

듀얼 스테이지 변환과 비선형 PI제어를 기반으로 하는 태양광 시스템의 MPPT 및 출력전압 조절

MPPT and Output Voltage Regulation of a Photovoltaic System Based on Dual-stage Conversion and Nonlinear PI Control

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Abstract: The performance of solar photovoltaic systems is heavily dependent on environmental factors such as solar irradiance, ambient temperature, and partial shading. To maximize energy extraction under these variable conditions, maximum power point tracking (MPPT) algorithms are typically integrated with a boost converter; however, while MPPT ensures operation at the maximum power point, the resulting output voltage still fluctuates due to environmental and load variations. This study proposes a dual-stage conversion approach that simultaneously implements MPPT control and voltage regulation: the first stage employs a boost converter governed by the incremental conductance algorithm for maximizing power output, and the second uses a buck converter controlled by a nonlinear proportional-integral (NPI) controller to maintain a stable, desired output voltage. By integrating experimental data with a hybrid genetic algorithm, the photovoltaic cell parameters are identified and then applied to construct a detailed SIMULINK model for optimizing NPI controller gains. Finally, simulations are conducted to demonstrate the effectiveness of the proposed method, particularly under partial shading conditions.

Keywords: photovoltaic, dual-stage conversion, maximum power point tracking, output voltage regulation, nonlinear PI control, hybrid genetic algorithm

1. INTRODUCTION

Photovoltaic (PV) systems have emerged as a cornerstone in the global transition toward sustainable energy, driven by their global availability and the ability to convert sunlight directly into electricity efficiently [1]. As the demand for renewable energy sources escalates, PV technology has found diverse applications ranging from residential rooftops to large-scale solar farms, significantly contributing to energy independence and environmental preservation [2].

A vital step in getting the most out of PV systems is modeling and parameter estimation, especially when integrating maximum power point tracking (MPPT) and voltage regulation. These methods offer a mathematical framework that explains the system's behavior, allowing for optimized energy harvesting. This is done by identifying the ideal operating conditions, even in difficult situations like partial shading (PS). PS occurs when obstacles like trees, buildings, or dirt accumulation block sunlight from reaching the solar panels, leading to significant energy losses [3, 4]. The performance of PV systems can be hindered by environmental factors such as irradiance levels and temperature, with PS being particularly detrimental. To counteract these effects, various MPPT techniques have been developed to optimize energy extraction from PV modules [3-7]. Two of the most widely used methods are perturb and observe (P&O) and incremental conductance (InCon).

Both are online algorithms, meaning they continuously find the maximum power point (MPP) by taking real-time measurements of the PV system's voltage and current [5]. However, they can struggle in dynamic environments, particularly when frequent shading changes occur. These changes introduce multiple local peaks in the power-voltage ($P - V$) curve.

In order to overcome the challenges of dynamic environments and PS, which cause multiple peaks in the $P - V$ curve, several MPPT algorithms have been developed, each offering unique advantages and disadvantages. The modified adaptive hill climbing algorithm is accurate and adaptable, but computationally intensive and may respond slowly [6]. The constant voltage algorithm is simple and maintains a steady voltage near the maximum power point, but lacks adaptability [7]. The lookup table-based algorithm uses precomputed data for quick adjustments, relying on the quality of the lookup table [8]. Model predictive control predicts optimal operating points using system models and has been applied in ultra-step-up boost converters [9]. Metaheuristic optimization, such as particle swarm optimization and genetic algorithms treat the MPPT problem as an optimization challenge, systematically searching the entire $P - V$ curve to find the absolute MPP [10,11]. However, a key disadvantage of these approaches is the difficulty in evaluating the performance of all

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potential individuals in the population within a practical, finite time when implemented in an actual PV system. More critically, the presence of even a few bad individuals can drastically lower the overall performance of the system.

The challenge in PV systems arises because even though the MPPT stage constantly adjusts the system to maintain the PV array at its MPP, the resultant output voltage is inherently variable and unstable due to changing environmental conditions. This variable voltage is generally unsuitable for the downstream load or grid, which critically requires a highly stable, fixed DC voltage for proper operation. Therefore, the separate voltage-regulation stage is essential for decoupling the power optimization task from the voltage stabilization task, ensuring that the maximum power extracted by the MPPT stage is delivered with the necessary quality and stability for utilization by external systems. While traditional control strategies, such as proportional-integral-derivative (PID) controllers, have been used to maintain output voltage, they often fail to adequately address the complexities introduced by PS [12]. Recent advancements in intelligent control methods, such as fuzzy logic and neural networks [13], show promise but often require extensive tuning and adaptation to specific system configurations. While various MPPT and voltage regulation techniques exist, as indicated above, most studies focus separately on either MPPT or voltage regulation in PV systems rather than addressing both simultaneously [14].

This study presents an integrated control approach that optimally combines MPPT and output-voltage regulation via a dual-stage power-conversion system. In the MPPT stage, a boost converter is employed, and its operation is controlled by the InCon algorithm to achieve effective MPPT. Following this, in the voltage regulation stage, a buck converter is utilized, and its output voltage is stably maintained using a nonlinear proportional-integral (NPI) controller. To achieve the research goals, the work will begin by selecting an appropriate PV cell model and determining its parameters using experimental data. This crucial parameter estimation will be performed with a hybrid genetic algorithm (HGA) [15], which is essential for accurate system modeling, effective implementation of the control strategy, and the subsequent optimization of the NPI controller's gains. Finally, the performance of the two integrated control methods will be assessed through a series of MATLAB SIMULINK simulations. These simulations will be evaluated across four different irradiance scenarios to thoroughly enhance PV system efficiency and ensure stable operation under variable environmental conditions, including PS.

II. IDENTIFICATION OF A PV CELL

Successful design and analysis of a PV system begins with identifying the controlled object, which requires prior knowledge of the PV cell model. The PV cell identification task is broken down into four key steps: data collection, model selection, parameter estimation, and model validation. The resulting model will then be applied to the MPPT control and controller design for voltage regulation in the subsequent section.

1. Model Selection of a PV Cell

A solar cell can be modeled using various approaches, including single-diode and two-diode models [16]. This work utilizes the single-diode model, represented by an electrical equivalent circuit composing a constant current source in parallel with a diode, as illustrated in Fig. 1.

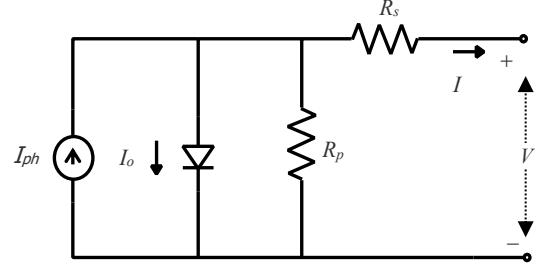


그림 1. PV 셀의 등가회로.

Fig. 1. Equivalent circuit of a PV cell.

To obtain a model from the equivalent circuit and estimate its parameters, data are obtained from a reference module under standard test conditions (STC), which are a cell temperature of 25°C, a solar irradiance of 1,000W/m², and an air mass of 1.5. Under STC, the output current I can be expressed by [12]

$$I = I_{ph} - I_o \left[\exp \left(\frac{V + IR_s}{aKT_r / q} \right) - 1 \right] - \frac{V + IR_s}{R_p} \quad (1)$$

where V and I are the output voltage and current of a PV cell, respectively; I_{ph} , I_o , R_s , R_p , a and T_r are the photodiode current, the reverse saturation current, the series resistance, the shunt resistance, the ideality factor, and the reference temperature at STC, respectively; K is the Boltzmann constant ($= 1.38 \times 10^{-23}$ J/K) and q is the charge of an electron ($= 1.6 \times 10^{-19}$ C).

However, varying solar irradiance and temperature in a real environment may change these parameters. In this case, Equation (1) can be rewritten by

$$I = I_{ph} - I_o \left[\exp \left(\frac{V + IR_s}{aKT / q} \right) - 1 \right] - \frac{V + IR_s}{R_p} \quad (2)$$

where I_{ph} , I_o and T are the photodiode current, the reverse saturation current, and the temperature in a real environment, respectively. The relationship between the parameters in Equations (1) and (2) is as follows:

$$I_{ph} = \left[I_{phr} + K_i (T - T_r) \right] \frac{G}{G_r} \quad (3)$$

$$I_o = I_{or} \left(\frac{T}{T_r} \right)^3 \exp \left[\frac{qE_g}{aK} \left(\frac{1}{T_r} - \frac{1}{T} \right) \right] \quad (4)$$

where K_i denotes the short-circuit current temperature coefficient, G the solar irradiance (W/m²), G_r the nominal solar irradiance (typically 1,000W/m²), and E_g the bandgap energy of the semiconductor.

A single PV cell typically generates a low power output between 1 to 2 watts under STC. To amplify the overall output, multiple PV cells are connected in series and/or parallel, encapsulated within a protective frame and materials, known as a PV module. The model of a PV module composed of N_p parallel cells and N_s series cells is defined by

$$I = N_p I_{ph} - N_p I_o \left[\exp \left(\frac{V + I R_s \Lambda}{a N_s K T / q} \right) - 1 \right] - \frac{V + I R_s \Lambda}{R_p \Lambda} \quad (5)$$

where V and I mean the output voltage and current of the PV module, respectively; $\Lambda = N_s / N_p$; $R_s \Lambda$ and $R_p \Lambda$ denote the equivalent series and parallel resistances of the PV module, respectively.

2. Parameter Estimation of the PV Module

The next phase is to estimate the five unknown parameters (I_{ph} , I_o , a , R_s and R_p) of the PV module. This is done using voltage (V) and current (I) measurements. The Kyocera KC200GT module is selected as the reference. Under STC, this module with $N_s=54$ and $N_p=1$ exhibits voltage ranging from 0 to 32.9V and current ranging from -2.65 to 8.23A. At STC, I_{ph} and I_o are equal to their reference values, I_{phr} and I_{or} , respectively. These are estimated from the measured data set of $\{V, I\}$ using an optimization technique. By rearranging the terms, Equation (4) becomes

$$f(x, V, I) = I_{ph} - I_o \left[\exp \left(\frac{V + I R_s N_s}{a N_s K T / q} \right) - 1 \right] - \frac{V + I R_s N_s}{R_p N_s} - I \quad (6)$$

where $x = [I_{ph}, I_o, a, R_s, R_p]^T$. $f(x, V, I)$ represents the error between the physical PV module and the model. The objective of parameter estimation is to tune the five parameters to minimize the performance index. To quantitatively evaluate the goodness-of-fit for different parameter sets, the root mean square error (RMSE) is used as the performance index.

$$\text{RMSE} = \sqrt{\frac{1}{M} \sum_{i=1}^M f^2(x, V, I)} \quad (7)$$

where M denotes the total number of collected $I-V$ data points; in this study, $M = 69$.

Ultimately, estimating the five parameters results in a multivariate optimization problem. The HGA is used to solve this problem by minimizing Equation (7) within a defined search space:

$X = \{x \mid x^{(L)} \leq x \leq x^{(U)}\}$, where $x^{(L)}$ and $x^{(U)}$ represent the lower and upper bounds of x , respectively. The procedure of the HGA is as follows [15]:

Step 1: Initialize a population of size N randomly;

Step 2: Evaluate individuals via Equation (7) and determine the global best $x_{\text{global}}(t)$ and its function value $f_{\text{global}}(t)$, and the local worst

function value $f_{\text{worst}}(t)$;

while <Termination criterion is not met> do Steps 3-5

Step 3: Perform the affine combination-based reproduction to update each individual $x_i(t)$ as

$$x_i(t+1) = x_i(t) + \eta_i \gamma_i(t) [x_{\text{global}}(t) - x_i(t)] \quad (8)$$

$$\gamma_i(t) = \frac{f_{\text{global}}(t) - f_i(t)}{f_{\text{global}}(t) - f_{\text{worst}}(t)} \quad (9)$$

where $x_i(t)$ and $f_i(t)$ are an individual and its function value,

respectively. η_i is a positive constant defined by the user and is drawn from a Gaussian distribution $N(\eta, \sigma^2)$, where η is the mean and σ is the standard deviation. As a result, each individual receives a value typically close to η , subject to some degree of variation.

Step 4: Perform the non-uniform mutation [17]:

$$x'_j = \begin{cases} x_j + \Delta(t, x_j^{(U)} - x_j), & \text{if } \tau = 0 \\ x_j - \Delta(t, x_j - x_j^{(L)}), & \text{if } \tau = 1 \end{cases} \quad (10)$$

$$\Delta(t, y) = y \left[1 - r^{(1-t/t_{\max})^b} \right] \quad (11)$$

where x_j is the chosen gene, x'_j is the mutated gene, τ is a random digit (0 or 1), r is a uniform random number, $t_{\max}$ is the maximum number of generations and b is the shape parameter.

Step 5: Evaluate individuals via Equation (7) and determine $x_{\text{global}}(t)$, $f_{\text{global}}(t)$, and $f_{\text{worst}}(t)$;

end while

For the HGA, the parameters are configured as follows: a population size of $N=40$; reproduction settings with $\eta=1.8$ and $\sigma=0.01$; non-uniform mutation probability $P_m=0.04$ and $b=6$. The search bounds were defined by the lower bound $x^{(L)}=[0, 0, 0, 0, 0]^T$ and the upper bound $x^{(U)}=[20, 0.1, 5, 1, 400]^T$. These ranges were established via preliminary simulations to guarantee comprehensive exploration of the parameter space. The maximum number of generations was set to 4000. The HGA's convergence capability and speed are highly sensitive to the randomly generated initial population. Therefore, to obtain reliable, stable results, we conducted 20 independent runs with different random seeds. Subsequently, Table 1 averaged the resulting estimated parameters.

3. Model Validation

To validate the estimated model, the $I-V$ and $P-V$ characteristics curves were plotted against the measured data in Fig. 2. The agreement was statistically confirmed by an R-squared (R^2) value of 99.98%, indicating excellent agreement between the HGA-based estimated parameters and the measured data. Further analysis of the estimated model's performance begins with Fig. 3, which displays the $I-V$ and $P-V$ curves under varying temperatures at a constant irradiance of 1,000W/m². Following this, Fig. 4 shows the $I-V$ and $P-V$ curves under varying irradiance levels at a constant temperature of 25°C.

표 1. 단일 다이오드 모델의 파라미터 추정치.

Table 1. Parameter estimates of the single diode model.

Parameters	Symbol	Estimates
Photodiode current	I_{ph} (A)	8.158
Reverse saturation current	I_o (μ A)	0.061
Ideality factor	a	1.258
Series resistance	R_s (Ω)	0.005
Shunt resistance	R_p (Ω)	103.459

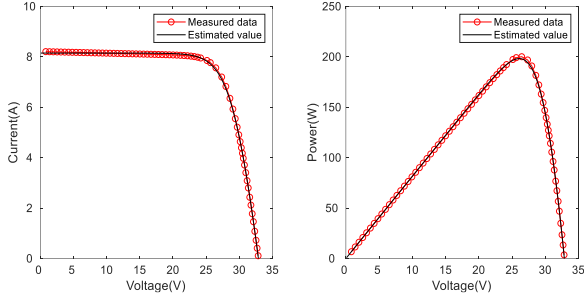


그림 2. STC에서 측정된 데이터와 추정된 모델의 I - V 및 P - V 특성.

Fig. 2. I - V and P - V characteristics of measured data and the estimated model at STC.

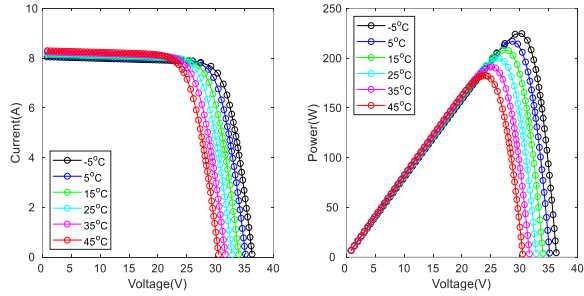


그림 3. $1,000\text{W/m}^2$ 의 일사량에서 다양한 온도 변화에 따른 추정 모델의 I - V 및 P - V 특성.

Fig. 3. I - V and P - V characteristics of the estimated model under varying temperature at an irradiance of $1,000\text{W/m}^2$.

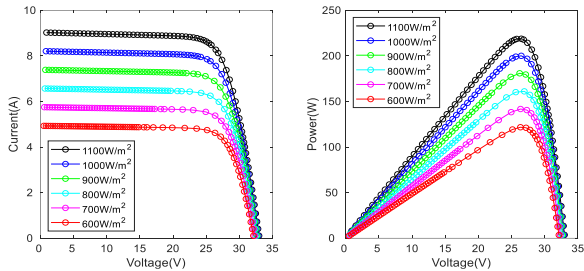


그림 4. 25°C 온도에서 다양한 일사량 변화에 따른 추정 모델의 I - V 및 P - V 특성.

Fig. 4. I - V and P - V characteristics of the estimated model under varying irradiance at a temperature of 25°C .

III. CONTROL STRATEGY FOR THE PV SYSTEM

1. Proposed Control Strategy

The proposed PV control strategy utilizes a dual-stage conversion system, implementing a decoupled control scheme in Fig. 5. In this scheme, the first-stage (boost converter) handles MPPT, while the second-stage (buck converter) manages output voltage regulation. This separation of control tasks is crucial for ensuring maximum energy extraction while maintaining a stable power output.

2. MPPT Algorithm

The first-stage converter, directly connected to the PV panel, is controlled by an MPPT algorithm to produce the maximum power output under a given set of environmental conditions. The boost converter's duty cycle is continuously regulated by the MPPT algorithm.

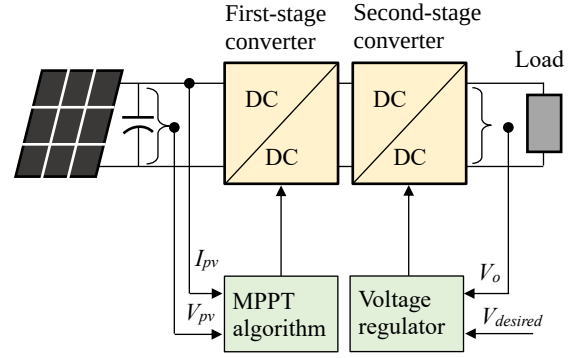


그림 5. PV 시스템용 듀얼 스테이지 변환 시스템의 블록선도.

Fig. 5. Block diagram of the dual-stage conversion system for the PV system.

A number of MPPT algorithms have been proposed in the literature, including P&O and InCon [18]. We utilize the popular and high-performing InCon algorithm, which is briefly summarized here.

The InCon algorithm operates based on the fundamental relationship between the instantaneous slope of the P - V curve and the MPP. The slope of the P - V curve is obtained by taking the derivative of the power ($P = V \cdot I$) with respect to voltage (V):

$$\frac{dP}{dV} = \frac{d(V \cdot I)}{dV} = V \frac{dI}{dV} + I = V \left(\frac{dI}{dV} + \frac{I}{V} \right) \quad (12)$$

where dI/dV represents the incremental conductance, and I/V represents the instantaneous conductance. The algorithm constantly compares the two values from Equation (12) to guide the operating point toward the MPP. This slope is then used to determine the direction in which the operating voltage must be changed:

- At MPP $\frac{dP}{dV} = 0$, then $\frac{dI}{dV} = -\frac{I}{V}$
- Left MPP $\frac{dP}{dV} > 0$, then $\frac{dI}{dV} > -\frac{I}{V}$ (Increase V to move right towards MPP)
- Right MPP $\frac{dP}{dV} < 0$, then $\frac{dI}{dV} < -\frac{I}{V}$ (Decrease V to move left towards MPP)

3. Nonlinear PI Controller

The first-stage boost converter produces a variable voltage because it tracks the MPP under changing environmental conditions. The subsequent buck converter must stabilize the fluctuating input to maintain a constant output voltage (V_o) for the load. This can be managed by a feedback control loop (typically PID), which measures V_o , compares it to the desired setpoint ($V_{desired}$), and adjusts the buck converter's duty cycle to maintain the required constant output.

However, due to the high-frequency switching ripple from PWM operation in the converters, the derivative term in standard PID controllers is problematic, as it amplifies this ripple, leading to instability and chattering. Consequently, the derivative term is often filtered or omitted. We therefore employ a NPI controller, a modification of the author's nonlinear PID controller [19]. The NPI controller is of the following form:

$$v(t) = k(e)e(t) \quad (13)$$

$$u(t) = u_0 + K_p e(t) + K_i \int v(t) dt \quad (14)$$

where u and u_0 are the control input and the nominal control input, respectively, e is the error between the setpoint and the output voltage, and K_p and K_i are the proportional and integral gains, respectively. $v(t)$ is the scaled error and $k(e)$ is a nonlinear gain defined as:

$$k(e) = b \exp \left[-\frac{e^2(t)}{2\sigma^2} \right] \quad (15)$$

where b is a positive constant and σ is a user-defined constant. Substituting (15) in (13) gives

$$v(t) = be(t) \exp \left[-\frac{e^2(t)}{2\sigma^2} \right] \quad (16)$$

To ensure the nonlinear gain amplifies small errors for offset reduction while attenuating larger errors to prevent accumulation, b is selected so that $v(t)$ matches $e(t)$ specifically when $e(t)$ reaches the threshold σ .

$$1 = b \exp \left[-\frac{1}{2} \right] \quad (17)$$

By rearranging (17) and substituting the result into (15), the following equation is obtained:

$$k(e) = 1.6487 \exp \left[-\frac{e^2(t)}{2\sigma^2} \right] \quad (18)$$

Fig. 6 shows the error plots before and after scaling with a typical value of $\sigma = 1$.

The NPI controller's integral action can improve control performance by slightly increasing small errors to accelerate convergence and by scaling down large errors to prevent the cumulative error from growing excessively. This scaling is crucial because the unrestricted accumulation of error, known as integral windup, leads to significant performance degradation, causing large overshoots, delayed recovery, increased oscillation, and instability. Setting σ to one-third of the maximum setpoint change is recommended for a desirable response.

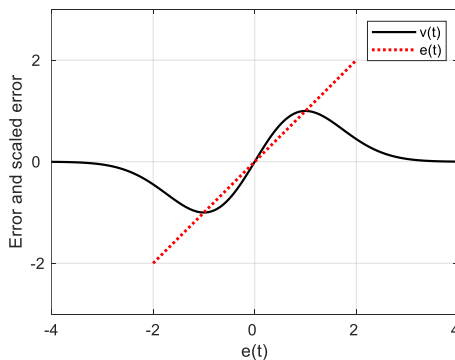


그림 6. 스케일링 전후의 오차 그래프.

Fig. 6. Error plots before and after scaling.

4. Optimum Tuning of the NPI Controller Using the HGA

Like other controllers, the NPI controller relies on its two gains (K_p , K_i) for effective voltage regulation. Traditional empirical tuning methods are unsuitable due to the NPI's nonlinear element. Consequently, we use another HGA to optimize the gains based on the MATLAB/SIMULINK model. The optimization utilizes the integral of absolute error (IAE) as the performance measure.

$$IAE = \int_0^\infty |e(t)| dt \quad (19)$$

where $e(t)$ is the difference between the setpoint and the output voltage as $e(t) = V_{desired}(t) - V_o(t)$.

IV. SIMULATION AND RESULT DISCUSSION

The proposed method was validated through simulations performed in SIMULINK, utilizing the model illustrated in Fig. 7. The overall system comprises serially connected PV modules (Kyocera KC200GT), the boost and buck converters, the InCon algorithm, the NPI controller, and a load.

1. Design of the Two Converters

The SIMULINK model for the dual-stage DC-DC converter was built by defining specific component parameters. The input source uses three series-connected PV panels rated for a maximum power of 600W ($V_{MPP} = 26.3V$, $I_{MPP} = 7.61A$ at STC). The boost and buck converters are designed for output voltages of 100V and 32V, respectively. Utilizing a conservative 90% system efficiency and setting ripple constraints (max output voltage ripple $\leq 1\%$; max input current ripple $\leq 30\%$; input PV voltage ripple $\leq 0.5\%$), the component parameter values are provided in Table 2. The calculated minimum input necessary capacitance (C_{in}) to meet the voltage ripple constraint is 7.22 μF .

2. Controller Gain Settings

The gains of the NPI controller were optimized using the SIMULINK model (Fig. 7), under STC. The optimization employed the HGA using the same parameters as described in Section II and the two gains were searched within the bound $0 < K_p, K_i < 3$. For a fair comparison, the NPI controller's performance was benchmarked against the standard PI controller. The PI controller gains were also optimized by minimizing the performance index defined in Equation (19). The final optimized results for both the NPI and PI controllers are presented in Table 3.

표 2. 설계된 구성요소의 값.

Table 2. Designed component values.

Description	Boost Converter	Buck Converter
Input voltage	78.9V (PV V_{MPP})	100V (Boost output)
Output voltage	100V	32V (Buck output)
Switching freq. (f_s)	100kHz	100kHz
Nom. duty cycle (D)	0.211	0.32
Inductor (L_1, L_2)	72.9 μH	43.52 μH
Output cap. (C_1, C_2)	12.0 μF	19.53 μF

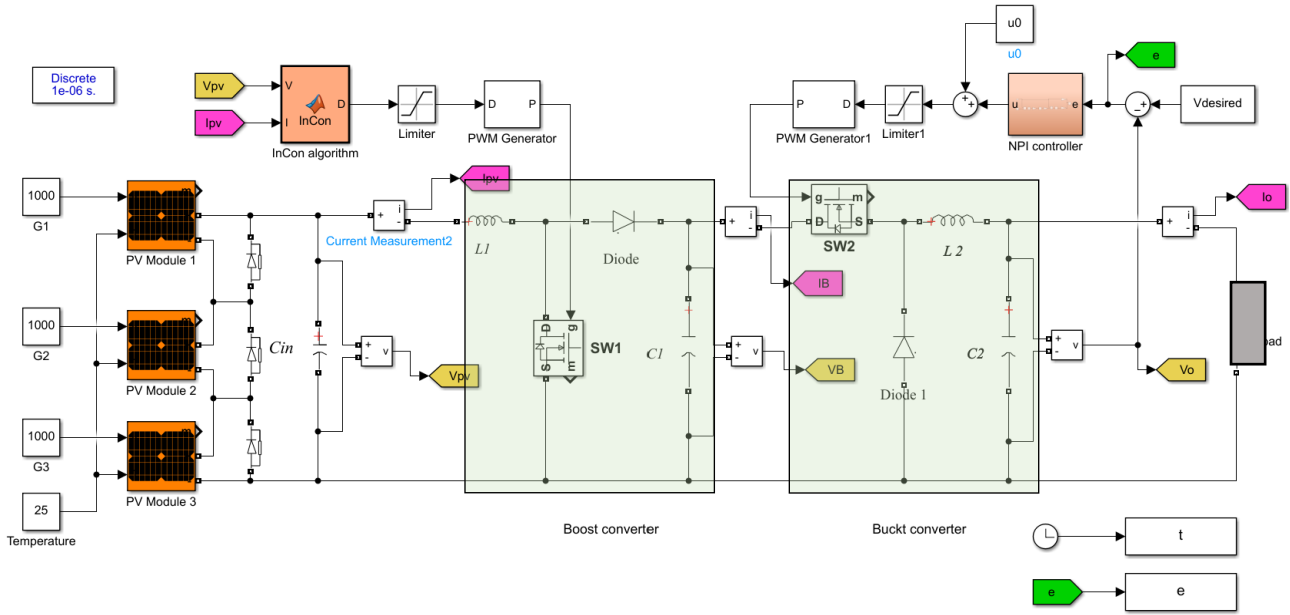


그림 7. 듀얼 스테이지 DC-DC 컨버터 시스템 구현을 위한 SIMULINK 모델.

Fig. 7. SIMULINK model for implementing the dual-stage DC-DC converter system.

표 3. NPI 및 PI 제어기의 최적 이득.

Table 3. Optimized gains of the NPI and PI controllers.

Controllers	Gains	
	K_p	K_i
NPI	0.177	0.632
PI	0.276	0.233

3. Performance Test

The designed system was simulated under two distinct conditions: STC and PS. PS was modeled to account for typical causes like shadows and varying solar angles. Temperature variations were excluded from the study because they change much more slowly than irradiance. Consequently, the temperature was kept constant at 25°C. The responses and comparative performance of the two control methods were evaluated across four distinct irradiance scenarios. For quantitative analysis, the following metrics were calculated: overshoot (M_p), rise time (t_r), settling time (t_s) and IAE as defined in (19).

To simplify nomenclature for the comparison, the system combining the NPI controller and the InCon algorithm is denoted as NPI-InCon. Similarly, the combination of the PI controller and the InCon algorithm is referred to as PI-InCon.

3.1 Case 1 : Constant STC

All panels were assumed to operate under STC. The desired voltage was stepwisely changed from 0V to 32V. Fig. 8 displays the resultant buck converter's output voltage and power responses to this voltage change. As anticipated, the HGA-optimized gains ensured both the NPI and PI controllers achieved the required voltage within 0.4ms. The responses exhibit a minor initial oscillation, primarily due to the MPPT process using the InCon algorithm. The quantitative performance metrics are summarized in Table 4. Analysis of these values indicates that the PI-InCon method marginally outperformed the NPI-InCon method.

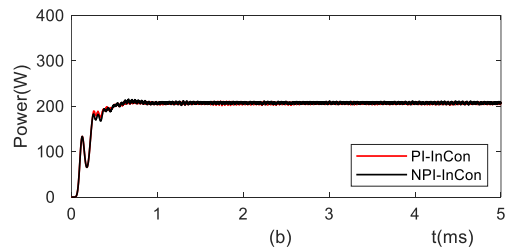
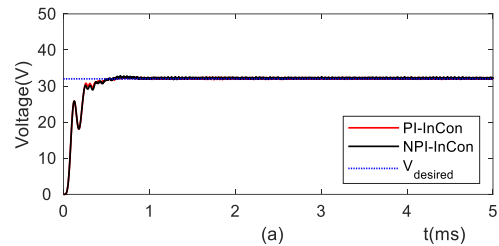


그림 8. 사례 1에 대한 계단상 설정치 변화에 따른 버크 컨버터의 출력: (a) 전압, (b) 전력.

Fig. 8. Output of the buck converter to stepwise setpoint change for Case 1: (a) voltage, (b) power.

표 4. 사례 1에 대한 두 방법의 정량적 성능 비교.

Table 4. Quantitative performance comparison of the two methods for Case 1.

Methods	Performance			
	M_p (%)	t_r (ms)	t_s (ms)	IAE
NPI-InCon	2.647	0.184	0.364	0.011
PI-InCon	1.801	0.184	0.355	0.010

3.2 Case 2 : Constant PS

The subsequent simulation was performed under constant PS conditions, where the three panels received unequal irradiance: G_1

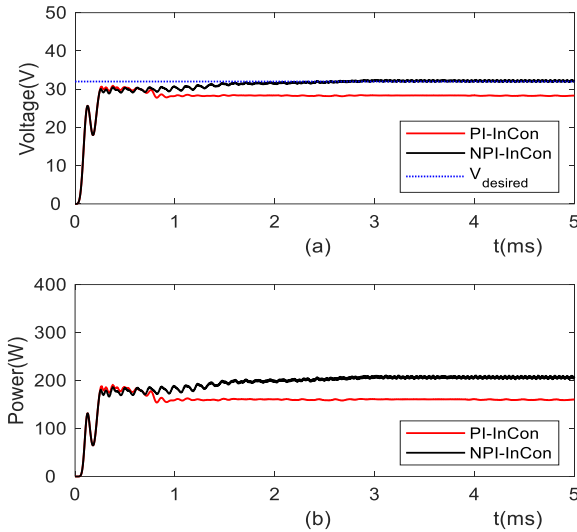


그림 9. 사례 2에 대한 계단상 설정치 변화에 따른 버크 컨버터의 출력: (a) 전압, (b) 전력.

Fig. 9. Output of the buck converter to stepwise setpoint change for Case 2: (a) voltage, (b) power.

표 5. 사례 2에 대한 두 방법의 정량적 성능 비교.

Table 5. Performance comparison of the two methods for Case 2

Methods	Performance			
	M_p (%)	t_r (ms)	t_s (ms)	IAE
NPI-InCon	1.622	0.186	1.313	0.010
PI-InCon	NaN	0.186	NaN	0.098

$=1000\text{W/m}^2$, $G_2 = 600\text{W/m}^2$, and $G_3 = 400\text{W/m}^2$. Fig. 9 illustrates the controllers' responses to the same stepwise voltage input.

Despite reduced power output due to shading, the NPI-InCon method reached the setpoint quickly, settling within approximately 1.3ms. In contrast, the PI-InCon method performed poorly, failing to settle even within 5ms. This observed failure of the PI-InCon method stems from the static nature of its gain tuning at STC, which proves inadequate when the setpoint shifts under PS conditions.

Table 5 summarizes the quantitative performance metrics. Based on these calculated values, the NPI-InCon method demonstrated superior effectiveness compared to the PI-InCon method under the tested conditions.

3.3 Case 3: Dynamic shading

This simulation was conducted under dynamic PS conditions. The three PV panels, initially operating at STC, were progressively shaded over time. The specific shading profile applied is as follows: At 30ms, G_3 drops from 1000W/m^2 to 400W/m^2 . At 60ms, G_2 drops from 1000W/m^2 to 600W/m^2 . This time-varying irradiance profile is shown graphically in Fig. 10(a). Figs 10(b) and 10(c) show the system responses to the same stepwise input, while Fig. 10(d) depicts the resulting changes in the duty cycle.

Both controllers maintained the output voltage consistently near the setpoint under shading conditions. For quantitative evaluation, their IAEs were calculated. Although the PI-InCon method showed a marginally smaller IAE of 19.03 compared to the NPI-InCon method's 19.93, the duty cycle response of the PI-InCon method displayed larger fluctuations than that of the NPI-InCon method.

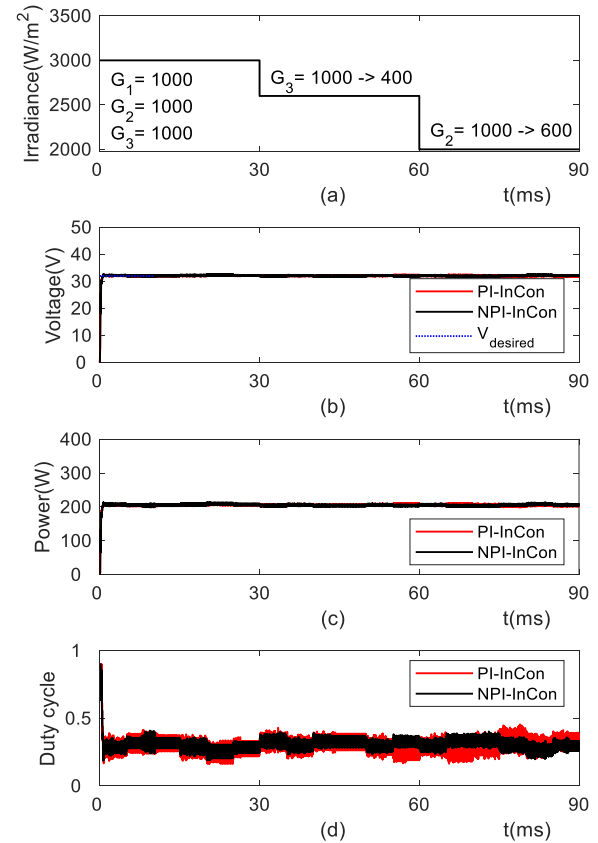


그림 10. 사례 3에 대한 계단상 설정치 변화에 따른 버크 컨버터의 출력: (a) 일사량, (b) 전압, (c) 전력, (d) 듀티.

Fig. 10. Output of the buck converter to stepwise setpoint change for Case 3: (a) irradiance, (b) voltage, (c) power, (d) duty cycle.

3.4 Case 4: Dynamic shading restoration

The final simulation investigated the system's responses to dynamic irradiance restoration. The test began under an initial PS state, with irradiances set at $G_1 = 1000\text{W/m}^2$, $G_2 = 600\text{W/m}^2$, and $G_3 = 400\text{W/m}^2$. The shading was then progressively removed in two stages: At 30ms, G_2 was restored from 600W/m^2 back to 1000W/m^2 (STC). At 60ms, G_3 was restored from 400W/m^2 to 1000W/m^2 .

Fig. 11 shows the system's response to dynamic irradiance restoration. Specifically, Fig. 11(a) illustrates the irradiance test profile, while Figs. 11(b) and 11(c) show the resulting output voltage and delivered power for both control methods. Finally, Fig. 11(d) depicts the corresponding switching duty cycle used to regulate the converter.

In Case 4, the output voltage behavior varied significantly between the two methods. The output voltage of the PI-InCon method reached the setpoint only after G_2 was partially restored around 30ms. On the other hand, the NPI-InCon method maintained the output voltage at the setpoint consistently, regardless of the shading restoration event. For quantitative assessment, the IAEs were calculated. The NPI-InCon method demonstrated vastly superior performance with an IAE of 20.07, compared to the PI-InCon method's high IAE of 116.68. Regarding the duty cycle response, the NPI-InCon's duty cycle remained comparatively stable with smaller fluctuations, while the PI-InCon's duty cycle displayed significantly larger fluctuations, reflecting its poorer stability during the transient event.

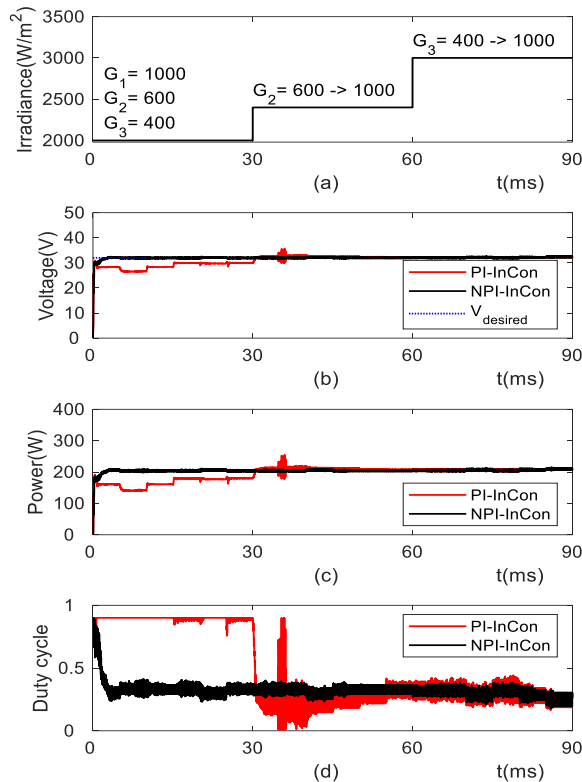


그림 11. 사례 4에 대한 계단상 설정치 변화에 따른 버크 컨버터의 출력 전압 및 전력.

Fig. 11. Output voltage and power of the buck converter to stepwise setpoint change for Case 4.

V. CONCLUSION

This study introduced and evaluated a control strategy for a PV system utilizing a dual-stage conversion system, featuring a decoupled approach: InCon-based MPPT on the boost stage and voltage regulation on the buck stage. For the first task, the PV cell identification was carried out to estimate the parameters of a PV cell model. The core of this strategy is to use the effective NPI controller for output voltage regulation, whose gains were optimized using the HGA. A set of simulations were conducted using the SIMULINK model. The responses and performance of the two control methods were evaluated across four distinct irradiance scenarios.

Simulation results confirmed that both the NPI-InCon and PI-InCon methods provided rapid voltage regulation under STC, settling within 0.4ms. Crucially, the NPI-InCon demonstrated significant superiority under PS: in constant shading, NPI achieved the setpoint in approximately 1.3ms, substantially faster than the PI-InCon's stabilization time of over 5ms. Furthermore, in dynamic shading scenarios, the NPI-InCon method exhibited smaller steady-state duty-cycle fluctuations, indicating better dynamic stability. Overall, the NPI controller provides greater effectiveness in voltage regulation and power harvesting efficiency in PV systems than the conventional PI controller.

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