Small-Scale PV Emulator for Experimental Control Validation

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Abstract

The transition to renewable energy sources is crucial to alleviate and regulate the global climate regime. Redefining the current energy grid is a crucial step towards replacing carbon-based sources, such as oil and coal, with cleaner, renewable alternatives. Such transition plays a key role in achieving the different Sustainable Development Goals (SDGs) of Agenda 2030, particularly SDG 7. In this context, photovoltaic solar energy has emerged as a promising solution, especially in Brazil, where the average annual solar irradiance exceeds 5 kWh/m² per day across most of the vast territory. Accordingly, we discuss herein the development of a small-scale realistic photovoltaic emulator and its corresponding closed-loop control system design. In our study, we identify the photovoltaic plant's dynamic behaviour and static characteristics using standard Least-Square arguments and a Linear Parameter Varying model. Furthermore, we tune a robust PI controller such that the proposed system becomes able to emulate different solar energy generation profiles in closed-loop. The developed test-bench serves to conduct realistic solar energy generation experiments, supporting both control systems research and educational outreach activities.

Keywords: Photovoltaics; System identification; Linear Parameter Varying Systems; PI control; Brazil.

1. Introduction

Energy is the functional foundation of contemporary societies, enabling everyday activities and complex industrial processes. Its absence, even if temporary, is enough to interrupt essential services and compromise urban infrastructure. In a global scenario marked by continuous population growth and intensification of economic activities, energy demand continues to rise, posing increasingly complex technical, environmental, and geopolitical challenges (Lup et al., 2023). Moreover, fossil fuels still dominate the global energy structure, being inherently unsustainable and severely impacting the Earth's climate (Zuluaga et al., 2022).

Given the aforementioned context, a suitable transition from the current energy grid to a renewable, safe, and low-impact scenario is an ethical imperative. Among the different emerging engineering alternatives, photovoltaic (PV) energy stands out for its abundance, modularity, and increasing technological viability (dos Santos Carstens and da Cunha, 2019; Ferreira et al., 2018). PV cells convert solar radiation directly into electricity—without moving parts or local pollutant emissions— which makes them particularly attractive for distributed generation (Du et al., 2019; Wang et al., 2022). In this work, we consider the Brazilian PV scenario, as discussed by (Rigo et al., 2019): the country has very high solar incidence regions, which makes PV systems strategic to reduce dependence on fossil fuels and foster national technological development.

In relation to distributed energy generation, the concept of microgrids arises as a paradigm shift (Bordons et al., 2020), enabling the local integration of renewable energy carriers and storage to meet local demands with high efficiency and reduced grid-dependency. In practice, microgrids typically incorporate PV arrays as a primary energy source, cf. (Bacha et al., 2015: Sen & Kumar, 2022). Since PVs are inherently non-dispatchable, and the power outlet depends on stochastic meteorological conditions, Energy Management Systems (EMS) are introduced to supervise and optimize the energy flows within a microgrid, i.e. determining when to use PV generation directly to supply demand, when to store surplus energy, and how best to balance local loads and storage in response to rapidly changing weather and demand patterns, cf. (Vergara-Dietrich et al, 2019; Morato et al., 2021). Although extensive research has been conducted on EMS

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algorithms and control strategies for PV-based microgrids, most scientific efforts are based on simulation environments due to the high cost and logistical challenges of building full-scale experimental platforms.

Considering the stochastic and non-dispatchable nature of PV generation, there is a clear need for accessible experimental tools to validate robust control and EMS strategies in PV-based microgrids. Full-scale testbeds are often prohibitively expensive and complex, which limits both hands-on research and educational initiatives. Moreover, a low-cost PV emulator could serve not only to advance research validation aspects, but also to be used as a valuable pedagogical tool for outreach activities on the importance of control to renewable energy generation and to the energy transition paradigm. Accordingly, we discuss the development of a low-cost experimental platform based on a miniature PV panel illuminated by an artificially controlled light source. The developed testbed is able to emulate the behaviour of real PV systems under different meteorological conditions by means of a dedicated control scheme. The main novelty is that our system can support both academic research in modelling and control and educational and outreach activities. Specifically, our main contributions are the following: (1) The implementation of an experimental bench, composed of a modular PV panel and a high-power LED, with brightness control via PWM signals generated by an Arduino Uno; (2) The identification and validation of a non-trivial Linear Parameter Varying (LPV) model, via Least Squares, to accurately describe the system for different dynamic responses and light incidence levels; and (3) The design of a corresponding robust LPV proportional-integral (PI) control scheme that, in closed-loop, enables the testbed to emulate a variety of realistic PV scenarios. The remainder of this paper is structured as follows. In Section 2, the proposed methodology and the experimental framework are detailed. Section 3 presents and discusses the main results. Finally, Section 4 draws the conclusions and outlines future work.

2. Methodology and Experiments

2.1. Experimental Setup

The developed system aims to analyze the dynamic and static behavior of a small-scale photovoltaic (PV) panel under controlled illumination conditions. For this purpose, a white high-power LED 3W, 7000 was used, powered directly by the PWM digital output of an Arduino Uno microcontroller. The LED was positioned at a fixed, perpendicular distance from the PV panel to ensure standardized conditions of light incidence, as shown in Fig. 1 (right). The LED module itself is detailed in Fig. 1 (left). This setup enabled the direct control of the light intensity incident on the PV panel by modulating the voltage applied to the LED. For data collection, step input signals were applied (varying from 1V to 5V), holding each voltage level constant for enough time to capture the full dynamic response of the system. The output voltage was acquired with an Analog-to-Digital Converter (ADC), as shown in the overall block diagram (Fig. 2).

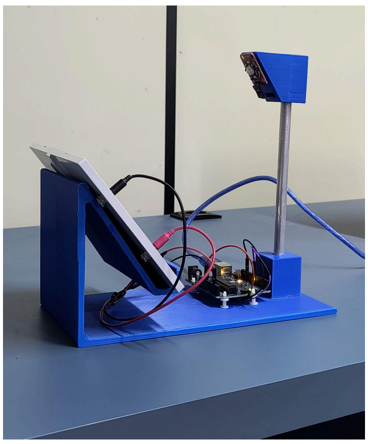

Fig.1: High-power LED module 3W used for PV panel excitation. (left); Physical mounting of the experimental setup. (right)

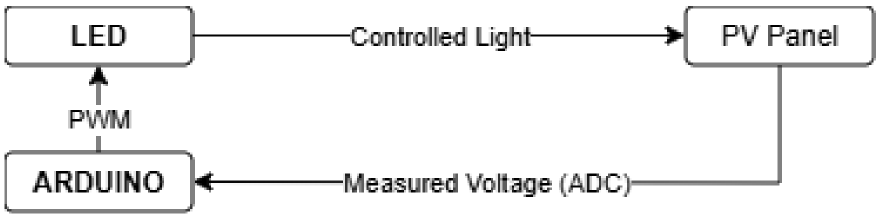

Fig 2: Block diagram of the Arduino-based PV emulation system.

2.2. Experimental Identification

Accordingly, we obtained data by holding each voltage level constant long enough to capture the full dynamic response of the PV system (the voltage to light incidence relation). From the data dictionary, the following parameters were obtained using a standard Least-Squares identification procedure, for each input-output pair: (i) a time constant (τ) obtained from the PV's settling time; and (ii) a static gain (K_e). Then, rather than developing a separate model for each operating point, we sought an unified model that adapts continuously across the entire operating range. To achieve this, the collected (τ, K_e) pairs were fitted using linear regression to a first-order Linear Parameter-Varying (LPV) affine model, given by:

$$\tau(\rho(t))\frac{dy(t)}{dt} + y(t) = K_e(\rho(t))u(t) \qquad (eq.\ 1)$$

Where y(t) represents the outlet tension measured by the ADC and u(t) the applied PWM signal. In eq. 1, the model parameters are expressed as affine functions of a bounded scheduling variable $\rho(t)$, that is: $\tau(\rho(t)) = \tau_0 + \tau_1\rho(t)$ and $K_e(\rho(t)) = K_{e0} + K_{e1}\rho(t)$, where ρ is selected as $\rho(t) = 0.1r(t)$, being $r(t)$ a solar irradiance reference (to be emulated). That is, for each desired PV behaviour - described by the time-varying signal $r(t)$ - the model in eq. 1 maps the corresponding dynamic response of the LED-to-PV pair.

2.3. Adaptive PI Controller Design

Considering the (validated) LPV model discussed in the prequel, we also design a robust PI scheme, as illustrated in Fig. 3. In particular, our PI control works as follows: Given a reference signal r(t) — associated with the solar generation curve to be emulated — the error e(t) = r(t) - y(t) is processed by the controller, resulting in the command signal u(t) applied to the LED are computed as follows:

$$u(t) = K_p(\rho(t))e(t) + K_i(\rho(t))\int_0^t e(x)\,dx \qquad (eq.\ 2)$$

The proportional and integral parameters $K_p(\rho(t))$ and $K_i(\rho(t))$ are gains implied to be affine on $\rho(t)$. To determine these control parameters, the (LPV) Bounded Real Lemma (Li & Zhang, 2012) was applied by means of Linear Matrix Inequalities (LMIs).

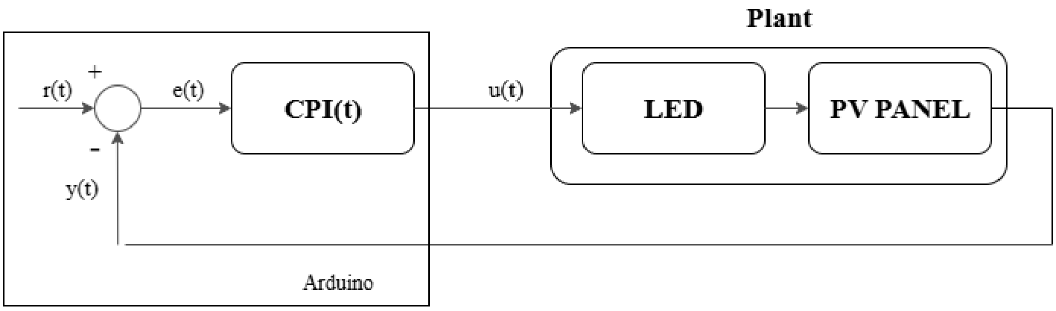

Fig. 3: Block diagram of the closed-loop control system: CPI represents the adaptive PI control scheme.

3. Experimental Results

In this Section, we present the main results obtained from our experimental setup, which include: (i) the data related to the identification procedure, and (ii) closed-loop results using the proposed Adaptive PI controller.

3.1. Identification Results

The open-loop test is presented in Fig. 4, showing jointly the input signals applied to the LED (steps from 0V to 5V) and the corresponding PV panel response y(t). These tests were performed to excite the system and analyze its dynamic behavior.

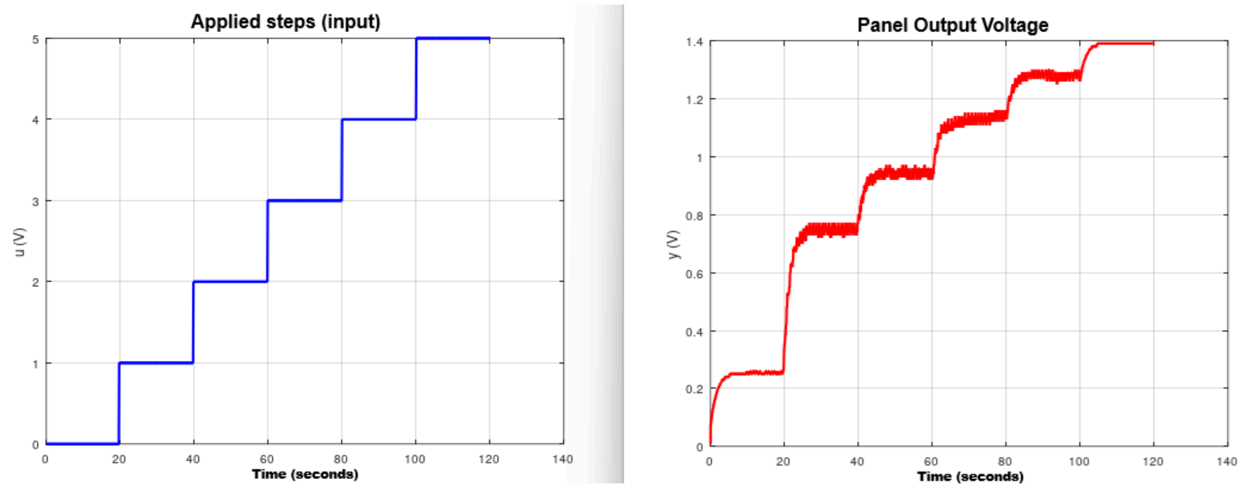

Fig. 4: Input steps (0V–5V) applied to the LED and the corresponding dynamic response of the PV panel.

The panel's response is observed to follow a typical first-order profile, with smooth transitions up to the steady-state regime. As the voltage applied to the LED increased, a reduction in the static gain K_e was noted, as shown in Table 1.

From these data, the static gain K_e was calculated and the time constant τ was estimated for each test. The time constant was determined using the 63% method, representing the time required for the output to reach 63% of its total steady-state change. These results provided the basis for obtaining the static characteristic curve (Fig. 6) and for the mathematical modeling of the system. The experimental data are summarized in Table 1.

Table 1: Step Response Data. The columns Input ui and Input uf denote the initial and final input voltages for each experimental step, respectively.

Input ui (V)	Input uf (V)	Steady-State y (V)	Gain Ke	y63% (V)	tau (s)
0.00	1.00	0.76	0.50	0.57	1.50
1.00	2.00	0.96	0.20	0.89	1.60
2.00	3.00	1.14	0.18	1.07	1.60
3.00	4.00	1.28	0.14	1.23	1.80
4.00	5.00	1.39	0.11	1.35	1.30

It is also noted that, for the case of null input V = 0, the panel presents a residual voltage of approximately 0.26V. This value should not be interpreted as gain but rather as an offset resulting from the test conditions (such as ambient light in the laboratory). Furthermore, it was observed that the time constant tau did not remain fixed, presenting variation throughout the tests: in general, it proved to be smaller at the extremes of the input range and larger in the intermediate region.

3.2 Static Curve

The obtained static characteristic curve (Fig. 5) demonstrates the system's non-linear behavior. It is observed that the effective gain varies across the entire operating range, which makes the use of a single linear model unfeasible for representing the system's full dynamics. This characteristic reinforces the need for Linear Parameter-Varying (LPV) modeling, as it enables interpolation between different local models, ensuring a more faithful representation of the observed behavior. Furthermore, the uncertainties inherent in the experiment justify the adoption of robust control techniques to guarantee stability and satisfactory performance throughout the operating region.

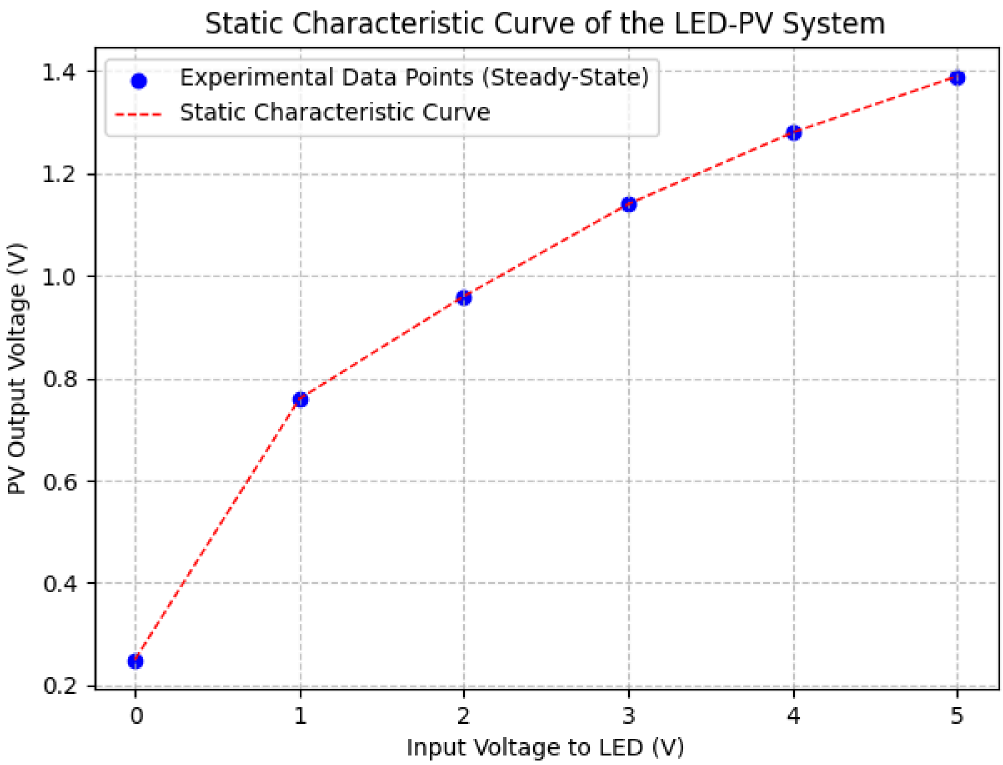

Fig. 5: Static characteristic curve of the system, obtained from the relation between the input voltage applied to the LED and the output measured on the solar panel.

3.3 Closed-Loop Validation

3.3.1 Simulation Results

Prior to hardware implementation, the performance of the LPV model and the robust PI control scheme were verified through numerical simulation in MATLAB/Simulink.

Fig. 6 presents the results obtained during the closed-loop validation. With the adaptive PI controller designed based on the identified LPV model, the system was able to precisely track a reference curve representative of actual photovoltaic generation.

The results confirm the controller's efficacy, which guaranteed adequate tracking under different operating conditions. This validation demonstrates the potential of the developed testbed as a tool for real-time experiments, applicable to both control strategies research and educational activities.

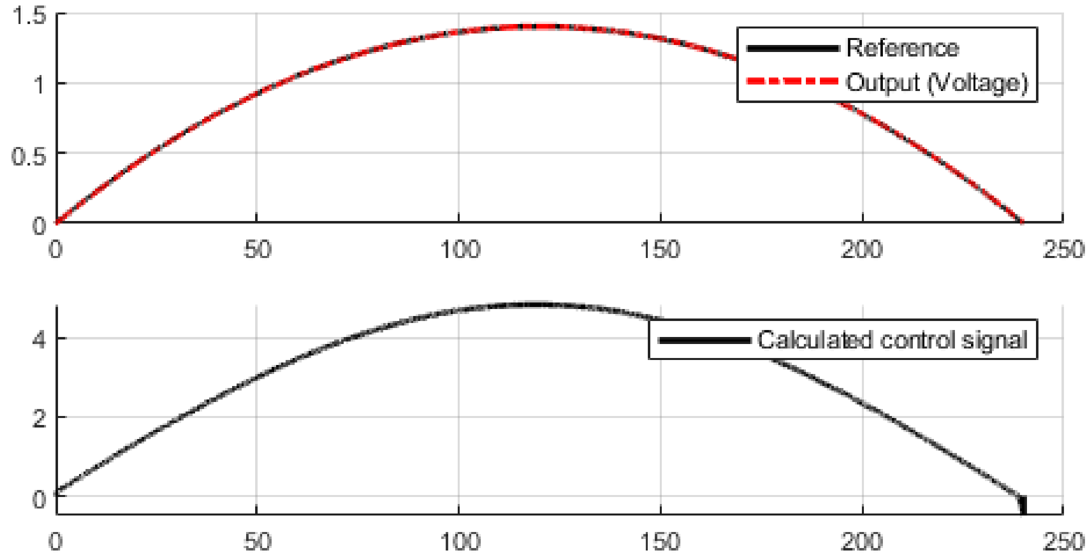

Fig. 6: simulated closed-loop data

3.3.2 Real-Time Experimental Results

Following the successful simulation studies, the adaptive PI controller was implemented and validated experimentally on the small-scale PV emulator hardware. The objective of this test was to evaluate the controller's real-time tracking performance and its robustness to physical hardware constraints. The system was subjected to a solar generation reference curve based on the same profile used in the simulations.. Fig. 7 illustrates the key closed-loop signals recorded during this experimental validation.

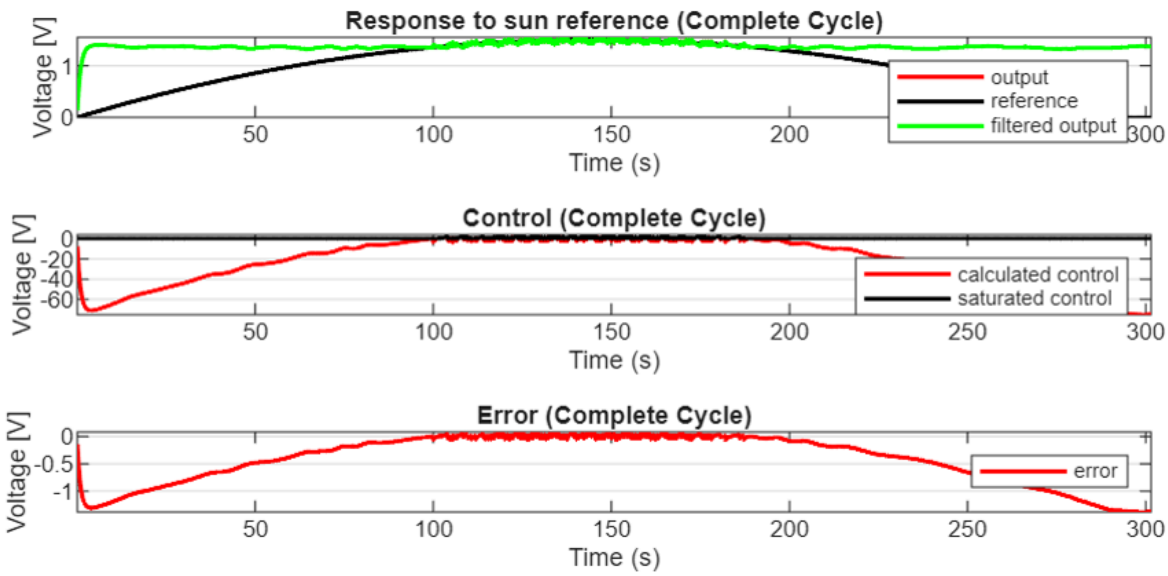

Fig 7: real closed-loop data showing significant initial offset

To mitigate the offset observed during the identification phase, primarily caused by ambient light interference in the laboratory, the PV panel was enclosed within an opaque test chamber (Fig. 8). This measure proved fundamental in ensuring that the panel's response was caused only by the controlled LED excitation, as evidenced by the top plot in Fig. 9 (Response to sun reference), where the output faithfully tracks the reference without the significant offset previously observed.

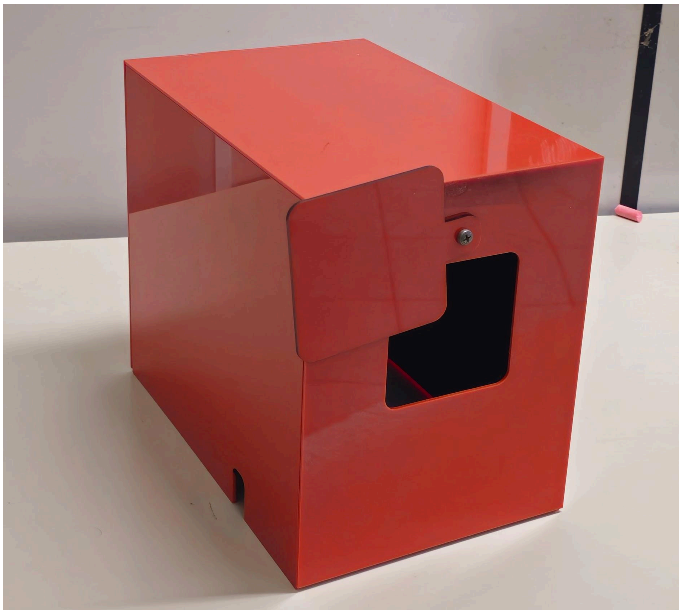

Fig 8: opaque test chamber

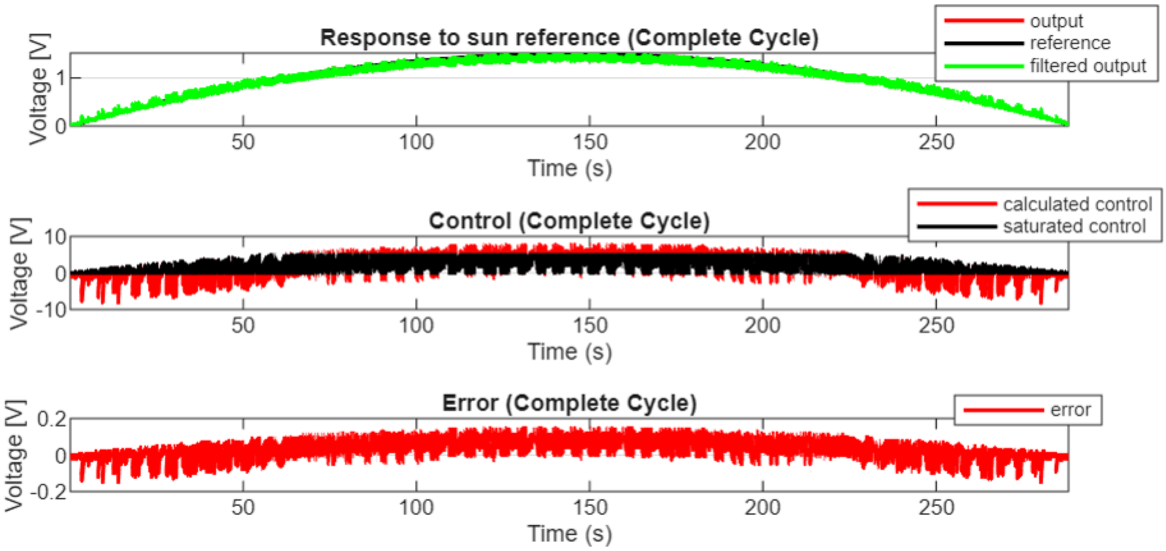

Fig 9: real closed-loop response following offset suppression

When comparing the experimental performance to the simulation results (Fig. 6), the presence of high-frequency oscillations in the measured output is noticeable. Such oscillations are attributed mainly to the inherent noise of the Analog-to-Digital Converter (ADC) acquisition process and residual high-frequency disturbances in the environment.

Notwithstanding the noise, the experimental results confirm the controller's efficacy, which guaranteed adequate tracking under different operating conditions (especially within the system's varying gain region). This validation demonstrates the potential to develop the PV panel as a tool for real-time experiments.

4. Conclusion

This work discusses the development of a scaled experimental PV emulation test-bench that realistically assesses the operation of real PV systems under controlled conditions. Using a small-scale solar panel, a 3W

LED and an opaque test chamber, dynamic step response tests and Least-Squares procedures were performed to identify an LPV model. Then, an adaptive LPV PI controller was synthesized via LMIs and successfully tested in closed-loop. Our results demonstrate that the proposed platform is easy to implement, low-cost, and highly reproducible, making it suitable for both academic research and educational applications in renewable energy and control. Moreover, our experimental kit is ready to be integrated and tested with EMS algorithms for microgrids. Future work includes three main areas: the real-time control implementation using irradiance sensors, the development of adaptive parameter identification techniques, and the implementation of noise reduction strategies.

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