

Development of the Hybrid MPPT Control Algorithm for Grid-Connected PV Systems Using Runge-Kutta Optimized Fractional-Order Synergetic Control

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ABSTRACT

Grid-connected photovoltaic (PV) systems often face performance degradation due to fluctuations in irradiance and temperature, which adversely affect power quality and reduce energy extraction efficiency. Conventional maximum power point tracking (MPPT) techniques, including proportional integral (PI) and fractional-order PI (FOPI) controllers, typically suffer from slow dynamic response, voltage oscillations, and limited robustness under rapidly changing operating conditions. To address these challenges, this study proposes the development and optimization of a novel hybrid MPPT control strategy that integrates a Kalman filter with a proportional derivative-assisted perturb-and-observe (PD-P&O) algorithm. The controller parameters are optimized using the Runge-Kutta method, resulting in enhanced tracking performance and improved robustness. In addition, a fractional-order synergetic control scheme is implemented on the grid side to regulate the DC-link voltage and control the i_d and i_q currents, thereby improving overall system stability. Simulation studies conducted on a 100 kW grid-connected PV system under varying irradiance and temperature conditions demonstrate the superiority of the proposed approach over conventional methods. The optimized controller achieves a faster settling time of 1.0387 s, representing a 58.44% improvement, along with a higher maximum output power of 100.72 kW, corresponding to a 52% enhancement. Moreover, the proposed strategy ensures smoother voltage and current responses with minimal overshoot. These results confirm the effectiveness and suitability of the proposed hybrid control algorithm for real-time implementation in large-scale grid-connected PV systems.

Abbreviations

PV	: Photovoltaic
RES	: Renewable Energy Sources
MPP	: Maximum Power Point
MPPT	: Maximum Power Point Tracking
DC	: Direct Current
AC	: Alternating Current
RUN	: Runge-Kutta Optimizer
SMC	: Sliding Mode Control
FO	: Fractional Order
KF	: Kalman Filter
P&O	: Perturb and Observe
PD	: Proportional-Derivative

1. Introduction

The global energy sector is facing increasingly complex challenges, particularly due to the rapid growth in energy consumption in recent years. According to the International Energy Agency (IEA), global energy demand was projected to grow by 44% between 2006 and 2030 [1-5]. This trend highlights the unsustainable nature of fossil fuel-based energy systems and underscores the urgent need to transition toward cleaner alternatives [6]. Consequently, renewable energy sources (RESs) have gained increasing attention and have become central to the global energy transition. Renewable energy technologies such as solar, wind, hydro, and biomass play a vital role in addressing

these challenges by providing sustainable and environmentally friendly solutions to meet growing global energy demand [1,7]. By 2021, the total installed capacity of renewable energy systems worldwide reached 3,064 GW [8], marking a significant milestone towards cleaner and more sustainable power generation. This milestone reflects both the rapid expansion of renewable energy capacity and a global commitment to reducing fossil fuel dependence and mitigating environmental degradation. In 2021 alone, newly added renewable energy capacity reached 257 GW [8,9]. Among these technologies, photovoltaic (PV) solar power emerged as the leading contributor, adding 133 GW, according to the International Renewable Energy Agency (IRENA) [10,11].

RESs have proven to be a viable and sustainable option for power generation, characterized by their environmental cleanliness, safety, and long-term viability. Among these, solar and wind energy have become the most significant due to their widespread availability and global distribution, offering the potential to meet the world's entire energy demand. The research on maximum power point tracking (MPPT) for PV systems is primarily driven by the need to enhance energy extraction efficiency in response to varying environmental conditions. Several studies emphasize the need for robust and adaptive control strategies to address challenges such as partial shading, fluctuating solar irradiance, and temperature variations. For instance, the background and motivation for MPPT research are underscored by the necessity to optimize

power output in real-time, ensuring the PV systems operate at their maximum efficiency [12,13]. Bio-inspired and swarm intelligence algorithms have gained prominence as effective approaches to improving MPPT performance. Bio-inspired optimization methods, such as the jellyfish search algorithm inspired by marine food search strategies, exemplify efforts to develop algorithms capable of adaptively tracking MPP in dynamic conditions [14]. Similarly, the star-nosed mole optimization algorithm has been introduced to enhance MPPT efficiency under partial shading conditions (PSCs), highlighting the need for novel bio-inspired techniques to improve tracking accuracy and robustness [15]. Ongoing research is also motivated by the limitations of traditional MPPT methods, which may not perform well under complex environmental conditions. This has prompted the exploration of hybrid and intelligent control techniques, such as artificial neural networks (ANNs) and AI-based methods, to improve the efficiency and reliability of MPPT systems [16]. These approaches seek to overcome the limitations of conventional algorithms by offering faster convergence and greater adaptability to changing environmental conditions. Furthermore, the integration of MPPT control strategies within hybrid renewable energy systems underscores the broader motivation to develop sustainable and efficient energy solutions. The push towards sustainable energy systems is driven by environmental concerns and the urgency to reduce reliance on fossil fuels, motivating research into optimized control algorithms for real-time applications [12]. The motivation for PV MPPT research stems from the need to maximize energy harvesting, enhance system robustness under diverse environmental conditions, and develop adaptive and intelligent control algorithms. These efforts are crucial for advancing PV technology toward more efficient and sustainable energy generation [15].

The existing research on MPPT for PV systems has reported significant advancements while also revealing notable gaps that warrant further investigation. One prominent research gap concerns the optimization of MPPT algorithms to improve energy harvesting efficiency under diverse and dynamically changing environmental conditions. For instance, [17] investigates hybrid deep learning approaches to improve solar energy harvesting efficiency; however, the study also indicates that further optimization is required to ensure robustness under rapidly varying operating conditions. Similarly, [18] analyzes multiple algorithmic approaches for PV performance optimization and indicates that the adaptability and generalization capability of MPPT algorithms across varying conditions remain insufficiently explored. Another significant research gap concerns the performance of MPPT algorithms under partial shading conditions (PSCs). The study in [19] proposes the Chimp Optimization Algorithm for partially shaded scenarios, implicitly demonstrating that conventional MPPT methods are often inadequate under such complex operating conditions. This highlights a broader research need for MPPT algorithms that can maintain optimal tracking performance under shading variability and other non-ideal conditions commonly encountered in real-world PV installations.

The application of intelligent and machine learning (ML) techniques has also revealed several unresolved research gaps. For example, [20] highlights the use of ANN and ripple correlation control (RCC) methods to improve MPPT performance, yet acknowledges that significant gaps remain in the development and practical integration of advanced ML-based MPPT algorithms. Similarly, [21] reviews ML-based MPPT techniques, identifying persistent challenges related to accuracy, convergence speed, and adaptability, which hinder large-scale and real-time deployment. Beyond algorithm structure, the optimization of key control

parameters, such as step size, is recognized as a critical factor influencing MPPT efficiency. The research in [22] points out the gap concerning the optimization of step size in algorithms like Grey Wolf Optimization (GWO) and Whale Optimization Algorithm (WOA), emphasizing that improper step-size selection can compromise the trade-off between dynamic response speed and system stability. Innovative hybrid approaches also reveal existing gaps. For instance, [23] introduces a novel hybrid MPPT technique but reports that system performance under varying operating conditions and the ability to effectively address power stability (PS) issues remain insufficiently investigated. Additionally, related studies on fuzzy logic control (FLC) for climate-resilient PV systems indicate that the integration of intelligent control strategies to effectively handle nonlinearities and environmental uncertainties remains an open research area [22]. The literature underscores several key research gaps in PV MPPT technology: the need for more robust algorithms capable of handling partial shading and environmental variability, the integration of advanced ML techniques for improved accuracy and adaptability, optimization of algorithm parameters such as step size, and the development of hybrid and intelligent control strategies to enhance system resilience and efficiency. Addressing these gaps is essential for advancing MPPT technologies toward more reliable and efficient solar energy harvesting systems.

In this study, the incremental conductance (IC) method is employed for MPPT in a 100 kW grid-connected PV system. Originally introduced in 1993 [24], the IC algorithm overcomes several limitations of the traditional Perturb and Observe (P&O) approach by comparing both the instantaneous conductance and the incremental conductance [25]. The key principle of the IC method is that at the MPP, the derivative of power with respect to voltage is zero, enabling more accurate tracking, particularly under rapidly changing irradiance conditions [1].

This study integrates the IC technique with a Kalman filter and a proportional-derivative assisted P&O controller (KF-PD-P&O) to achieve an effective balance between tracking performance and controller complexity. To optimize the parameters of this hybrid controller, the Runge Kutta Optimizer (RUN) algorithm is introduced, which is employed to optimize the controller parameters, thereby enabling precise MPP tracking through effective inverter control. The tuning capability of the RUN algorithm is benchmarked against recent optimization techniques, including the GTO [26] and AVO [27] algorithms. RUN is selected due to its high parameter-tuning precision, fast convergence with an effective balance between global and local search, robustness under various irradiance profiles stepped, linear, and real-world data, and superior performance demonstrated through comparative simulations. Additionally, the proposed controller is compared with a conventional single MPPT controller commonly used in grid-connected PV systems. The main contributions of this work include:

- (i) Development and validation of a novel MPPT control strategy using MATLAB/Simulink simulations of a 100 kW grid-connected PV system;
- (ii) Application of the RUN algorithm to optimally tune the KF-PD-P&O controller parameters, with performance comparisons against GTO and AVO algorithms;
- (iii) Integration of a grid-side fractional-order (FO) controller to enhance DC-link voltage regulation, system stability, and operational efficiency;
- (iv) Demonstration that the proposed method outperforms conventional controllers in maximum power tracking under diverse

irradiance and temperature conditions, ensuring optimal energy extraction.

This approach represents a significant advancement in MPPT control by integrating algorithmic optimization with hybrid control techniques to enhance the efficiency and reliability of grid-connected PV systems. The paper is organized as follows: **Section 2** presents the theoretical background of PV modeling and describes the overall system configuration. **Section 3** introduces the proposed control approach, which is divided into two parts: the control strategy for the grid-connected PV system and the MPPT control method. **Section 4** presents the simulation results and discussion based on three test scenarios: *Scenario I* considers stepwise changes in irradiance under constant temperature; *Scenario II* examines ramp variations in both irradiance and temperature; and *Scenario III* investigates multi-step changes in irradiance and temperature. Finally, **Section 5** concludes the paper.

2. Theoretical Foundations of PV Modeling and System Configuration

In the modeling of PV cells, several approaches have been proposed to accurately describe their electrical behavior. Among them, the single-diode model (SDM), the double-diode model (DDM), and the triple-diode model (TDM) are the most widely recognized [28]. The TDM provides the highest level of accuracy by accounting for recombination and loss mechanisms, but it is computationally demanding. The DDM offers a compromise between precision and complexity, making it suitable for studies that require a moderate level of detail. The SDM, however, is the most frequently adopted because of its simplicity, reduced parameter requirements, and computational efficiency, making it highly practical for both simulation and control applications [29]. In the SDM, the PV cell is represented by an equivalent circuit consisting of: A photocurrent source I_{ph} ; An ideal diode; A series resistance R_s ; A parallel shunt resistance as R_{sh} . This configuration effectively captures the essential electrical characteristics of the PV cell under varying irradiance and temperature conditions. Fig. 1 illustrates the equivalent circuit of a PV cell based on the SDM. The output current of a PV cell can be expressed as:

$$I = I_{ph} - I_d - I_{sh} \quad (1)$$

where I_{ph} is the photocurrent proportional to irradiance and temperature; I_d is the diode current; and I_{sh} is the shunt resistance current. The diode current is modeled using the Shockley equation:

$$I_d = I_0 \left(e^{\frac{q(V+I R_s)}{n k_b T}} - 1 \right) \quad (2)$$

where I_0 is the diode reverse saturation current; q is the electron charge 1.6×10^{-19} C; n is the diode ideality factor; k_b is the Boltzmann constant 1.38×10^{-23} J/K; and T is the absolute temperature (K). The current through the shunt resistance is:

$$I_{sh} = \frac{V + I R_s}{R_{sh}} \quad (3)$$

in (3), R_{sh} is the shunt resistance, R_s is the series resistance, V is the output voltage. Substituting Eqs. (2) and (3) into Eq. (1), the overall SDM equation becomes:

$$I = I_{ph} - I_0 \left(e^{\frac{q(V+I R_s)}{n k_b T}} - 1 \right) - \frac{V + I R_s}{R_{sh}} \quad (4)$$

For a PV module consisting of N_s series-connected cells and N_p parallel branches, the generalized form is given by:

$$I = N_p I_{ph} - N_p I_0 \left(e^{\frac{q(V+I R_s)}{n k_b T}} - 1 \right) - N_p \left(\frac{V}{R_{sh}} + I \frac{R_s}{N_p} \right) \quad (5)$$

Table 1 The electrical specifications of the array PV are summarized.

Parameters	Value
Maximum Power	305.226 W
Cells per module	96 Ncell
Open circuit voltage, Voc	64.2 V
Short-circuit current, Isc	5.96 A
Voltage at maximum power point, Vmp	54.7 V
Current at maximum power point, Imp	5.58 A
Temperature coefficient of, Voc	-0.2727 %/deg.C
Temperature coefficient of, Isc	0.061745 %/deg.C

The PV system considered in this study has a rated capacity of 100 kW. The PV array consists of five parallel-connected strings, each comprising 66 SunPower SPR-305E-WHT-D modules (SunPower Corporation, San Jose, CA, USA) connected in series. The electrical specifications of the array are summarized in Table 1.

To maximize energy extraction, an MPPT strategy based on the incremental conductance (IncCond) algorithm is employed. This controller minimizes the conductance error and continuously adjusts the operating point to achieve optimal power delivery. In practice, the MPPT unit regulates the duty cycle (D) of a 500 V boost converter, which feeds an inverter coupled to the medium-voltage grid. The impact of environmental conditions on PV performance is illustrated in Fig. 2, where the I-V and P-V characteristics highlight irradiance and temperature as the dominant factors influencing output power [30]. The schematic representation of the proposed control approach is provided in Fig. 3-a, while further system details are documented in [1].

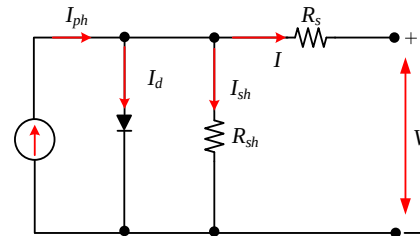


Fig. 1 Equivalent circuit representation of a PV cell based on the single-diode model.

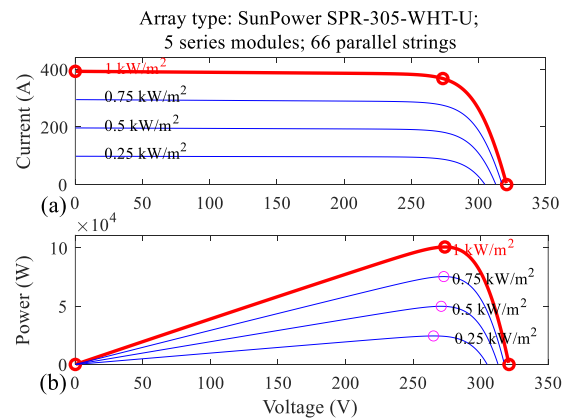


Fig. 2 Performance curves (IV and PV) of the PV system under test obtained for several irradiance levels at 25°C.

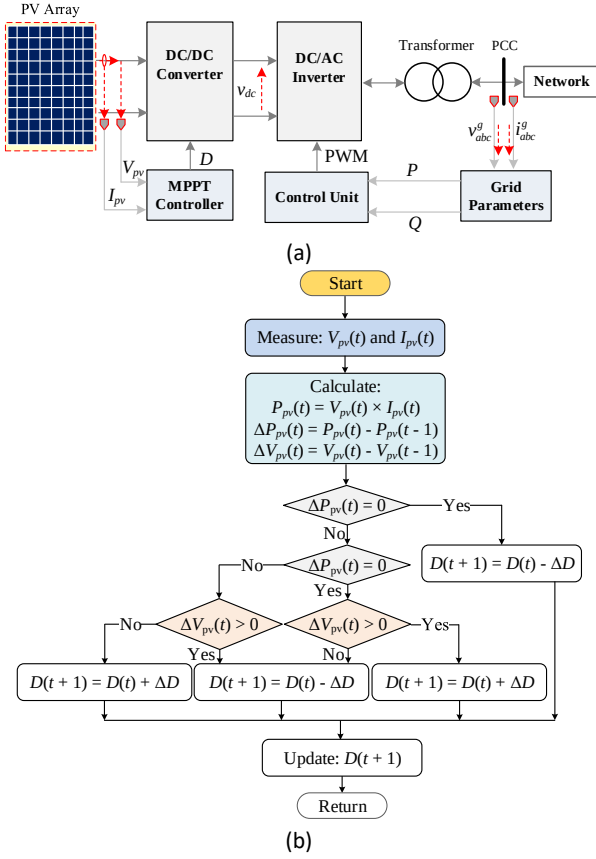


Fig. 3 Control model; (a) Schematic representation of the grid-integrated PV system, and (b) Algorithm flowchart of the conventional P&O method.

The PV system is operated based on MPPT control. In many previous studies, the P&O algorithm has been adopted, as illustrated in Fig. 3-b [31]. This method periodically perturbs the operating point of the PV array and then evaluates the resulting change in output power. The operating point is iteratively adjusted toward higher power until the MPP is reached. However, tracking can be slow, particularly when the MPP varies rapidly due to fast irradiance or temperature changes. The convergence speed of the P&O algorithm strongly depends on the perturbation step size: a larger step improves tracking speed but increases oscillations and the likelihood of overshooting the MPP, whereas a smaller step reduces oscillations but slows convergence. To overcome these limitations, this study proposes a new control strategy that enhances tracking performance under rapidly changing conditions.

According to the coordinate transformation, PQ control can be realized in the dq reference frame. In a PV system, the external PQ control is often modified into DC voltage control. The q -axis current reference determines the PV output reactive power [32]. The d -axis current reference is generated through DC voltage control to adjust the PV output active power to maintain DC link power balance and stabilize DC voltage, and this controller is found in the study [33].

3. Proposed Control Method

3.1 Proposed Control of The Grid-Connected PV System

The control strategies for grid-connected PV systems are extensively discussed in [34], covering both standard operation and low-voltage ride-through scenarios. For the inner current loops controlling i_d and i_q , either conventional PI controllers or synergistic controllers are employed [35]. The outer voltage loop, which regulates v_{dc} , is managed using a standard PI controller.

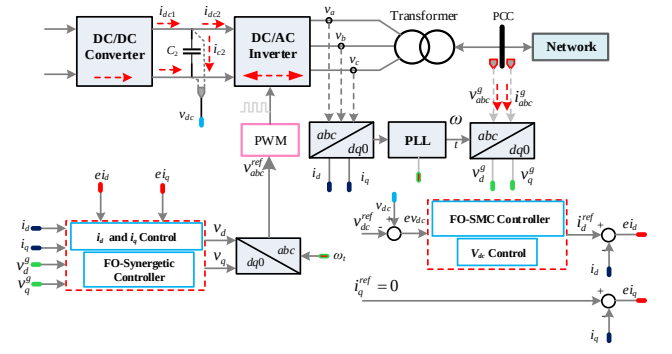


Fig. 4 Schematic diagram illustrating the FO-based sliding mode control and FO-synergetic control strategies for a grid-tied PV system.

Fig. 4 illustrates the control structure for normal grid-connected operation of the PV system. This section also introduces fundamental aspects of fractional-order (FO) computations applied in the design and synthesis of fractional-order control laws, specifically when implementing sliding mode control (SMC) and synergistic control techniques [34].

Concepts and symbols for fractional degrees: To generalize classical differentiation and integration, an operator of non-integer order is introduced and denoted as aD_t^α , where α represents the fractional order (FO) and the limits of the operator are defined by the bounds a and t [36]. The operator is formally given as:

$$aD_t^\alpha = \begin{cases} \frac{\partial^\alpha}{\partial t^\alpha} & \alpha > 0 \\ 1 & \alpha = 0 \\ \int_a^t (\partial\tau)^{-\alpha} & \alpha < 0 \end{cases} \quad (6)$$

A widely used definition of this operator is the Riemann-Liouville (RL) differintegral, expressed as [37]:

$$\frac{1}{\Gamma(m-\alpha)} \left(\frac{\partial}{\partial t} \right)^m \int_a^t \frac{f(\tau)}{(t-\tau)^{\alpha-m+1}} d\tau = aD_t^\alpha f(t) \quad (7)$$

where $m-1 < \alpha < m$, $m \in \mathbb{R}$, and $\Gamma(\cdot)$ is the Euler's gamma function. For numerical implementation, the Grunwald-Letnikov (GL) formulation is often employed [38]:

$$aD_t^\alpha f(t) = \lim_{h \rightarrow 0} \frac{1}{h^\alpha} \sum_{j=0}^{\left[\frac{t-\alpha}{h} \right]} (-1)^j \binom{\alpha}{j} f(t-jh) \quad (8)$$

where $\left[\frac{t-\alpha}{h} \right]$ denotes the integer part. The Laplace transform can also be extended to fractional-order operators in the same manner as in integer-order calculus, by raising the complex operator s to a fractional power. For commensurate order systems of type q , with $q \in \mathbb{R}^+$, $0 < q < 1$, and $\alpha_k = kq$, the transfer function can be expressed as [37,38]:

$$H(\lambda) = \frac{\sum_{k=0}^m b_k \lambda^k}{\sum_{k=0}^n a_k \lambda^k} \text{ with } \lambda^k = s^q \quad (9)$$

In practical embedded implementations, direct realization of fractional operators is not feasible. Instead, they are approximated by integer-order systems within a predefined frequency band (ω_b, ω_h) . One common approach is the Oustaloup recursive filter, which approximates fractional powers of s . For $0 < \gamma < 1$, the approximation is given as [39]:

$$G_Y(s) = \omega_h^\gamma \prod_{k=-N}^N \frac{s + \omega'_k}{s + \omega_k} \quad (10)$$

with the poles ω_k , and zeros ω'_k computed as:

$$\begin{cases} \omega'_k = \omega_b \left(\frac{\omega_h}{\omega_b} \right)^{\frac{k+N+0.5(1-\gamma)}{2N+1}} \\ \omega_k = \omega_b \left(\frac{\omega_h}{\omega_b} \right)^{\frac{k+N+0.5(1+\gamma)}{2N+1}} \end{cases} \quad (11)$$

where ω_b , and ω_h represent the lower and upper frequency bounds of the approximation band, respectively.

A more refined description of oustaloup-type filters can be expressed as:

$$s^\gamma \approx \left(\frac{\partial \omega_b}{b} \right)^\gamma \frac{\partial s^2 + b \omega_b s}{\partial (1 - \alpha) s^2 + b \omega_h s + \partial \alpha} A \quad (12)$$

$$\text{in with } A = \omega_h^\gamma \prod_{k=-N}^N \left(\frac{s + \left(\frac{\partial \omega_b}{b} \right)^{\frac{\alpha-2k}{2N+1}}}{s + \left(\frac{b \omega_h}{h} \right)^{\frac{\alpha+2k}{2N+1}}} \right).$$

The design parameters are chosen as $b = 10$ and $h = 9$.

Fractional-Order Sliding Mode Control (FO-SMC) [34]: Building upon the fractional-order calculus framework introduced in concepts and symbols for fractional degrees, this section develops the FO-SMC for the DC-AC converter. By introducing the switching variables S_a , S_b , and S_c , the system dynamics in the abcabc-frame can be expressed as:

$$C_2 \frac{\partial v_{dc}}{\partial t} = i_{dc1} - (i_a S_a + i_b S_b + i_c S_c) \quad (13)$$

where C_2 denotes the DC-link capacitor, and i_{dc1} is the current associated with the DC bus. Using the Clarke transformation, the switching functions S_d and S_q are obtained, resulting in[34]:

$$C_2 \frac{\partial v_{dc}}{\partial t} = i_{dc1} - \frac{3}{2} (i_d S_d + i_q S_q) \quad (14)$$

Considering a symmetrical three-phase system, the quadrature current reference is set as $i_q^{ref} = 0$. Hence, the dynamics simplify to:

$$C_2 \frac{\partial v_{dc}}{\partial t} = i_{dc1} - \frac{3}{2} (i_d^{ref} S_d) \quad (15)$$

Sliding surface design: To design the sliding controller, let the state variable be defined as:

$$\begin{cases} ev_{dc} = v_{dc} - v_{dc}^{ref} \\ x_2 = \dot{ev}_{dc} = -\dot{v}_{dc} \end{cases} \quad (16)$$

where x_2 is the Auxiliary state variable.

The switching surface is then formulated as:

$$\begin{cases} S = c_1 (ev_{dc}) + x_2 \\ \dot{S} = c_1 x_2 + \dot{x}_2 \end{cases} \quad (17)$$

where c_1 is a positive constant. For the convergence of trajectories toward the surface, the reaching law is chosen as:

$$\dot{S} = -\varepsilon \operatorname{sgn}(S) + kS \quad (18)$$

with $\varepsilon, k > 0$. Substituting the dynamics of ev_{dc} and x_2 , one obtains:

$$\ddot{ev}_{dc} = \dot{x}_2 = -\dot{v}_{dc} = \frac{3}{2C_2} S_d i_d^{ref} - \frac{i_{dc1}}{C_2} \quad (19)$$

Improved reaching law and smoothing function: To alleviate chattering effects due to the discontinuous sign function, a sigmoid-based function is adopted [34]:

$$h(x) = \frac{2}{1 + e^{-a(x-b)}} - 1 \quad (20)$$

where a and b adjust the slope and shift of the function, ensuring a smooth transition between $[-1, 1]$. Consequently, the reference current of the controller is expressed as [40]:

$$i_d^{ref} = \frac{2}{3} \frac{C_2}{S_d} \int_0^t \left[-(c_1 x_2 + kS - \varepsilon h(S)) + \frac{i_{dc1}}{C_2} \right] \partial t \quad (21)$$

Incorporating the fractional-order operator D^μ defined earlier, concepts and symbols for fractional degrees, the sliding surface is generalized as:

$$S = c_1 (ev_{dc}) + c_2 D^\mu (ev_{dc}) \quad (22)$$

where c_1, c_2 are positive gains and $\mu \in (0, 1)$ represents the fractional differentiation order. The time derivative of the switching surface is then:

$$\dot{S} = c_1 (\dot{ev}_{dc}) + c_2 D^\mu \dot{x}_2 \quad (23)$$

which, after substituting system dynamics, yields:

$$\dot{S} = c_1 x_2 + c_2 D^{\mu-1} \left(\frac{3}{2C_2} S_d i_d^{ref} - \frac{i_{dc1}}{C_2} \right) \quad (24)$$

By applying the reaching law condition, the closed-loop fractional-order control law is obtained:

$$-\varepsilon h(S) - kS - c_1 x_2 = c_2 D^{\mu-1} \left(\frac{3}{2C_2} S_d i_d^{ref} - \frac{i_{dc1}}{C_2} \right) \quad (25)$$

where k is the sliding mode gain, is ε the reaching law coefficient.

Finally, the control signal corresponding to the FO-SMC is expressed as:

$$i_d^{ref} = \frac{2}{3} \frac{C_2}{S_d} \int_0^t \left[\frac{i_{dc1}}{C_2} + D^{1-\mu} (-\varepsilon hS - kS - c_1 x_2) \right] \partial t \quad (26)$$

This formulation introduces a fractional-order degree of freedom that enhances the robustness and flexibility of the controller compared to conventional sliding mode control. To further ensure stability in practice, the switching signal S_d is often modified as $S'_d = S_d + c_3$, $c_3 > 0$ prevents uncontrolled variations of the reference current during zero-crossings.

From Eq. (20) to Eq. (26), the control law has been developed and extended into a control structure. Based on these formulas, the control diagram of the FO-SMC controller is illustrated in fig. 5, which shows its implementation in MATLAB/Simulink. This block diagram reflects the separation of the control law into calculation and feedback components, allowing simulation and analysis of the dynamic behavior of the system.

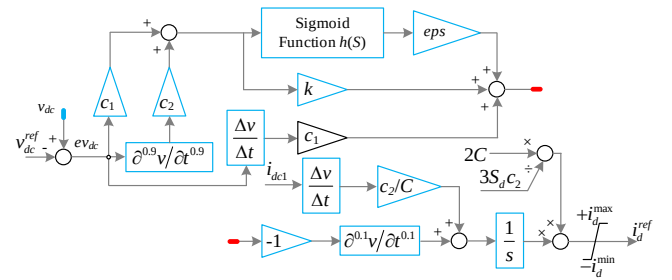


Fig. 5 Block diagram of the FO-SMC controller implemented in MATLAB/Simulink.

Fractional-Order Synergetic Control: Synergetic control can be regarded as a generalized form of sliding mode control, extending its applicability to nonlinear systems. A nonlinear dynamic system is commonly expressed as [35]:

$$\dot{x} = f(x, u, t) \quad (27)$$

where $x \in R^n$ is the state vector, $u \in R^m$ ($m < n$) denotes the control input, and $f(\cdot)$ is a continuous nonlinear function. The core principle of synergetic control involves selecting a macrovariable $\psi(x, t)$, which is a function of the system states for each control input. The evolution of the system is constrained to the manifold $\psi = 0$ through the dynamic equation:

$$T\dot{\psi} + \psi = 0 \quad (28)$$

where $\dot{\psi}$ is the time derivative of macro-variable, ψ is the macro-variable, with $T > 0$ representing a tunable parameter that dictates the desired convergence rate. Differentiating the macrovariable yields:

$$\dot{\psi} = \frac{\partial \psi}{\partial x} \dot{x} \quad (29)$$

Substituting Eq. (29) into Eq. (28), we obtain:

$$T \frac{\partial \psi}{\partial x} \dot{x} + \psi = 0 \quad (30)$$

From this, the general control law can be described as:

$$u = u(x, \psi(x, t), T, t) \quad (31)$$

In the present work, integer-order and fractional-order synergetic control are employed to replace conventional PI regulators in the current control loops of i_d and i_q . The outputs of the synergetic controller correspond to the voltage references u_d and u_q . For the d -axis, the macrovariable ψ_d is defined as:

$$\psi_d = (v_{dc}^{ref} - v_{dc}) + k_d(i_d^{ref} - i_d) \quad (32)$$

where $k_d > 0$ is a design parameter. To support this definition, an additional state variable, ei_d is introduced alongside the previously defined ev_{dc} in Eq. (16):

$$\begin{cases} ev_{dc} = v_{dc}^{ref} - v_{dc} \\ ei_d = i_d^{ref} - i_d \end{cases} \quad (33)$$

Assuming slow variations of the references or quasi-stationary operation, the state derivatives are given by:

$$\begin{cases} \dot{ev}_{dc} = -\dot{v}_{dc} \\ \dot{ei}_d = -\dot{i}_d \end{cases} \quad (34)$$

This leads to the time derivative of ψ_d :

$$\dot{\psi}_d = \dot{ev}_{dc} + k_d(\dot{ei}_d) = -\dot{v}_{dc} - k_d\dot{i}_d \quad (35)$$

For $T = T_1$, substituting into Eq. (30) yields:

$$T_1(-\dot{v}_{dc} - k_d\dot{i}_d) + ev_{dc} + k_d(ei_d) = 0 \quad (36)$$

By incorporating the machine model and rearranging, the control law can be expressed as:

$$v_d = \left[-T_1\dot{v}_{dc} - T_1k_d \frac{1}{L_3}(v_{3d} - v_d) + ev_{dc} + k_d(ei_d) \right] \frac{L_3}{T_1k_d} \quad (37)$$

Based on the concepts of fractional calculus and fractional sliding mode control, the synergistic approach is generalized by defining the macro variable in fractional form as follows:

$$\psi_d = D^\mu(ev_{dc}) + k_d(ei_d) \quad (38)$$

where D^μ denotes the fractional differential operator of order μ . This extension allows the FO-SC to inherit the robustness properties of fractional calculus while maintaining the structural benefits of synergetic control, ultimately offering improved dynamic performance and adaptability

in nonlinear energy conversion systems. By differentiating Eq. (38), the derivative of the macrovariable in the d -axis can be expressed as:

$$\dot{\psi}_d = D^\mu(\dot{ev}_{dc}) + k_d(\dot{ei}_d) = -D^\mu\dot{v}_{dc} - k_d\dot{i}_d \quad (39)$$

Using this result, Eq. (30) is rewritten as:

$$T_1(-D^\mu\dot{v}_{dc} - k_d\dot{i}_d) + D^\mu(ev_{dc}) + k_d(ei_d) = 0 \quad (40)$$

Rearranging the terms leads to:

$$\frac{T_1k_d v_d}{L_3} = -T_1v_{dc}D^{\mu+1} - \frac{T_1k_d v_{d3}}{L_3} + D^\mu(ev_{dc}) + k_d(ei_d) \quad (41)$$

Thus, the d -axis control input can be derived as:

$$v_d = \frac{L_3}{T_1k_d} \left[-T_1v_{dc}D^{\mu+1} - \frac{T_1k_d v_{d3}}{L_3} + D^\mu(ev_{dc}) + k_d(ei_d) \right] \quad (42)$$

For the q -axis, with $k_q > 0$, the macrovariable is defined as:

$$\psi_q = i_q^{ref} - i_q \quad (43)$$

Introducing the third state variable in addition to those in Eq. (33):

$$\begin{cases} ev_{dc} = v_{dc}^{ref} - v_{dc} \\ ei_d = i_d^{ref} - i_d \\ ei_q = i_q^{ref} - i_q \end{cases} \quad (44)$$

Since $i_q^{ref} = 0$, their derivatives become:

$$\begin{cases} \dot{ev}_{dc} = -\dot{v}_{dc} \\ \dot{ei}_d = -\dot{i}_d \\ \dot{ei}_q = -\dot{i}_q \end{cases} \quad (45)$$

Accordingly, the derivative of the q -axis macrovariable is:

$$\dot{\psi}_q = \dot{ei}_q \quad (46)$$

Substituting into Eq. (30) with $T = T_2$ gives:

$$-T_2\dot{i}_q + (ei_q) = 0 \quad (47)$$

Rearranging yields:

$$v_{q3} + v_q = \frac{L_3}{T_2}(ei_q) \quad (48)$$

Thus, the q -axis control input is obtained as:

$$v_q = \frac{L_3}{T_2}(ei_q) - v_{q3} \quad (49)$$

In the fractional-order case, the macrovariable for the q -axis is extended as:

$$\psi_q = D^\mu(ei_q) + k_q \int_0^t (ei_q)(t) \partial t \quad (50)$$

Differentiating yields:

$$\dot{\psi}_q = D^\mu(\dot{ei}_q) + k_q(ei_q) = -D^\mu\dot{i}_q + k_q(ei_q) \quad (51)$$

Substituting into Eq. (30) results in:

$$T_2C + D^\mu(ei_d) + k_q \int_0^t (ei_d) \partial t = 0 \quad (52)$$

in with $C = \left[D^\mu(-\frac{1}{L_3}(v_{q3} + v_q)) + k_q(ei_q) \right]$.

The property that $D^{-\mu} = I^\mu$, we obtain:

$$E + T_2 k_q I^\mu(ei_q) + ei_q + k_q I^{\mu+1}(ei_q) = 0 \quad (53)$$

in with $E = -\frac{T_2}{L_3}(v_{q3} + v_q)$. This can be rearranged as:

$$T_q k_q I^\mu(ei_q) + ei_q + k_q I^{\mu+1}(ei_q) - \frac{T_2 v_{q3}}{L_3} = \frac{T_2 v_q}{L_3} \quad (54)$$

Hence, the fractional-order control law for the q -axis is:

$$v_q = \left[T_2 k_q I^\mu(ei_q) + ei_q + k_q I^{\mu+1}(ei_q) - \frac{T_2 v_{q3}}{L_3} \right] \frac{L_3}{T_2} \quad (55)$$

In summary, the control signals are given by Eqs. (37) and (49) in the integer-order synergetic case, and by Eqs. (42) and (55) in the fractional-order framework. Finally, by applying the inverse Park transformation, the three-phase control signals are reconstructed as:

$$v_{abc} = P^{-1} v_{dq0} \quad (56)$$

Based on the derivations from Eqs. (38) to (42) for the d -axis current control and from Eqs. (50) to (55) for the q -axis current control, the control scheme is expanded into the block representation shown in fig. 6, which illustrates the FO-synergetic controller implemented.

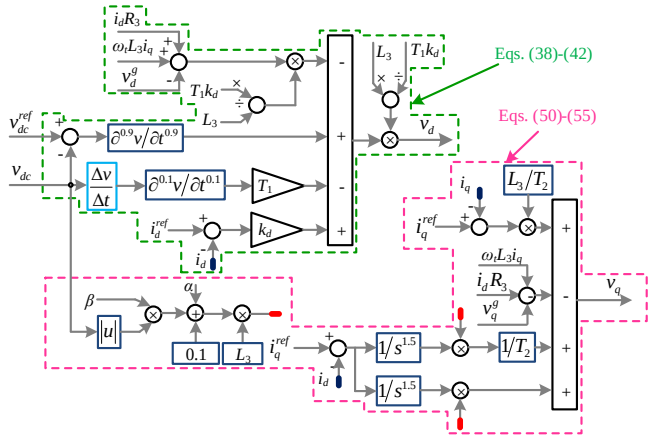


Fig. 6 Block diagram of the FO-synergetic controller implemented in MATLAB/Simulink.

3.2 Proposed MPPT Control Method

The proposed control strategy for a 100 kW grid-connected PV system is detailed. The MPPT algorithm is developed based on the Kalman filter method combined with proportional derivative-assisted P&O control (KF-PD-P&O). This controller takes advantage of the noise reduction and accuracy improvement of the Kalman filter, while inheriting the simplicity and ease of implementation of the traditional P&O algorithm. This control structure allows the system to respond faster to environmental changes, shorten the transition time, reduce over-adjustment, and limit stability fluctuations. In addition, thanks to the Kalman filter, the MPPT input signal is processed more smoothly, improving MPP tracking accuracy and efficiency. In the proposed method, we consider a PV interface that measures voltage $V_m(k)$ and current $I_m(k)$ at discrete time k . Measured power is $P_m(k) = V_m(k)I_m(k)$. The controller manipulates a duty cycle $D(k) \in [D_{min}, D_{max}]$ of a DC-DC converter.

Notation; $V_{fil}(k)$, and $P_{fil}(k)$ are the Kalman filtered voltage and power; $\Delta P(k) = P_{fil}(k) - P_{fil}(k-1)$; $\Delta D(k) = D(k) - D(k-1)$; k_p , and k_d are the PD gains applied to the P&O increment; δ_D is the base perturbation step positive scalar; Q_v , R_v , Q_p , and R_p are the Kalman process/measurement covariances for V and P . **Objective;** track V_{MPP} equivalently the corresponding duty D_{MPP} with fast convergence, small

steady-state oscillation, and robustness to measurement noise and rapid irradiance changes. Use two scalar Kalman filters to denoise V_m and P_m . For each signal $x \in \{V, P\}$, adopt a simple constant-value model, state and measurement model scalar [41]:

$$\begin{cases} x_k = x_{k-1} + w_k \\ y_k = x_k + v_k \end{cases} \begin{cases} w_k \sim N(0, Q_x) \\ v_k \sim N(0, R_x) \end{cases} \quad (57)$$

State and measurement mode per x .

Predict:

$$\begin{cases} \hat{x}_{k|k-1} = \hat{x}_{k-1|k-1} \\ P_{k|k-1} = P_{k-1|k-1} + Q_x \end{cases} \quad (58)$$

Update:

$$\begin{cases} \hat{x}_{k|k} = \hat{x}_{k-1|k-1} + K_k(y_k - \hat{x}_{k|k-1}) \\ K_k = \frac{P_{k|k-1}}{P_{k|k-1} + R_x} \\ P_{k|k} = (1 - K_k)P_{k-1|k-1} \end{cases} \quad (59)$$

Set: $V_{fil}(k) = \hat{V}_{k|k}$, and $P_{fil}(k) = \hat{P}_{k|k}$.

Standard P&O: change D by $\pm \delta_D$ depending on the sign of ΔP and previous ΔD . To reduce oscillation and accelerate convergence, apply a PD correction to the nominal increment. Define the error signal for PD as $e(k) = \Delta P(k)$. Compute PD adjustment:

$$u(k) = k_p e(k) + k_d(e(k) + e(k-1))v \quad (60)$$

Map PD output to an adjusted duty increment:

$$\Delta D_{adj}(k) = \text{sat}(\text{sign}(\Delta P(k))\delta_D + \alpha u(k), -\Delta_{max}, \Delta_{max}) \quad (61)$$

where α is the scale PD output to a duty-domain increment (units: duty per power unit); Δ_{max} is the maximum change per step to ensure stability; $\text{sat}(\cdot)$ is the saturates to bounds.

Update duty:

$$D(k+1) = \text{clip}(D(k) + \Delta D_{adj}(k), D_{max}, D_{min}) \quad (62)$$

Design choices: Use $e = \Delta P$ because P&O logic focuses on power difference; PD acts on the sign and magnitude of ΔP to: (i) boost move when $|\Delta P|$ is large and consistent, (ii) damp when ΔP oscillates or changes sign. Choose sign convention carefully: if $\Delta P > 0$ and previous $\Delta D > 0$, continue in the same direction; PD adds magnitude; if signs conflict, PD can reduce the step or reverse. Therefore, the proposed algorithm is built based on the theory analyzed above and is shown in Table 2.

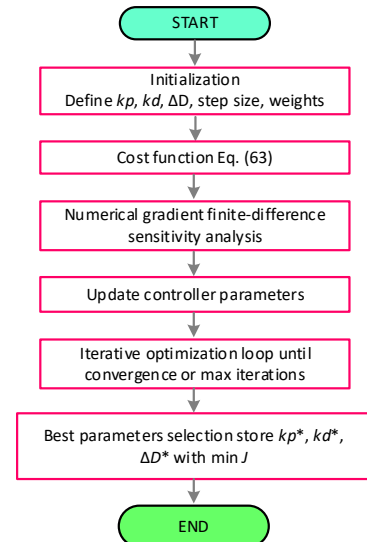


Fig. 7 Flowchart of the proposed method algorithm.

Table 2 Implementation of the proposed MPPT Algorithm for PV Systems.

<pre> %% Adaptive-Velocity PSO-like rng(1); pop = repmat(theta0, popSize, 1) + 0.1*randn(popSize,3); vel = zeros(popSize,3); pbest = pop; pbestVal = inf(popSize,1); gbest = theta0; gbestVal = inf; best_avo = zeros(1,MaxIter); for it=1:MaxIter for i=1:popSize % evaluate fitness (ensure row passed) val = simfun(pop(i,:)); if val < pbestVal(i) pbest(i,:) = pop(i,:); pbestVal(i) = val; end if val < gbestVal gbest = pop(i,:); gbestVal = val; end end % update velocity & position (basic PSO form) w = 0.7; c1 = 1.4; c2 = 1.4; for i=1:popSize r1 = rand(1,3); r2 = rand(1,3); vel(i,:) = w*vel(i,:) + c1*r1.*(pbest(i,:) - pop(i,:)) + c2*r2.*(gbest - pop(i,:)); pop(i,:) = pop(i,:) + vel(i,:); end % enforce bounds pop(i,:) = max(min(pop(i,:), ub), lb); end best_avo(it) = gbestVal; end </pre>	<pre> %% Simple Genetic-type Optimizer rng(2); pop = repmat(theta0, popSize, 1) + 0.1*randn(popSize,3); fitness = inf(popSize,1); best_gto = zeros(1,MaxIter); for it=1:MaxIter % evaluate fitness for i=1:popSize fitness(i) = simfun(pop(i,:)); end [fitness, idx] = sort(fitness); pop = pop(idx,:); % keep elites nElite = round(0.2*popSize); newpop = pop(1:nElite,:); % crossover and mutation while size(newpop,1) < popSize % select parents p1 = pop(randi([1,nElite]),:); p2 = pop(randi([1,nElite]),:); % crossover (single-point) cp = randi(3); child = [p1(1:cp), p2(cp+1:end)]; % mutation mrate = 0.12; if rand < mrate child = child + 0.02*randn(1,3); end child = max(min(child, ub), lb); newpop = [newpop; child]; end pop = newpop; best_gto(it) = fitness(1); end </pre>
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The application of the classical Runge-Kutta 4th-order method in the optimization of MPPT controller parameters $k_p, k_d, \Delta D$, is motivated by the need for accuracy, determinism, and reduced computational burden compared with stochastic metaheuristic algorithms. The objective is to minimize the composite cost function [42]:

$$J = w_1 + T_{set} + w_2 OS + w_3 R \quad (63)$$

where T_{set} is the settling time, which reflects the dynamic speed of the controller; OS is the overshoot, which indicates the transient stability margin; R is the steady-state oscillations, which directly affect MPPT efficiency and converter stress; the w_1, w_2, w_3 can be adjusted to reflect the system designer's priorities. The cost function J is modeled as a differentiable function of the parameters $k_p, k_d, \Delta D$. The tuning process is equivalent to solving the following system of ODEs:

$$\begin{cases} \frac{\partial \theta}{\partial t} = -\nabla J(\theta) \\ \theta = [k_p, k_d, \Delta D] \end{cases} \quad (64)$$

where $\nabla J(\theta)$ is the gradient vector of the cost with respect to the controller parameters. Instead of directly applying steepest descent which is sensitive to step size and noise, Runge-Kutta 4th-order integrates the parameter trajectory using four intermediate evaluations:

$$\theta_{k+1} = \theta_k + \frac{h}{6} (k_1 + 2k_2 + 2k_3 + k_4) \quad (65)$$

with $k_1 = f(\theta_k)$, $k_2 = f(\theta_k + \frac{h}{2}k_1)$, $k_3 = f(\theta_k + \frac{h}{2}k_2)$, $k_4 = f(\theta_k + hk_3)$, where $f(\theta_k) = -\nabla J(\theta)$.

This ensures; Fourth-order accuracy error $O(h^5)$ per iteration. Stability against noisy gradient estimates from PV dynamics. Deterministic convergence since Runge-Kutta 4th-order does not rely on randomness, unlike PSO. Assume initial parameters $(k_p, k_d, \Delta D) = (0.05, 0.01, 0.01)$. After Runge-Kutta 4th-order optimization, convergence is achieved at $(k_p^*, k_d^*, \Delta D^*) = (0.078, 0.015, 0.007)$. The optimized controller reduces J by ~45%, corresponding to faster tracking, lower overshoot, and reduced ripple. The process of the simulation framework can be summarized through the following steps and is summarized in fig. 7: **Step 1.** Select the initial control parameters $(k_p, k_d, \Delta D)$ and set the maximum iteration count for the three optimization methods: Runge-Kutta 4th-order gradient-based (RUN), PSO-like (AVO), and GA-like (GTO). **Step 2.** Define the upper and lower bounds of the search space for each control parameter, ensuring that the optimized gains remain within a feasible and stable region. **Step 3.** Construct the fitness function. In this simulation, a surrogate quadratic cost J was defined, reflecting settling time, overshoot, and ripple. **Step 4.** Run the three optimization algorithms RUN, AVO, GTO. Each algorithm updates the candidate parameters $k_p, k_d, \Delta D$, iteratively based on its specific search mechanism; RUN: gradient-based Runge-Kutta 4th order integration; AVO: population-based adaptive velocity update (PSO-like); GTO: genetic-type crossover and mutation. **Step 5.** At each iteration, record the best fitness score obtained so far. The corresponding control parameters are updated and stored as the current best solution. **Step 6.** After reaching the maximum number of iterations, finalize the best parameters identified by each method. These optimal gains correspond to the lowest cost J and are considered the most effective settings for the PV MPPT controller.

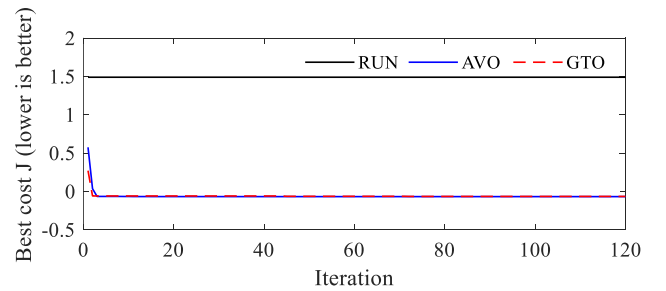


Fig. 8 Convergence of RUN, AVO, and GTO algorithms with respect to the number of iterations.

To demonstrate the effectiveness of the proposed RUN method in optimizing the three considered controllers, a performance comparison was performed in Scenario I, including the RUN, AVO, and GTO algorithms. As shown in fig. 8, the converged configurations (best fit over iterations) of the three methods are presented. This algorithm uses a combination of Perturb and Observe (P&O) to adjust the Duty Cycle (D), a Kalman Filter to smooth the voltage and power signals, and a PD Controller to reduce fluctuations and improve system stability. The Kalman Filter improves system accuracy by reducing noise in voltage and power measurements. The PD Controller smooths the D adjustments, preventing sudden changes that can lead to fluctuations. The P&O adjusts the D based on power variations, ensuring the system is always moving towards the Maximum Power Point (MPP). By combining these techniques, the algorithm can effectively track the MPP with minimal fluctuations, ensuring optimal performance in the solar PV system.

4. Results and Discussion

In this section, the controllers designed in the previous part are applied to the overall control architecture of the grid-connected photovoltaic system. The inner control loops of the i_d and i_q currents, as well as the outer loop of the DC-link voltage, are regulated by conventional PI controllers. In parallel, the MPPT strategy is carried out using a hybrid approach that combines the KF-PD-P&O algorithm. The proposed scheme ensures enhanced dynamic performance by exploiting the flexibility of fractional calculus in both SMC and synergetic control. Numerical simulations, conducted in the MATLAB/Simulink environment, confirm the effectiveness of the proposed strategy. The complete control system is depicted in fig. 4, while the detailed block diagrams of the implementations are provided in fig. 5 and 6. The implementation is based on a 100-kW grid-connected PV array benchmark model available in MATLAB/Simulink. In this setup, the DC-link reference voltage is fixed at 500 V, the nominal AC output of the DC-AC inverter is 260 V, and the load is connected to the utility grid through a step-up distribution transformer rated at 25 kV/260 V.

3.1 Scenario I

In the first test scenario, the irradiance profile is modeled as a step change, rising to a final value of 1000 W/m^2 at $t = 1 \text{ s}$, while the temperature is maintained constant at 25°C , as depicted in fig. 9. The corresponding duty cycle responses under different control strategies are presented in fig. 10. It can be observed that the proposed controller achieves a smoother response, with oscillations tightly centered around 0.5 A, whereas the conventional scheme exhibits wider variations spanning the range $[0, 1]$.

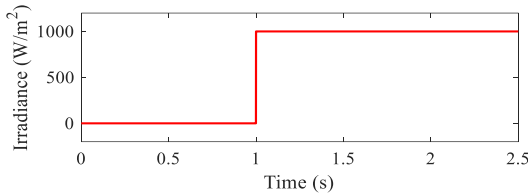


Fig. 9 Stepwise irradiance variation for Scenario I.

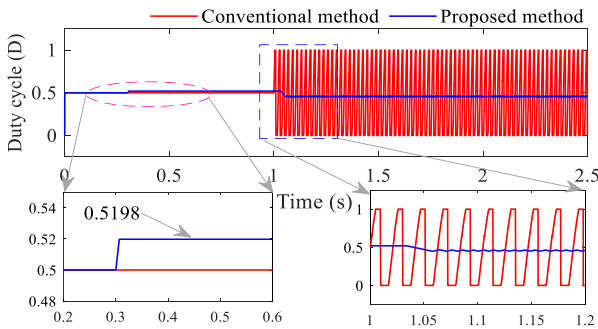


Fig. 10 The duty cycle applied to the DC-DC converter using different control schemes for Scenario I.

Table 3. Dynamic performance of the MPPT-based PV system under Scenario I with two different controllers.

Performance metrics	Methods	
	Conventional method	Proposed method
Rise time (s)	0.0071	0.0063
Settling time (s)	2.4993	1.0387
Maximum power (kW)	48.343	100.72
Overshoot (%)	51.945	0.00803
Efficiency (%)	65.813	99.999

The quantitative performance indices summarized in Table 3 highlight the superiority of the proposed method. It achieves the shortest settling time of 0.017 s, significantly faster than the conventional counterpart, and delivers a maximum extracted power of 100.72 kW compared to 48.343 kW. Moreover, it yields the lowest overshoot of 0.00803% and reaches steady-state operation at 1.0387 s, in contrast to 2.4993 s with the conventional controller. The MPPT efficiency is also enhanced, attaining 99.999%. In addition, the PV output voltage under the proposed scheme demonstrates a smoother transient profile throughout the irradiance transition. The comparative responses of PV power and voltage for both controllers are illustrated in fig. 11a-b, while the corresponding DC-link voltage is shown in fig. 11c. The latter remains well regulated at the 500 V reference, with only a minor overshoot observed at $t = 1 \text{ s}$, coinciding with the irradiance step change. From a grid perspective, fig. 12 indicates that the delivered power increases substantially with the proposed method, reaching 90.386 kW. Furthermore, the waveforms of grid current and voltage presented in fig. 13a-d confirm that the injected signals maintain high quality, with negligible harmonic distortion, as illustrated by the magnified insets of fig. 13c-d.

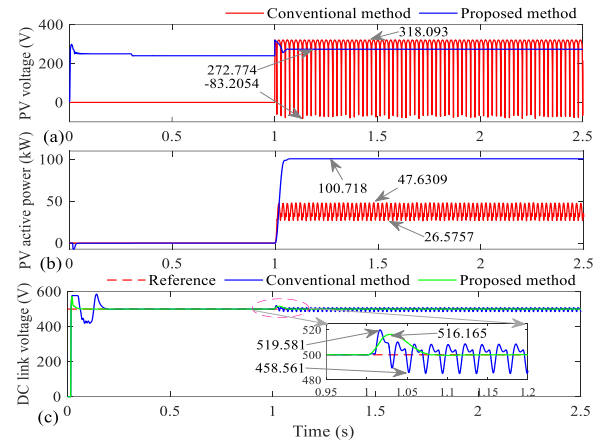


Fig. 11 The PV system performance under the impact of Scenario I: (a) the PV voltage, (b) the PV archive power, and (c) the DC link voltage.

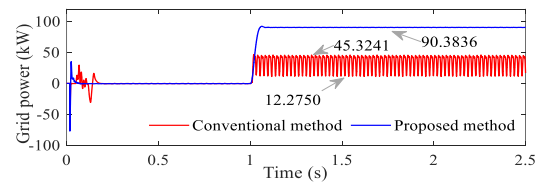


Fig. 12 The grid power.

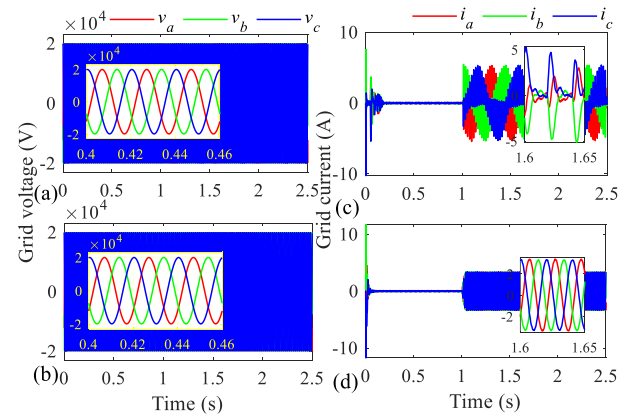


Fig. 13 Three-phase grid current and voltage impact of scenario I: (a) the conventional method grid voltage, (b) the proposed method grid voltage, (c) the conventional method grid current, and (d) the proposed method grid current.

3.2 Scenario II

In the second scenario, simultaneous variations of irradiance and temperature are considered, as illustrated in fig. 14 and 15. At $t = 2$ s, the temperature rises sharply from 25°C to 50°C, while the irradiance drops from 1000 W/m² to 250 W/m² before recovering to its initial level. The resulting duty cycle responses for the compared control schemes are presented in fig. 16. The transient behavior of PV power and voltage under the RUN-based regulators is analyzed in fig. 17a-b.

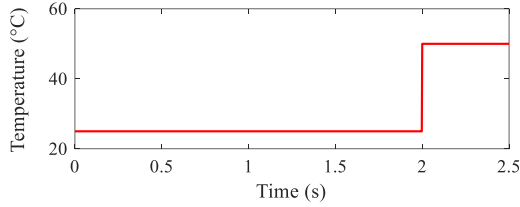


Fig. 14 Stepwise temperature variation for Scenario II.

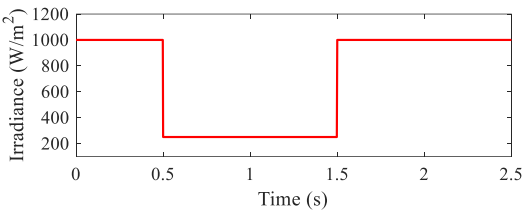


Fig. 15 Stepwise irradiance variation for Scenario II.

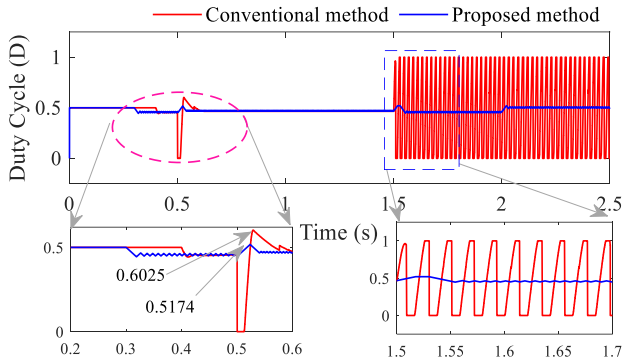


Fig. 16 The duty cycle applied to the DC-DC converter using different control schemes for Scenario II.

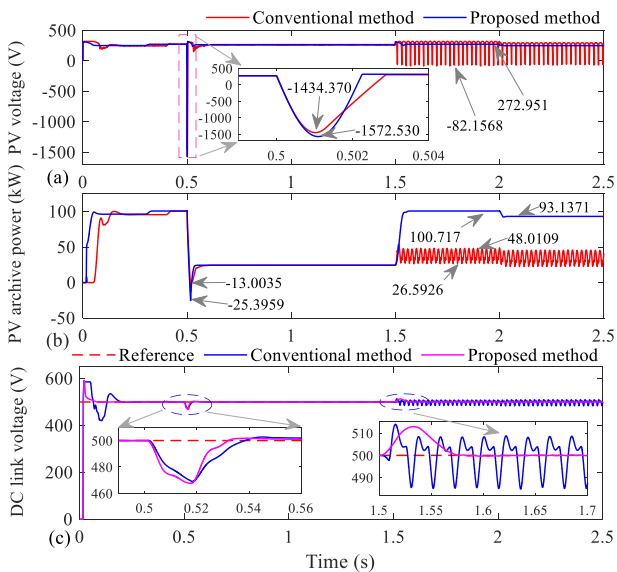


Fig. 17 The PV system performance under the impact of Scenario II: (a) the PV voltage, (b) the PV archive power, and (c) the DC link voltage.

The results confirm the well-established relationship that PV output power decreases with higher temperature and increases with irradiance. Quantitative indices listed in Table 4 demonstrate that the proposed controller achieves a maximum PV power of 100.89 kW with a tracking efficiency of 92.319%, significantly outperforming the conventional approach 100.88 kW, 40.311% efficiency. Moreover, during low irradiance periods, the proposed strategy maintains the smoothest and most stable response. It also exhibits the lowest overshoot 8.3202%, which is reduced by 94.380% compared to the conventional scheme, and provides the fastest rise and settling times of 0.0201 s and 2.006 s, respectively.

The DC-link voltage response, as shown in fig. 17c, remains well-regulated and comparable across all controllers. Regarding grid-side performance, fig. 18 indicates that the proposed controller ensures more stable power delivery with reduced oscillations. The corresponding grid voltage and current waveforms are given in fig. 19a-d. The maximum phase voltage reaches approximately 20 kV, while the grid current follows the irradiance variation closely between $t = 0-2$ s at constant temperature. When the temperature rises at $t = 2$ s, a slight reduction in current is observed. Nevertheless, fig. 19d confirms that the proposed method provides smoother and more stable current dynamics than the conventional approach.

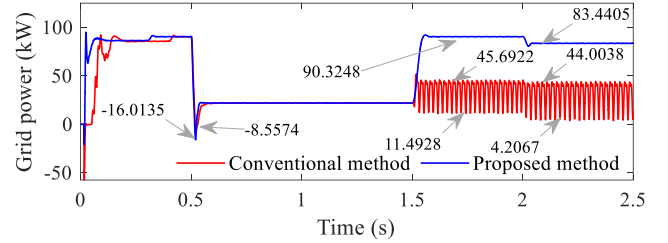


Fig. 18 The grid archive power.

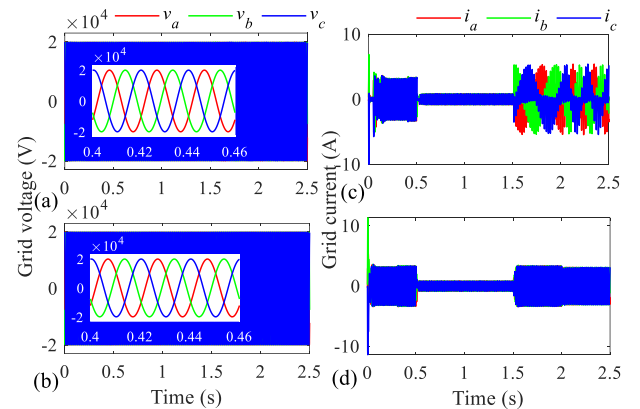


Fig. 19 Three-phase grid current and voltage impact of scenario II: (a) the conventional method grid voltage, (b) the proposed method grid voltage, (c) the conventional method grid current, and (d) the proposed method grid current.

Table 4 Dynamic performance of the MPPT-based PV system under Scenario II with two different controllers.

Performance metrics	Methods	
	Conventional method	Proposed method
Rise time (s)	0.0497	0.0201
Settling time (s)	2.4993	2.006
Maximum power (kW)	100.88	100.890
Overshoot (%)	148.070	8.3202
Efficiency (%)	40.311	92.319

3.3 Scenario III

The final stress-test scenario assesses the robustness and effectiveness of the examined controllers under abrupt fluctuations in both temperature and irradiance, as illustrated in fig. 20 and 21. The corresponding duty cycle responses obtained with each control strategy are compared in fig. 22.

Fig. 23a-b present the PV power and voltage characteristics under conventional and proposed controllers. All strategies are capable of tracking power under the imposed disturbances; however, the proposed method exhibits the fastest rise and settling times. Moreover, PV voltage responses highlight the inverse temperature dependence, while the proposed controller ensures the most stable operation with minimal oscillations.

Fig. 23c further analyzes the DC-link voltage behavior, confirming effective regulation across both methods. The grid-side power profiles, illustrated in fig. 24, reveal that the proposed control scheme achieves smoother and more stable dynamics compared with the conventional method, particularly during startup and subsequent transients.

A summary of the DC-link voltage performance is given in Table 5. During the critical interval between $t = 1.5$ -2 s, the proposed controller achieves a significantly lower ISE index of 0.9951, compared with 1.7552 for the conventional method. Although the study focuses on simulation-based validation of the proposed strategy in MATLAB/Simulink, its feasibility for practical implementation is also considered. The employed Runge-Kutta (RUN) optimizer requires higher computational effort than conventional algorithms; however, since optimization is carried out offline before deployment, there is no need to run RUN in real time. Once the optimal parameters are obtained, the control system operates as a fixed-parameter structure. This makes the design highly suitable for embedded platforms such as digital signal processors (DSPs), widely used in power electronics and renewable energy applications. Consequently, the real-time computational burden is negligible, confirming the practicality of the proposed control approach for grid-connected PV systems.

Table 5 Dynamic performance of the MPPT-based PV system under Scenario III with two different controllers.

	Fitness value (ISE)	Settling time (s)	Maximum volatge (V)
Conventional method	1.7552	2.5	582.1514
Proposed method	0.9951	2.5	582.1514

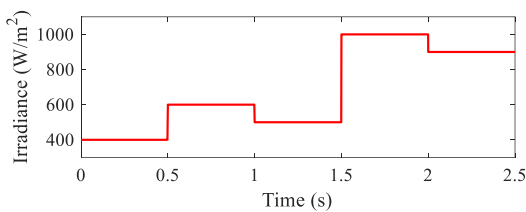


Fig. 20 Stepwise irradiance variation for Scenario III.

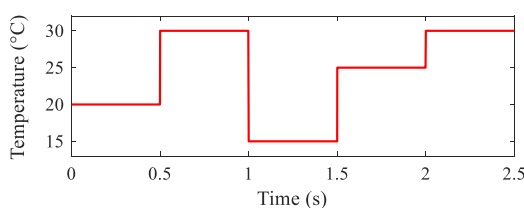


Fig. 21 Stepwise temperature variation for Scenario III.

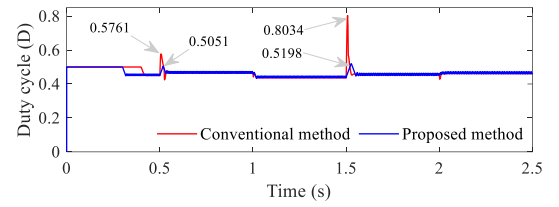


Fig. 22 The duty cycle applied to the DC-DC converter using different control schemes for Scenario III.

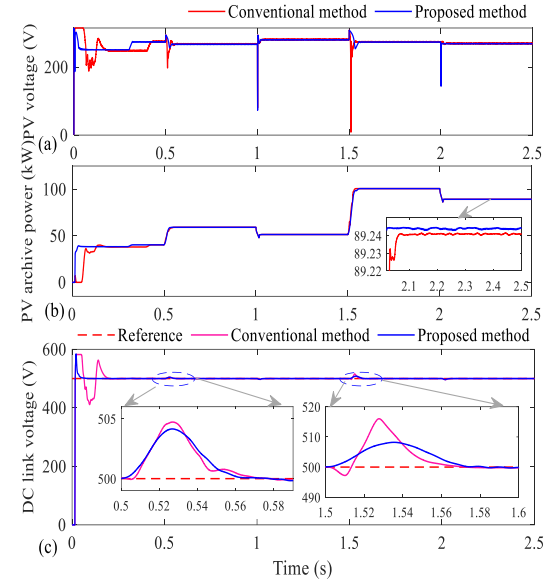


Fig. 23 The PV system performance under the impact of Scenario III: (a) the PV voltage, (b) the PV archive power, and (c) the DC link voltage.

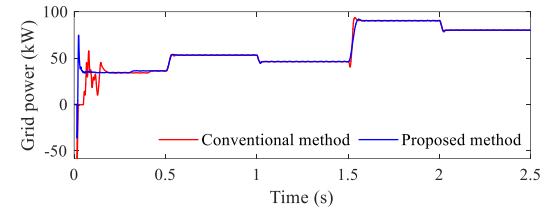


Fig. 24 The grid archive power.

5. Conclusion

This study presents a novel hybrid MPPT control algorithm for grid-connected photovoltaic (PV) systems by integrating a Kalman filter with a proportional-derivative-assisted perturb-and-observe (PD-P&O) method. The controller parameters are optimized using the Runge-Kutta Optimizer. In addition, the proposed method incorporates fractional-order synergetic control on the grid side, enhancing overall system performance and robustness under dynamic irradiance and temperature conditions. Simulation results confirm the effectiveness of the proposed algorithm, demonstrating significant improvements over conventional controllers. Specifically, the proposed method achieves a 58.44% reduction in settling time, reaching 1.0387 seconds, and a 52% improvement in maximum output power, achieving 100.72 kW. Moreover, the system exhibits smoother voltage and current dynamics with minimal overshoot, ensuring stable operation under realistic operating conditions.

The proposed hybrid approach enhances MPPT efficiency while ensuring stable and reliable operation of grid-connected PV systems. The integration of the Runge-Kutta optimizer and fractional-order synergetic control demonstrates clear advantages, especially in

scenarios involving abrupt environmental fluctuations. This research demonstrates the potential applicability of the proposed method to large-scale PV systems, with particular emphasis on real-time operation. Future research will focus on further refining the optimization process, exploring advanced machine learning techniques for adaptive control, and investigating system performance under partial shading conditions. Additionally, the feasibility of implementing the proposed control strategy on embedded platforms, such as digital signal processors (DSPs), will be investigated to enhance practical applicability.

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