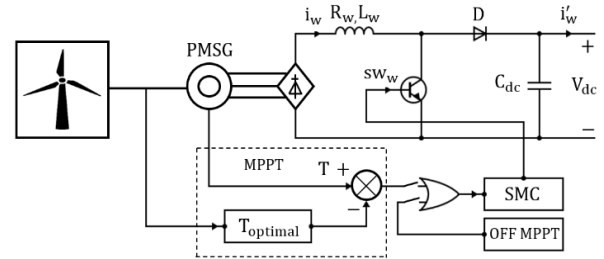


Fig. 2. Configuration of the wind-turbine system

In this work, MPPT is achieved using the optimal torque control (OTC) method, which offers simplicity and high accuracy [34]. The technique modifies the PMSG torque for a given wind speed so that it matches the turbine's maximum reference torque. Under the assumption of operation at the optimal tip-speed ratio and peak power coefficient, λ and C_p are replaced with λ_{op} and C_{pmax} . Hence, (3) can be expressed as:

$$P_{w,op} = \frac{1}{2} \rho A r^3 \frac{\omega_w^3}{\lambda_{op}^3} C_{pmax} \quad (4)$$

Since $P_{w,op} = T_{w,op} \omega_w$, (4) can be rewritten as,

$$T_{w,op} = \frac{1}{2} \rho A r^3 \frac{\omega_w^2}{\lambda_{op}^3} C_{pmax} \quad (5)$$

where $T_{w,op}$ is the optimal torque reference. The wind-turbine current reference is then

$$I_{w,ref} = \frac{T_{w,op} \omega_w}{v_w} \quad (6)$$

where V_w is the DC output voltage of the uncontrolled rectifier. Acting as an equivalent load, the DC–DC boost converter regulates the PMSG rotational speed. Its averaged dynamics are

$$\frac{di_w}{dt} = \frac{V_w}{L_w} - \frac{R_w i_w}{L_w} - (1 - u_w) \frac{V_{dc}}{L_w} \quad (7)$$

$$\frac{dv_{dc}}{dt} = (1 - u_w) \frac{i_w}{C_{dc}} - \frac{i'_w}{C_{dc}} \quad (8)$$

where i_w , L_w , V_{dc} , u_w , C_{dc} , and i'_w denote the wind-turbine output current, input inductance, DC-bus voltage, averaged converter control input, DC-link capacitance, and converter output current, respectively. Here, V_w and R_w denote the rectifier output voltage and the inductor series resistance, respectively.

C. Dynamic Modeling of the Photovoltaic System

The PV energy system comprises a PV module and a boost converter. The high-level controller selects either MPPT or off-MPPT operation. The MPPT strategy uses a regression-plane model based on irradiance G (W/m²) and temperature T (°C) to compute the PV reference voltage $V_{pv,ref}$ as follows [35]:

$$V_{pv,ref} = 322 - 0.00964G - 1.34T \quad (9)$$

As shown in the configuration in Fig. 3, the PV energy system employs a boost converter. By applying averaged state modeling, the system's operational dynamics are derived and expressed through the differential equations provided below:

$$\frac{di_{pv}}{dt} = \frac{V_{pv}}{L_{pv}} - \frac{R_{pv} i_{pv}}{L_{pv}} - (1 - u_{pv}) \frac{V_{dc}}{L_{pv}} \quad (10)$$

$$\frac{dv_{dc}}{dt} = (1 - u_{pv}) \frac{i_{pv}}{C_{dc}} - \frac{i'_{pv}}{C_{dc}} \quad (11)$$

where i_{pv} , V_{pv} , L_{pv} , R_{pv} , u_{pv} , V_{dc} , C_{dc} , and i'_{pv} denote the PV-side current, PV voltage, input inductance, parasitic resistance, averaged converter control input, DC-bus voltage, DC-link capacitance, and converter output current, respectively.

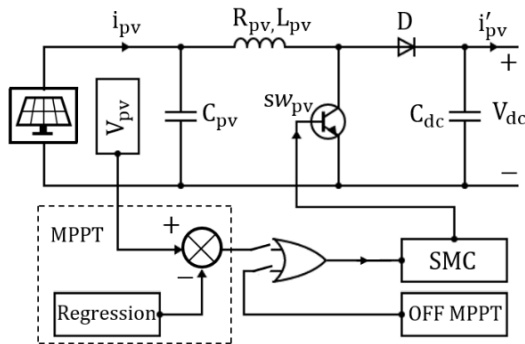


Fig. 3. Configuration of the PV system

D. Dynamic Modeling of the Battery System

The battery is connected to the DC bus through a bidirectional buck–boost converter that supports DC-bus

regulation and controls battery charging and discharging according to the load and state of charge (SoC). Using the averaged converter model, the battery subsystem is described by (12)–(15). As illustrated in Fig. 4, the bidirectional battery converter provides separate switching paths for discharging (boost) and charging (buck) operation.

In the discharging (boost) mode, switch sw_{b1} is activated, whereas sw_{b2} operates as a diode. The battery then supplies energy to the DC bus, and the converter is described by,

$$\frac{di_{bat}}{dt} = \frac{V_{bat}}{L_{bat}} - \frac{R_{bat} i_{bat}}{L_{bat}} - (1 - u_1) \frac{V_{dc}}{L_{bat}} \quad (11)$$

$$\frac{dv_{dc}}{dt} = (1 - u_1) \frac{i_{bat}}{C_{dc}} - \frac{i'_{bat}}{C_{dc}} \quad (12)$$

where i_{bat} , L_{bat} , u_1 , and i'_{bat} denote the battery current, input inductance, boost-mode duty-ratio command, and converter output current, respectively. The symbols V_{bat} , R_{bat} , V_{dc} , and C_{dc} denote the battery terminal voltage, battery-side series resistance, DC-bus voltage, and DC-link capacitance, respectively.

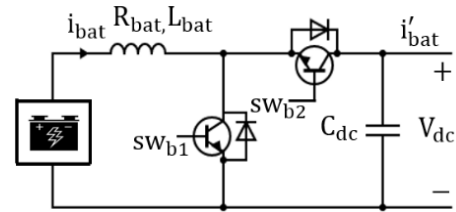


Fig. 4. Configuration of the battery system

In the charging (buck) mode, switch sw_{b2} is activated, whereas sw_{b1} operates as a diode. Here, u_2 denotes the buck-mode duty-ratio command. The converter model is

$$\frac{di_{bat}}{dt} = \frac{V_{bat}}{L_{bat}} - \frac{R_{bat} i_{bat}}{L_{bat}} - (u_2) \frac{V_{dc}}{L_{bat}} \quad (14)$$

$$\frac{dv_{dc}}{dt} = (u_2) \frac{i_{bat}}{C_{dc}} - \frac{i'_{bat}}{C_{dc}} \quad (15)$$

To obtain a unified model for both operating modes, define the virtual control input

$$u_{bat} = \mu_b(1 - u_1) + (1 - \mu_b)u_2 \quad (16)$$

where $\mu_b \in \{0,1\}$ is the operating-mode selector: $\mu_b = 1$ in discharging mode and $\mu_b = 0$ in charging mode. Substituting (16) into (12)–(15) gives the unified battery model

$$\frac{di_{bat}}{dt} = \frac{V_{bat}}{L_{bat}} - \frac{R_{bat} i_{bat}}{L_{bat}} - (u_{bat}) \frac{V_{dc}}{L_{bat}} \quad (17)$$

$$\frac{dv_{dc}}{dt} = (u_{bat}) \frac{i_{bat}}{C_{dc}} - \frac{i'_{bat}}{C_{dc}} \quad (18)$$

For reproducibility, the normalized battery state of charge $z_{soc} \in [0,1]$ is obtained by coulomb counting. The sign convention is $i_{bat} > 0$ during discharge and $i_{bat} < 0$ during charge:

$$\dot{z}_{\text{soc}} = -\frac{1}{Q_n} \left[\frac{\max(i_{\text{bat}}, 0)}{\eta_d} + \eta_c \min(i_{\text{bat}}, 0) \right], \quad (19)$$

$$\text{SoC}(\%) = 100 z_{\text{soc}}$$

Here, $Q_n = 34 \times 3600$ A s is the rated charge capacity, and $\eta_c, \eta_d \in (0, 1]$ are the charge and discharge coulombic efficiencies. The reported short-duration simulation uses the ideal coulomb-counting case $\eta_c = \eta_d = 1$.

E. State-Space Model of the DC Microgrid

The hybrid microgrid, comprising the wind and PV sources, battery storage, and the DC load, is represented by the following state-space model.

$$\dot{x}_1 = \frac{1}{L_w} (V_w - R_w x_1 - (1 - u_w) x_4) \quad (20)$$

$$\dot{x}_2 = \frac{1}{L_{pv}} (V_{pv} - R_{pv} x_2 - (1 - u_{pv}) x_4) \quad (21)$$

$$\dot{x}_3 = \frac{1}{L_{bat}} (V_{bat} - R_{bat} x_3 - u_{bat} x_4) \quad (22)$$

$$\dot{x}_4 = (1 - u_w) \frac{x_1}{C_{dc}} + (1 - u_{pv}) \frac{x_2}{C_{dc}} + (u_{bat}) \frac{x_3}{C_{dc}} - \frac{I_{dc}}{C_{dc}} \quad (23)$$

Where $x_1 = i_w$, $x_2 = i_{pv}$, and $x_3 = i_{bat}$ are the wind, PV, and battery inductor currents, respectively, and $x_4 = V_{dc}$ is the DC-bus voltage. The symbol I_{dc} denotes the total current drawn by the DC load.

Expanding the control-input terms makes the control-affine structure explicit: $\dot{x}_1 = f_1 + (x_4/L_w)u_w$; $\dot{x}_2 = f_2 + (x_4/L_{pv})u_{pv}$; $\dot{x}_3 = f_3 - (x_4/L_{bat})u_{bat}$. Here, $f_1 = (V_w - R_w x_1 - x_4)/L_w$; $f_2 = (V_{pv} - R_{pv} x_2 - x_4)/L_{pv}$; $f_3 = (V_{bat} - R_{bat} x_3 - x_4)/L_{bat}$.

The bus equation contains the input coefficients $-x_1/C_{dc}$, $-x_2/C_{dc}$, and x_3/C_{dc} . This expansion explains the positive wind/PV input coefficients and the negative battery-current input coefficient used in (36), (51), and (53).

III. CONTROL DESIGN FOR THE DC MICROGRID

The DC-microgrid controller combines conventional sliding mode control (CSMC), adaptive gain scheduling, and a nonlinear sliding surface. CSMC is first formulated for the wind-turbine, PV, and battery current loops. Gain scheduling then adjusts the available switching authority, whereas the NSS varies the sliding-surface scaling during the transient to accelerate tracking and reduce overshoot.

A. Conventional Sliding Mode Control

The conventional SMC design consists of a sliding surface, an equivalent control, and a switching control. The three current-loop sliding surfaces are defined as

$$S_1 = c n_1 \quad (24)$$

$$S_2 = c n_2 \quad (25)$$

$$S_3 = c n_3 \quad (26)$$

where S_1 , S_2 , and S_3 are the sliding surfaces for the wind-turbine, PV, and battery channels, respectively; $c > 0$ is the sliding coefficient; and $n_i = x_i - x_{id}$ is the current-tracking error. The subscript d denotes the desired current reference for channel i. Differentiating the surfaces gives

$$\dot{S}_1 = c(\dot{x}_1 - \dot{x}_{1d}) \quad (27)$$

$$\dot{S}_2 = c(\dot{x}_2 - \dot{x}_{2d}) \quad (28)$$

$$\dot{S}_3 = c(\dot{x}_3 - \dot{x}_{3d}) \quad (29)$$

Substituting $\dot{x}_1$, $\dot{x}_2$, and $\dot{x}_3$ from (20), (21), and (22) into (27), (28), and (29), respectively, gives

$$\dot{S}_1 = c \left(\frac{1}{L_w} (V_w - R_w x_1 - (1 - u_{w,eq}) x_4) - \dot{x}_{1d} \right) \quad (30)$$

$$\dot{S}_2 = c \left(\frac{1}{L_{pv}} (V_{pv} - R_{pv} x_2 - (1 - u_{pv,eq}) x_4) - \dot{x}_{2d} \right) \quad (31)$$

$$\dot{S}_3 = c \left(\frac{1}{L_{bat}} (V_{bat} - R_{bat} x_3 - u_{bat,eq} x_4) - \dot{x}_{3d} \right) \quad (32)$$

where $u_{w,eq}$, $u_{pv,eq}$, and $u_{bat,eq}$ are the equivalent controls for the wind-turbine, PV, and battery channels, respectively.

Setting $\dot{S}_i = 0$ yields the equivalent controls

$$u_{w,eq} = \frac{1}{x_4} (R_w x_1 - V_w + L_w \dot{x}_{1d}) + 1 \quad (33)$$

$$u_{pv,eq} = \frac{1}{x_4} (R_{pv} x_2 - V_{pv} + L_{pv} \dot{x}_{2d}) + 1 \quad (34)$$

$$u_{bat,eq} = \frac{1}{x_4} (V_{bat} - R_{bat} x_3 - L_{bat} \dot{x}_{3d}) \quad (35)$$

The switching component of SMC is defined as

$$u_{i,sw} = -\text{sgn}(b_i) A \text{sat} \left(\frac{S_i}{\vartheta} \right) \quad (35)$$

$$i \in \{1, 2, 3\} \quad (36)$$

where $A > 0$ is the switching gain, $\text{sat}(\cdot)$ is the unit saturation function, $\vartheta > 0$ is the boundary-layer thickness, and b_i is the input coefficient of channel i. From (20)-(22), $b_1 = x_4/L_w > 0$, $b_2 = x_4/L_{pv} > 0$, and $b_3 = -x_4/L_{bat} < 0$. The factor $-\text{sgn}(b_i)$ therefore gives negative switching terms for the wind and PV channels and a positive switching term for the battery channel.

$$u_w = \frac{1}{x_4} (R_w x_1 - V_w + L_w \dot{x}_{1d}) + 1 - A \operatorname{sat} \left(\frac{S_1}{\vartheta} \right) \quad (37)$$

$$u_{pv} = \frac{1}{x_4} (R_{pv} x_2 - V_{pv} + L_{pv} \dot{x}_{2d}) + 1 - A \operatorname{sat} \left(\frac{S_2}{\vartheta} \right) \quad (38)$$

$$u_{bat} = \frac{1}{x_4} (V_{bat} - R_{bat} x_3 - L_{bat} \dot{x}_{3d}) + A \operatorname{sat} \left(\frac{S_3}{\vartheta} \right) \quad (39)$$

B. Adaptive Gain Scheduling for the Switching Control

Adaptive SMC uses a channel-dependent switching gain $A_i(t)$ scheduled by the integral absolute error $IAE_i(t)$. The ASMC structure is shown in Fig. 5.

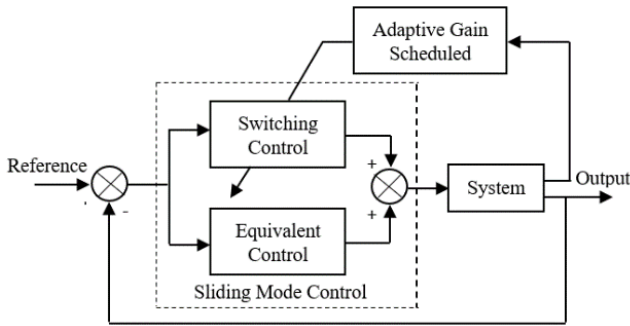


Fig. 5. Adaptive SMC scheme

The gain is scheduled as,

$$A_i(t) = \begin{cases} 90, & IAE_i(t) \leq 0.05, \\ 110, & 0.05 < IAE_i(t) \leq 0.10, \\ 130, & IAE_i(t) > 0.10, \end{cases} \quad (40)$$

$$IAE_i(t) = \int_0^t |n_i(\tau)| d\tau, \quad i \in \{1,2,3\}.$$

The (40) schedules the gain as a nondecreasing function of the accumulated tracking error, with IAE expressed in A.s. A larger gain increases reaching authority and robustness, although an unnecessarily large value can increase control activity and sensitivity to measurement noise. Because cumulative IAE is nondecreasing, the gain cannot return to a lower level after a threshold is crossed. A moving-window IAE should therefore be used if downward gain adaptation is required after a transient.

C. Adaptive Control with a Nonlinear Sliding Surface

Motivated by prior NSS formulations [29]–[32], the nonlinear sliding surface is introduced as a bounded, state-dependent scaling of the current-tracking error. The shaping function is defined in (41).

$$\psi_i(\zeta_i) = -\frac{\beta}{1 - \exp(-1)} \left[\exp(-(1 - \zeta_i^2)) - \exp(-1) \right] \quad (41)$$

Here, ψ_i is the nonlinear shaping function, and $\beta > 0$ sets its magnitude. The normalized progress variable is $\zeta_i = \operatorname{sat}_{[0,1]}(|x_i - x_i(0)|/|x_{id} - x_i(0)| + \varepsilon)$; therefore, $0 \leq \zeta_i \leq$

1. The small constant $\varepsilon = 10^{-6}$ A regularizes the denominator, and the absolute values make the normalization independent of the tracking direction. At the initial condition, $\zeta_i = 0$ and $\psi_i = 0$; as the current approaches its reference, $\zeta_i \rightarrow 1$ and $\psi_i \rightarrow -\beta$. Consequently, $q_i = \gamma - \varphi\psi_i$ increases from γ toward $\gamma + \varphi\beta$, modifying the sliding-surface scaling near the reference and helping to suppress overshoot. The three nonlinear sliding surfaces are

$$S_{1nl} = q_1 n_1 = (\gamma - \varphi\psi_1) n_1 \quad (42)$$

$$S_{2nl} = q_2 n_2 = (\gamma - \varphi\psi_2) n_2 \quad (43)$$

$$S_{3nl} = q_3 n_3 = (\gamma - \varphi\psi_3) n_3 \quad (44)$$

where $\gamma > 0$ and $\varphi > 0$ are design constants. The equivalent wind-turbine control is obtained by differentiating the nonlinear surface and imposing $\dot{S}_{1nl} = 0$.

$$\dot{S}_{1nl} = q_1 \dot{n}_1 - \varphi \dot{\psi}_1 n_1 \quad (45)$$

$$\dot{S}_{1nl} = q_1 (\dot{x}_1 - \dot{x}_{1d}) - \varphi \dot{\psi}_1 n_1 \quad (46)$$

Substituting (20) into (46) gives the compact expression

$$\dot{S}_{1nl} = q_1 (\dot{x}_1 - \dot{x}_{1d}) - \varphi \dot{\psi}_1 n_1, \quad q_1 = \gamma - \varphi\psi_1, \quad (47)$$

where $\dot{x}_1$ is given by (20). Solving the equivalent-control condition in (47) gives

$$u_{w,eqnl} = 1 + \frac{R_w x_1 - V_w + L_w \dot{x}_{1d}}{x_4} + \frac{L_w \varphi \dot{\psi}_1 n_1}{x_4 q_1} \quad (48)$$

The complete wind-turbine ASMC-NSS law is

$$u_{w,nl} = u_{w,eqnl} - A_1 \operatorname{sat} \left(\frac{S_{1nl}}{\vartheta_1} \right) \quad (49)$$

Using the baseline PV and battery equivalent controls in (34) and (35), respectively, the nonlinear equivalent and complete control laws are given in (50) and (51). The positive switching term in the battery law follows from the negative input coefficient in (22). In the simulations, the common boundary-layer setting in Table 2 corresponds to $\vartheta_1 = \vartheta_2 = \vartheta_3 = \vartheta$.

$$\left. \begin{aligned} u_{pv,eqnl} &= u_{pv,eq} + \frac{L_{pv} \varphi \dot{\psi}_2 n_2}{x_4 q_2} \\ u_{pv,nl} &= u_{pv,eqnl} - A_2 \operatorname{sat} \left(\frac{S_{2nl}}{\vartheta_2} \right) \end{aligned} \right\} \quad (50)$$

$$\left. \begin{aligned} u_{bat,eqnl} &= u_{bat,eq} - \frac{L_{bat} \varphi \dot{\psi}_3 n_3}{x_4 q_3} \\ u_{bat,nl} &= u_{bat,eqnl} + A_3 \operatorname{sat} \left(\frac{S_{3nl}}{\vartheta_3} \right) \end{aligned} \right\} \quad (51)$$

Table 2. System Parameters

Name	Parameter	Value
Converter	Inductor ($L_w; L_{pv}; L_{bat}$)	(30; 20; 33) mH
	Internal resistance ($R_w; R_{pv}; R_{bat}$)	(2; 2; 3.5) Ω
	Capacitor (C_{dc})	10 mF
	Load resistance (R)	(10.4 – 22.7) Ω
	Wind turbine parameters	
Wind turbine parameters	Air density	1.2 kg/m ³
	Wind speed	(6.5 – 7.5) m/s
	Rotor diameter	5.5 m
	λ_{opt}	7.5
	$C_{p,max}$	0.43
PV array parameters	Maximum power (P_{mpp})	1.5 kW
	Maximum output voltage (V_{mpp})	102.6 V
	Maximum output current (I_{mpp})	15.18 A
	Open-circuit voltage (V_{oc})	165.8 V
	Short-circuit current (I_{sc})	17.56 A
Battery specifications	Type	Lead acid
	Voltage	450 V
	Ah capacity	34 Ah
	Rated current	17.5 A
	Controller parameters	
Controller parameters	Sliding coefficient (c)	2
	Boundary layer (ϑ)	0.1
	Switching gain (A)	90; 110; 130
	Constant (γ)	2
	Nonlinear-shaping amplitude (β)	1 (normalized)
	NSS scale ($\varphi; \varphi\beta = 10$)	10

D. Controller-Parameter Selection and Sensitivity

The controller parameters were selected subject to the analytical conditions in (55) and (62), followed by matched-condition tuning on the averaged model. The minimum surface coefficient is fixed by $\gamma > 0$, whereas only the product $\kappa = \varphi\beta$ determines the range of q_i . The redundant parameterization is therefore normalized by setting $\beta = 1$; with $\gamma = 2$ and $\varphi = 10$, the implemented coefficient satisfies $2 \leq q_i(t) \leq 12$. If a different value of β is used, φ should be rescaled so that $\varphi\beta = 10$.

The minimum switching gain must provide a positive robustness margin in (62). The levels $A_i \in \{90, 110, 130\}$ increase reaching authority as the channel IAE crosses 0.05 and 0.10 A.s. The (61) shows that a larger minimum gain shortens the boundary-layer reaching-time bound, while (64)-(65) show that a smaller ϑ_i tightens the ultimate error bound. These benefits are balanced against greater sensitivity to measurement noise and control activity; accordingly, $\vartheta_i = 0.1$ is used for all channels. The baseline coefficient $c = 2$ is held fixed across the CSMC comparison, and the same plant, references, and evaluation interval are used for every controller.

E. Lyapunov Stability Analysis

This subsection establishes the closed-loop stability of the proposed adaptive sliding-mode controller with a nonlinear sliding surface (ASMC-NSS). Let $i \in \{1, 2, 3\}$ denote the wind-turbine, PV, and battery current channels, respectively. From (20)-(22), their dynamics can be expressed in the compact form

$$\dot{x}_i = f_i(x, t) + b_i(x, t)u_i + d_i(t), \quad (52)$$

where $d_i(t)$ is a lumped matched uncertainty representing parameter variations, unmodeled current-channel dynamics, external disturbances, practical actuator-saturation residuals, and derivative-estimation errors. The input coefficients associated with the three converter models are,

$$b_1 = \frac{x_4}{L_w} > 0, \quad b_2 = \frac{x_4}{L_{pv}} > 0, \quad b_3 = -\frac{x_4}{L_{bat}} < 0 \quad (53)$$

The negative sign of b_3 is essential: the stabilizing switching term of the battery controller must have the opposite sign to those of the wind and PV controllers, as implemented in (51). The analysis assumes that $x_4(t) \geq V_{\min} > 0$, so that $|b_i(x, t)| \geq b_{i,\min} > 0$; the reference currents x_{id} and their derivatives are bounded. No $[0, 1]$ bound is imposed on the ideal continuous control input; practical actuator saturation, if imposed, is treated through the matched residual in (52).

Define the tracking error, nonlinear coefficient, and nonlinear sliding variable as.

$$n_i = x_i - x_{id}, q_i(t) = \gamma - \varphi\psi_i(t), S_i \equiv S_{i,nl} = q_i(t)n_i \quad (54)$$

Because the progress variable in (41) is saturated to $0 \leq \zeta_i \leq 1$, the nonlinear function satisfies $-\beta \leq \psi_i(t) \leq 0$. Therefore, for $\gamma > 0$, $\varphi > 0$, and $\beta > 0$,

$$0 < q_{\min} = \gamma \leq q_i(t) \leq \gamma + \varphi\beta = q_{\max} \quad (55)$$

Consequently, $S_i = 0$ is equivalent to $n_i = 0$. The finite positive parameter β determines $q_{\max}$, whereas the small constant ε in (41) only regularizes the denominator used to construct ζ_i and does not alter the Lyapunov inequalities. Because $\varepsilon > 0$ prevents a singular denominator and ζ_i is constructed using absolute-value and saturation operations, ζ_i is locally absolutely continuous on every interval over which $x_i(t)$ and $x_{id}(t)$ are locally absolutely continuous. Consequently, the composite shaping function $\psi_i(\zeta_i)$ is differentiable almost everywhere, and its time derivative in (45)-(58) is understood in the almost-everywhere sense on intervals between reference discontinuities. At an isolated reference jump, the analysis is applied piecewise on the adjacent continuous intervals.

Since γ and φ are constants, the correct derivative of the nonlinear surface is,

$$\dot{S}_i = q_i(\dot{x}_i - \dot{x}_{id}) - \varphi\dot{\psi}_i n_i \quad (56)$$

The (56) includes (45) as the wind-turbine case. In particular, the second term is $-\varphi\dot{\psi}_i n_i$. Using the compact notation in (52), the equivalent and complete control laws can be written as,

$$u_{i,eq} = \frac{1}{b_i} \left[-f_i + \dot{x}_{id} + \frac{\varphi\dot{\psi}_i}{q_i} n_i \right], \quad (57)$$

$$u_i = u_{i,eq} - \text{sgn}(b_i) A_i(t) \text{sat} \left(\frac{S_i}{\vartheta_i} \right)$$

For $b_1, b_2 > 0$, (57) gives a negative switching component; for $b_3 < 0$, it gives a positive component. Substituting (57) into (52) and then into (56) yields,

$$\dot{S}_i = -q_i |b_i| A_i(t) \text{sat} \left(\frac{S_i}{\vartheta_i} \right) + q_i d_i(t) \quad (58)$$

Theorem 1 (ideal averaged model). Suppose that $d_i(t) = 0$, $q_i(t)$ satisfies (55), $A_i(t) \geq A_{i,\min} > 0$, and $b_{i,\min} > 0$. Then the equilibrium $S_1 = S_2 = S_3 = 0$ is asymptotically stable, and all three current-tracking errors converge to zero.

Proof. Consider the following common quadratic Lyapunov candidate:

$$V(S) = \frac{1}{2} \sum_{i=1}^3 S_i^2 = \frac{1}{2} (S_1^2 + S_2^2 + S_3^2) \quad (59)$$

The summation in (59) is appropriate because it combines the three scalar Lyapunov functions of the wind, PV, and battery current loops. It is positive definite with respect to $S = [S_1, S_2, S_3]^T$. Along the ideal closed-loop trajectories,

$$\dot{V} = -\sum_{i=1}^3 q_i |b_i| A_i(t) S_i \text{sat}\left(\frac{S_i}{\vartheta_i}\right) \quad (60)$$

For every $S_i \neq 0$, the product $S_i \text{sat}(S_i/\vartheta_i)$ is positive: it equals $|S_i|$ outside the boundary layer and S_i^2/ϑ_i inside it. Since $q_i > 0$, $|b_i| > 0$, and $A_i(t) > 0$, (60) gives $\dot{V} < 0$ for $S \neq 0$ and $\dot{V} = 0$ only at $S = 0$. Hence, the origin of the sliding-variable dynamics is asymptotically stable. Because $n_i = S_i/q_i$ and $q_i \geq q_{\min} > 0$, $n_i(t) \rightarrow 0$ for $i = 1, 2, 3$.

Outside the boundary layer, the saturation function becomes $\text{sgn}(S_i)$. An upper bound on the time required to reach $|S_i| \leq \vartheta_i$ is,

$$T_{i,BL} \leq \frac{\max(|S_i(0)| - \vartheta_i, 0)}{q_{\min} b_{i,\min} A_{i,\min}}. \quad (61)$$

with an ideal sign function, $\vartheta_i \rightarrow 0$ and (61) becomes a finite-time reaching bound for $S_i = 0$. With the saturation function used in this study, the ideal dynamics are exponentially convergent inside the boundary layer.

Theorem 2 (bounded matched uncertainties). Suppose that $|d_i(t)| \leq d_{i,\max}$ and that the minimum switching gain satisfies

$$b_{i,\min} A_{i,\min} \geq d_{i,\max} + \eta_i, \quad \eta_i > 0 \quad (62)$$

Then every sliding variable reaches the prescribed boundary layer in finite time and the current-tracking errors are uniformly ultimately bounded.

Proof. From (58), outside the boundary layer,

$$\dot{V} \leq -\sum_{i=1}^3 q_i \eta_i |S_i| < 0 \quad (63)$$

Inside the boundary layer, completing the scalar inequality for each channel gives the conservative bounds

$$\limsup_{t \rightarrow \infty} |S_i(t)| \leq \frac{\vartheta_i d_{i,\max}}{b_{i,\min} A_{i,\min}} \quad (64)$$

and, because $n_i = S_i/q_i$,

$$\limsup_{t \rightarrow \infty} |n_i(t)| \leq \frac{\vartheta_i d_{i,\max}}{q_{\min} b_{i,\min} A_{i,\min}} \quad (65)$$

Thus, a smaller boundary-layer thickness improves the theoretical tracking-error bound but increases sensitivity to chattering and sampling effects. Actuator saturation remains

admissible only when its residual is included in d_i and condition (62) is preserved.

The scheduled gains in (40) satisfy $A_i(t) \in \{90, 110, 130\}$, so $A_{i,\min} = 90 > 0$. The Lyapunov function in (59) is therefore common to all three gain levels, and no A_i term appears because A_i is not included as a Lyapunov state. Switching between gain levels does not invalidate the proof provided that (62) holds. The schedule in (40) is nondecreasing with cumulative IAE rather than continuously proportional to it. A moving-window IAE should be used if the gain is intended to decrease again after a transient.

Finally, (59)-(65) prove stability of the three inner current-tracking loops; they do not independently prove convergence of the fourth state $x_4 = V_{dc}$. Let $e_v = x_4 - V_{dc,ref}$. If the outer reference-current generator is designed so that the nominal bus-current balance produces $-k_v e_v$, $k_v > 0$, then (23) can be written as

$$C_{dc} \dot{e}_v = -k_v e_v + \Delta_I \quad (66)$$

$$\Delta_I = (1 - u_w) n_1 + (1 - u_{pv}) n_2 + u_{bat} n_3 \quad (67)$$

For $V_v = C_{dc} e_v^2/2$,

$$\dot{V}_v = -k_v e_v^2 + e_v \Delta_I, \quad \limsup_{t \rightarrow \infty} |e_v(t)| \leq \frac{\Delta_{I,\max}}{k_v} \quad (68)$$

Therefore, the DC-bus subsystem is input-to-state stable with respect to the inner-loop current mismatch. If Theorem 1 applies and the continuous averaged-model control inputs $u_w(t)$, $u_{pv}(t)$, and $u_{bat}(t)$ remain bounded along the closed-loop trajectories, then $n_i(t) \rightarrow 0$ implies $\Delta_I(t) \rightarrow 0$ through (67), and (68) consequently gives $e_v(t) \rightarrow 0$. This bounded-signal requirement is a closed-loop regularity assumption needed for the product terms in Δ_I ; it is not a hard amplitude constraint on the control variable. Thus, u_i is not restricted to $[0, 1]$ and remains an unconstrained continuous input of the averaged model. Under the conditions of Theorem 2, the DC-bus voltage is uniformly ultimately bounded. Without an explicitly defined outer-loop law satisfying (66)-(67), the formal Lyapunov claim must be limited to the three converter current-tracking loops, while DC-bus regulation is supported by the simulation results.

For the first-order current channels considered here, $q_i(t)$ is most rigorously interpreted as a state-dependent scaling of the sliding surface that modifies the reaching dynamics and control effort. A literal damping-ratio interpretation requires an explicitly defined second-order reduced error model; the stability conclusions above do not rely on that interpretation.

IV. RESULTS AND DISCUSSION

A. Simulation Scope and Operating Conditions

The simulations were performed in MATLAB/Simulink over a common 0–13 s interval using the fixed-step ode3 (Bogacki–Shampine) solver with a fixed-step size of 1×10^{-4} s. The discrete base rate and nominal converter switching frequency were both set to 10 kHz, corresponding to a base-rate sample time of 1×10^{-4} s. Because the converter plant is represented by the continuous-time averaged (7)-(23), individual PWM pulses and semiconductor switching ripple

at the nominal 10-kHz carrier frequency are not explicitly resolved; the switching frequency is reported as an implementation parameter. The simulation starts at $t = 0$ s, when the prescribed source, load, and current-reference profiles are applied. The DC-bus reference is 500 V, and the normalized battery SoC is initialized at 1.0 p.u. All controllers use identical plant parameters, reference trajectories, load events, numerical settings, and metric definitions.

The matched comparison includes the reported load-resistance, wind-speed, and temperature profiles, while irradiance is fixed at 900 W/m^2 . The series resistances in Table 2 represent fixed nominal conduction-loss terms rather than a converter-loss sensitivity study. The expanded campaign suggested by the reviewer—irradiance variation, a wider wind-speed range, additional sudden load changes, parameter uncertainty, detailed converter-loss variation, and sensor noise—was not performed in this revision and is reserved for future work. No numerical result is claimed for these unperformed cases.

The DC microgrid is simulated in MATLAB/Simulink using the parameters and configuration summarized in Table 2. The load, wind-speed, and temperature profiles used for the matched controller comparison are shown in Fig. 6 to Fig. 8, respectively.

As illustrated in Fig. 6, the load resistance begins at 10.4Ω and changes abruptly up to 22.7Ω . Fig. 7 shows wind-speed steps among 7.0, 7.5, and 6.5 m/s. The PV irradiance is held at 900 W/m^2 , while the temperature follows the profile in Fig. 8.

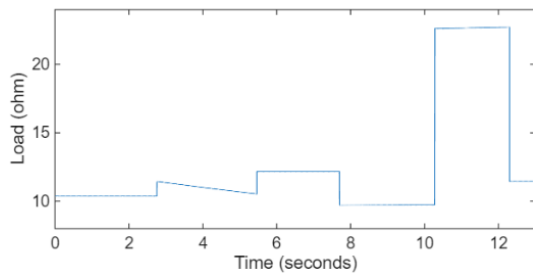


Fig. 6. Load profile

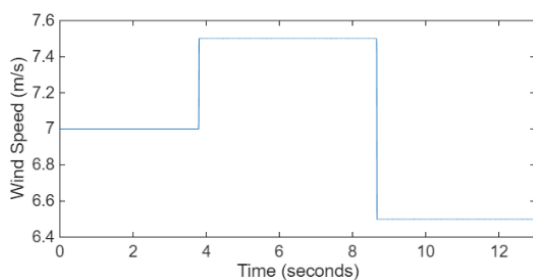


Fig. 7. Wind-speed profile

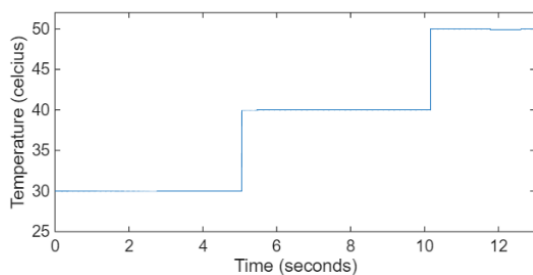


Fig. 8. Temperature profile

B. Quantitative Performance

The performance of the wind-turbine, photovoltaic (PV), and battery current loops is evaluated for three control strategies, as illustrated in Fig. 9 to Fig. 11. All three controllers distribute power to meet the DC-load demand, but their tracking responses differ. CSMC uses fixed switching gains and exhibits less precise tracking and more visible high-frequency variation in Fig. 9. The ASMC response in Fig. 10 benefits from gain scheduling as the accumulated tracking error crosses the prescribed thresholds. ASMC-NSS provides the closest agreement between measured and reference currents in Fig. 11 under the simulated generation and load variations.

Fig. 12 compares the output-current transients obtained with CSMC, ASMC, and the proposed ASMC-NSS under identical load changes. The quantitative indices in Table 3 use the same simulation interval for all controllers. IAE represents the accumulated error magnitude, whereas RMSE gives greater weight to larger instantaneous errors; therefore, reductions in both indices indicate improved tracking over the complete transient rather than only at a single operating point.

The current-overshoot entries in Table 3 are dimensionless ratios and are therefore reported in per unit (p.u.). Percentage reduction is calculated as $100 \times (\text{baseline} - \text{ASMC-NSS})/\text{baseline}$ using the reported values and is rounded to one decimal place.

Table 3. Quantitative current-tracking performance based on Fig. 12

Metric	CSMC	ASMC	ASMC-NSS
IAE (A·s)	15.13	11.27	1.43
RMSE (A)	4.78	4.29	1.33
Rise time (s)	0.370	0.280	0.031
Settling time (s)	0.510	0.370	0.054
Maximum overshoot (p.u.)	0.0103	0.0016	0.00025

Relative to CSMC, conventional ASMC lowers the current-tracking IAE by 25.5% and the RMSE by 10.3%. The addition of the NSS produces a substantially larger improvement: ASMC-NSS reduces IAE by 90.5% and RMSE by 72.2% against CSMC, and by 87.3% and 69.0%, respectively, against ASMC, as shown in Table 4. The rise time decreases from 0.370 s (CSMC) and 0.280 s (ASMC) to 0.031 s, corresponding to reductions of 91.6% and 88.9%. Likewise, the 0.054-s settling time is 89.4% shorter than CSMC and 85.4% shorter than ASMC, while the overshoot magnitude is reduced by 97.6% and 84.4%. These simultaneous improvements are consistent with the NSS varying the effective sliding-surface scaling during the transient, thereby accelerating reaching while suppressing the tracking error near the reference.

The saturation boundary layer attenuates discontinuous switching in the averaged current response, but the manuscript does not claim complete chattering elimination. A controller-output total-variation index would be strongly dependent on solver resolution in an averaged model and would not quantify semiconductor switching ripple. Chattering is therefore interpreted together with the current RMSE, overshoot, and plotted high-frequency variation under the same numerical settings. Device-level PWM simulations or experiments that report control-signal total variation and switching loss are identified as future work.

Table 4. Current-tracking error reduction achieved by ASMC-NSS

Baseline	IAE reduction	RMSE reduction
CSMC	90.5%	72.2%
ASMC	87.3%	69.0%

Fig. 13 evaluates voltage regulation around the 500 V reference. Table 5 summarizes the maximum overshoot, recovery time, IAE, and RMSE for the three controllers, while Table 6 reports the reduction obtained by ASMC-NSS relative to each baseline.

ASMC-NSS limits the maximum DC-bus overshoot to 0.28 V, which is 20.0% lower than CSMC and 17.6% lower than ASMC. Its 0.02-s recovery time is 88.9% shorter than CSMC and 85.7% shorter than ASMC. The IAE decreases to 1.69 V·s, giving reductions of 19.9% and 19.1%, whereas the RMSE decreases to 0.14 V, corresponding to reductions of 26.3% and 22.2%. The smaller percentage gains at the DC bus than in the current loops are expected because the DC-link capacitor buffers short-duration current imbalance and all three controllers already maintain a small absolute voltage error. Nevertheless, the consistently lower overshoot, recovery time, IAE, and RMSE show that the improved current tracking is translated into tighter DC-bus regulation.

Table 5. Quantitative DC-bus voltage performance based on Fig. 13

Metric	CSMC	ASMC	ASMC-NSS
Maximum overshoot (V)	0.35	0.34	0.28
Recovery time to ± 0.5 V band (s)	0.18	0.14	0.02
IAE (V·s)	2.11	2.09	1.69
RMSE (V)	0.19	0.18	0.14

For the 500 V reference, ± 0.5 V corresponds to a $\pm 0.1\%$ band. The reported value is therefore interpreted as recovery time to this tight band, rather than the conventional 10–90% rise time.

Table 6. DC-bus error reduction achieved by ASMC-NSS

Baseline	IAE reduction	RMSE reduction
CSMC	19.9%	26.3%
ASMC	19.1%	22.2%

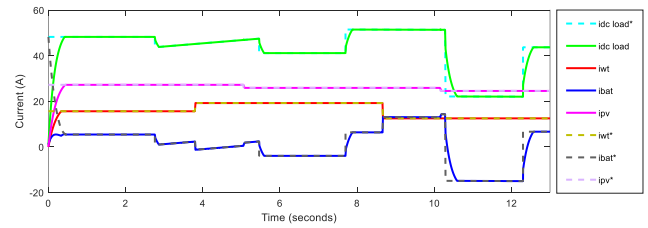
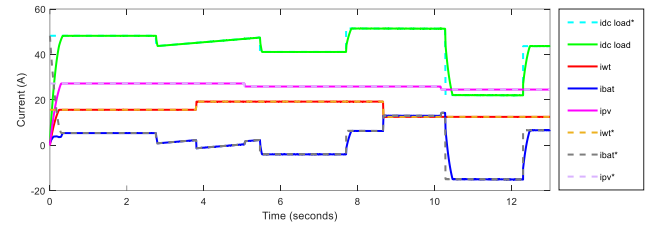
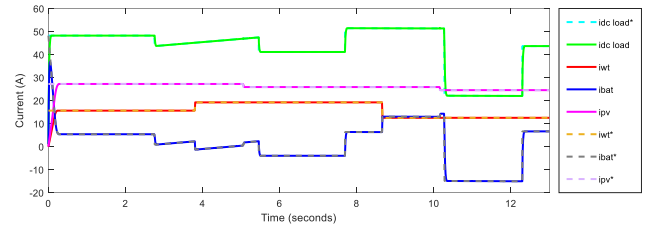
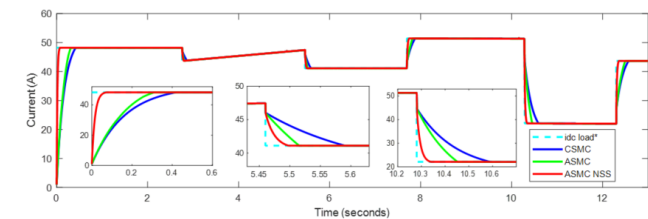
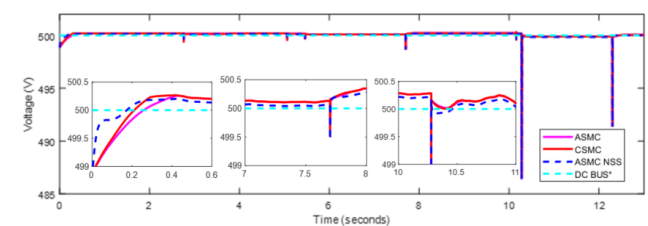
Finally, Fig. 14 shows the normalized battery SoC. Under the sign convention in (19), positive battery current decreases SoC during discharge, whereas negative current increases SoC during charging. The small excursion from approximately 1.0 p.u. is consistent with the 34-Ah capacity and the short 13 s simulation interval. Because battery ageing and electrochemical stress are not modeled, the figure is interpreted as an energy-balance indicator rather than evidence of degradation reduction.

The results from Fig. 9 to Fig. 14 and Table 3 to Table 6 confirm that the proposed ASMC-NSS improves both converter-current tracking and DC-bus voltage regulation. Relative to CSMC and ASMC, respectively, current-tracking IAE is reduced by 90.5% and 87.3%, while DC-bus IAE is reduced by 19.9% and 19.1%. The agreement among IAE, RMSE, rise/recovery time, settling time, and overshoot metrics supports the conclusion that the performance gain is not confined to a single index.

Theorem 2 establishes boundedness under matched uncertainty, but this analytical result does not replace numerical validation under the broader conditions suggested by the reviewer. Future work will therefore examine irradiance variation, a wider wind-speed range, additional load-step scenarios, coordinated parameter uncertainty,

detailed converter-loss variation, and sensor noise using a common plant model, controller settings, and evaluation protocol.

The numerical comparison deliberately uses CSMC and ASMC as nested baselines on the identical plant so that the incremental effects of adaptive gain scheduling and the nonlinear surface can be isolated. Direct numerical values from MPC, PI/PID, higher-order SMC, fuzzy-SMC, or RL-SMC studies are not combined with Table 3 to Table 6 because those studies use different converter topologies, objectives, constraints, sampling rates, and disturbance profiles. Table 1 provides a literature-based positioning instead; a matched-plant benchmark against one representative advanced controller is reserved for future work.

**Fig. 9.** Output currents using CSMC**Fig. 10.** Output currents using ASMC**Fig. 11.** Output currents using ASMC-NSS**Fig. 12.** Comparison of output-current responses**Fig. 13.** DC-bus voltage comparison

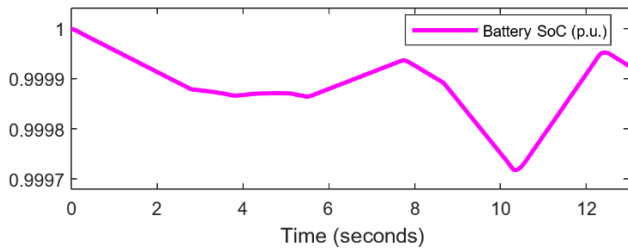


Fig. 14. Normalized battery SoC (p.u.; 1.0 p.u. = 100%)

V. CONCLUSION

This study developed an ASMC-NSS controller for the power converters of an islanded DC microgrid. The adaptive gain schedule maintains switching authority as the tracking error changes, while the NSS provides a bounded state-dependent scaling of the sliding surface to improve the transient response. The Lyapunov analysis establishes asymptotic stability of the ideal inner current loops and uniform ultimate boundedness in the presence of bounded matched uncertainties; the DC-bus result is interpreted through the stated outer-loop assumption.

Under the reported matched MATLAB/Simulink conditions, ASMC-NSS produces lower current-tracking and DC-bus error metrics than CSMC and standard ASMC. Current-tracking IAE is reduced by 90.5% relative to CSMC and by 87.3% relative to ASMC, while the corresponding DC-bus IAE reductions are 19.9% and 19.1%. The proposed controller achieves a 0.054-s current settling time, limits the maximum DC-bus overshoot to 0.28 V, and returns the 500 V bus to the ± 0.5 V band within 0.02 s.

Future work will extend the validation to irradiance variation, a wider wind-speed range, additional sudden load changes, coordinated parameter uncertainty, detailed converter-loss models, and sensor noise. These cases will be evaluated through a controlled simulation campaign using identical controller settings and metric definitions. Hardware-in-the-loop and prototype experiments will subsequently report control-signal total variation and switching loss. A matched-plant benchmark against one representative advanced controller, such as MPC or higher-order SMC, will be used to avoid an unstructured comparison across incompatible models. Multi-objective tuning of β , ϕ , θ_i , and the adaptive-gain thresholds will target shorter settling and recovery times, smaller DC-bus deviation and overshoot, and lower current IAE and RMSE. An explicit outer DC-bus controller will also be developed to extend the inner-loop Lyapunov result to the complete closed loop.

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