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MPPT and Controller Design Using Population-Based Algorithms for a Buck-Boost Converter Connected to a PV Panel

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ABSTRACT

In recent years, the increasing energy demand and the depletion of fossil fuels have driven researchers to focus on renewable energy sources. In this context, the efficient control of DC-DC power converters connected to photovoltaic (PV) panels commonly used for solar energy generation has become increasingly important. This study employs the recently developed Artificial Hummingbird Algorithm (AHA) and the Cheetah Optimization Algorithm (CO) to optimally control a Buck-Boost converter coupled with a PV panel. Both AHA and CO are applied to enhance control performance based on the Integral of Time-Weighted Squared Error (ITSE) criterion by tracking the maximum power point (MPPT) of the PV panel under varying temperature and irradiance conditions. The algorithm optimizes the parameters of the Proportional–Integral (PI) controller used in the converter, thereby improving the system's dynamic response. The findings demonstrate that the proposed approach delivers faster, more stable, and more accurate performance.

Keywords: Population-Based Algorithms, PV Panel, Buck-Boost Converter, MPPT.

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1 Introduction

The rapid increase in global energy demand, combined with the continuous depletion of fossil fuel reserves, has underscored the importance of renewable resources in energy production. Solar energy, in particular, has become a priority research area for both academic studies and industrial applications due to its clean, abundant, and sustainable nature (Hassan et al., 2024). Recent advances in solar energy technologies have improved the efficiency of PV systems and accelerated their widespread adoption. However, the output power of PV panels is directly influenced by environmental conditions, especially temperature and irradiance (Dada & Popoola, 2023). These factors can prevent the system from operating at its maximum power point (MPP), thereby reducing overall energy efficiency. Consequently, the use of MPPT algorithms has become essential in PV systems. MPPT methods continuously monitor the panel's operating point to ensure maximum power output (Pakkiraiah & Sukumar, 2016). DC-DC converters are widely preferred for optimizing the use of PV panels under varying operating conditions (Farahat et al., 2012). These converters adjust the voltage and current generated by the PV panel to appropriate levels for transfer to the load or grid. DC-DC converters such as Buck, Boost, Buck-Boost, Cuk, and SEPIC are notable for their adaptability to diverse input and output voltage conditions (Atallah et al., 2014; Chiang et al., 2008; Darwish et al., 2014). Among these, the Buck-Boost converter offers a flexible solution due to its ability to operate in both step-up (boost) and step-down modes. Properly setting the controller parameters is critical for maintaining system stability and efficiency.

Classical controller tuning methods, such as the Ziegler–Nichols technique, can provide acceptable basic solutions but often fail to achieve the desired performance—especially in PV systems where temperature and irradiance fluctuate continuously. Consequently, in recent years, optimization-based intelligent algorithms for controller design and maximum power point tracking have gained increasing attention. Metaheuristic optimization techniques, in particular, offer significant advantages, including rapid convergence, high accuracy, flexibility, and adaptability to changing conditions when addressing complex and nonlinear systems (Akgul et al., 2024; Çimen et al., 2022).

A review of studies in this area reveals the widespread use of various optimization-based approaches for maximum power point tracking and for improving controller parameters in PV systems. Notably, several studies have focused specifically on enhancing the efficiency of DC-DC converters and the performance of PI/PID controllers to ensure system stability under variable environmental conditions. Among these optimization-based approaches, the Particle Swarm Optimization (PSO) algorithm has been widely applied to optimize PI controller parameters in DC–DC converters, yielding superior convergence characteristics and improved steady-state accuracy compared to traditional tuning methods (Brahim et al., 2021). In addition to PSO, recently developed metaheuristic algorithms such as the Artificial Hummingbird Algorithm (AHA) and the Cheetah Optimization (CO) algorithm have gained increasing attention due to their strong global search capability, rapid convergence speed, and robust adaptability. For instance, (Alhumade et al. 2023) proposed a modified AHA-based single-sensor MPPT approach for photovoltaic systems, achieving effective global maximum power point tracking under partial shading conditions. Similarly, (Sunca & Koçkanat 2024) demonstrated the efficiency of the CO algorithm in harmonic analysis and optimization tasks, emphasizing its potential for fast and accurate convergence. These findings indicate that AHA and CO are highly promising tools for solving complex engineering optimization problems, as these algorithms have been successfully applied in various engineering applications due to their strong adaptability and computational efficiency. These studies report successful outcomes in reducing error metrics and improving the dynamic response of the proposed methods. The findings from this literature, which highlight the applicability of intelligent optimization-based control methods in PV panel-connected converters, are summarized in Table 1.

Table 1: Literature Review on Optimization Algorithms for MPPT in PV Systems.

Author	Improved Algorithm	Converter Type	Results
(Koad et al., 2016)	Particle Swarm Optimization (PSO)	Cúk DC–DC converter	The PSO algorithm enhanced with Lagrange interpolation improved MPPT under partial shading by achieving faster convergence and reduced oscillations. Compared to P&O and IC methods, it delivered more stable and reliable performance.
(Badis et al., 2017)	Genetic Algorithm (GA) – PID tuning	Boost DC–DC converter	A GA-optimized PID MPPT controller improved transient response under fast irradiation changes, achieving lower overshoot and shorter settling time compared to the conventional Pole Placement method.
(Eltamaly ,2021)	Musical Chairs Algorithm (MCA)	Boost DC–DC converter	By gradually reducing the number of search agents, the MCA achieves fast convergence and low steady-state oscillation under partial shading, outperforming PSO, BA, GWO, ABC, and CS in MPPT speed and stability.
(Banakhr et al., 2021)	Harmony Search (HS) – PI controller optimization	Buck DC–DC converter	An adaptive MPPT method based on HS-optimized PI control updated the reference voltage under varying temperature and irradiance, adjusting the converter duty cycle, and achieved higher efficiency and stability compared to P&O and IC methods.
(Elbaksawi et al., 2024)	Improved Grey Wolf BAT Optimization (IGWBO)	Boost DC–DC converter	IGWBO combined IGWO and BAT strengths to deliver faster convergence, lower oscillations, and higher efficiency in a 5.5 kW floating PV system. Annual power increased by 5.64% over IGWO, 10.58% over GWO, 17.54% over BAT, and 27.28% over uncontrolled PV, with significant CO_2 emission reduction.
(Guerra et al., 2021)	Intelligent MPPT – ANN, Fuzzy, ANFIS	Buck–Boost DC–DC converter	ANN, fuzzy, and ANFIS MPPT achieved faster tracking and negligible steady-state oscillations compared to P&O; ANN recovered up to 9.9% power. In selected scenarios, settling times were a few milliseconds shorter than P&O.
(Suganya et al., 2017)	Chaos Particle Swarm Optimization (CPSO)	Boost DC–DC converter	By integrating chaos search into PSO, CPSO located the global MPP under partial shading more quickly and reliably, reducing slow convergence caused by randomness. MATLAB/Simulink simulations showed CPSO outperformed conventional P&O in tracking speed and accuracy.

Literature reviews indicate that various methods have been proposed for MPPT and controller parameter optimization in PV systems. While these methods achieve successful results under certain conditions, their stability and accuracy may be limited when exposed to varying temperature and irradiance levels. Additionally, some techniques face practical challenges due to high computational complexity. In this context, the present study employs the recently developed AHA and the CO to optimize PI controller parameters for a buck-boost converter connected to a PV panel. The proposed approach aims to enhance the system's dynamic response under changing environmental conditions, minimize the ITSE performance criterion, and improve MPPT efficiency.

2 Materials and Methods

2.1 Artificial Hummingbird Algorithm

The AHA (Zhao et al., 2022) is an innovative optimization approach based on the homing, feeding, and migratory behaviours of hummingbirds in nature, introduced by Zhao, Wang, and Mirjalili in 2022. This method both diversifies the search process and provides a more balanced exploration-exploitation mechanism in the solution space by imitating axial, transverse, and multi-directional flight manoeuvres. This behaviour is given in equation 1.

$$X_j = LB + r \times (UB - LB), j = 1,2, \dots, N \tag{1}$$

At the beginning of the optimization process, candidate solutions were initialized with the help of random values generated between the lower (LB) and upper (UB) boundaries of the search space, 0≤ r ≤10.

$$VT_{j,i} = \{0, \quad if \quad j \neq i \; null \quad\quad j = i \, , j \; = \; 1, \dots, N, i \; = \; 1, \dots, N \tag{2}$$

In equation 2, the expression $VT_{j,i}$ = $null$ indicates that the hummingbird has exhausted the food source at the relevant location. The hummingbird then identifies the source with the highest nectar regeneration rate and moves towards it. Three different flight strategies are utilized during this movement.

$$D^i = \{1, \quad if \quad i = R \;\; 0, \quad\quad else \, , \; i \; = \; 1, \dots, d, \tag{3}$$

$$D^i = \{1, \; if \; i = P(j) \; 0, \quad\quad else \, , \; j \in [1, k] \, , \; i \; = \; 1, \dots, d, \tag{4}$$

$$P \; = \; randperm(k), k \; \in \; [2, [\, r1(d - \; 2),] + \; 1]$$

$$D^i \; = \; 1 \quad i \; = \; 1, \dots, d \tag{5}$$

Equation 3 describes the Axial Flight strategy. In this strategy, the hummingbird moves in only one dimension. That is, it moves along a randomly selected axis while remaining stationary in all other dimensions (Sunca & Boz, 2025). This represents linear, single-axis flight. Equation 4 describes the Diagonal Flight strategy. In this approach, the hummingbird moves simultaneously in multiple dimensions. Dimension selections are determined by a random permutation method, and the bird explores a larger area of the solution space by moving diagonally. Equation 5 describes the Versatile Flight strategy. In this strategy, the hummingbird moves simultaneously in all dimensions, thus achieving the most comprehensive exploration of the solution space.

The new location is updated by evaluating the candidate solution's fitness function $f(X)$ as in equation 6.

$$V_i(t + 1) \; = \; X_{i,t}(t) \; + \; a \; \times \; D \; \times \; (X_i(t) - \; X_{i,t}(t)), \quad a \; \in \; N(0, 1) \tag{6}$$

As shown in equation 7, the hummingbird abandons the source with the lowest nectar value and moves to a different spot;

$$X_w(t+1) = LB + r \times (UB - LB) \quad (7)$$

X_w represents the point with the lowest fitness value and is randomly moved to a new location when it remains fixed for a long time to ensure diversity.

2.2 Cheetah Optimization Algorithm

This research employs the CO algorithm, inspired by the natural hunting and exploration behaviours of cheetahs. The CO algorithm, first proposed by Akbari in 2022 (Akbari et al., 2022), aims to identify optimal solutions through the iterative refinement of a population of candidate solutions. It mimics the cheetah's behaviour by structuring the search process into exploration and exploitation phases. Exploration allows the cheetah to scout areas likely to contain prey, while exploitation involves focused attack strategies upon prey detection.

The algorithm's efficiency is further enhanced by its simple structure, low computational requirements, minimal parameter tuning, and rapid convergence. These characteristics make the CO algorithm well-suited for complex optimization problems where avoiding local optima is critical. The spatial updating of a cheetah's position during the search process can be represented mathematically as in equation 8:

$$X_{\mathrm{i},j}^{t+1} = X_{\mathrm{i},j}^{t} + r_{\mathrm{i},j}^{-1} \,.\, a_{\mathrm{i},j}^{t} \quad (8)$$

Where $X_{\mathrm{i},j}^{t+1}$ denotes the updated position of the i-th candidate in the j-th dimension at iteration $t+1$, $r_{\mathrm{i},j}^{-1}$ is a randomness factor, and $a_{\mathrm{i},j}^{t}$ represents the step size.

During the search phase, the cheetah may remain stationary to avoid startling potential prey, thereby increasing the likelihood of a successful hunt. This stationary or "sit-and-wait" behaviour is modelled as in equation 9:

$$X_{\mathrm{i},j}^{t+1} = X_{\mathrm{i},j}^{t} \quad (9)$$

If the prey attempts to escape, the cheetah engages its speed and agility to pursue the target. Additionally, CO can simulate group hunting, where multiple cheetahs coordinate their movements to reduce the prey's chance of evasion. The tracking dynamics in this exploitation phase can be formulated as shown in equation 10:

$$X_{\mathrm{i},j}^{t+1} = X_{B,j}^{t} + r_{i,j} \,.\, \beta_{\mathrm{i},j}^{t} \quad (10)$$

Here, $X_{B,j}^{t}$represents the best-known position obtained in the current iteration, $r_{i,j}$ adjusts the movement direction, and $\beta_{\mathrm{i},j}^{t}$ defines the intensity of interaction among cheetahs during coordinated hunting. Through this adaptive behavior, CO balances exploration and exploitation effectively, allowing it to efficiently navigate complex search spaces and converge towards optimal solutions.

2.3 Photovoltaic Panel

Photons in the light reaching solar panels are absorbed by the panel's semiconductor structure and converted into electrical energy. The current-voltage (I-V) curve of these panels is typically shown in Figure 1. The current, voltage, and power output of the panels vary depending on the properties of the semiconductor material used and the manufacturing technology. The A10Green A10J-S72-175 PV panel was used in this study. Its characteristic curve is presented in Figure 1. Maximum power can only be achieved at a specific point within the panel's operating range. However, the load connected to the panel or the amount of current drawn can shift the operating point away from the maximum power point. Therefore, to ensure the panel operates continuously at this point, the voltage or current must be monitored and adjusted accordingly. For this purpose, various algorithms such as Perturb and Observe (P&O) and Incremental Conductance (IC) have been proposed in the literature. IC was selected as the method in this study.

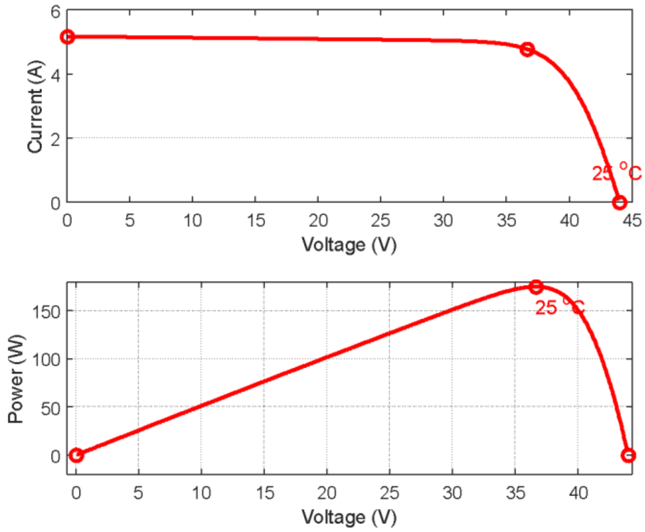

Figure 1: Current-Voltage graph and Power-Voltage characteristic curve of the panel at 25°C and 1000 W/m2 environment

In this study, the PI controller parameters of the buck-boost converter were optimized using the AHA and CO algorithms to track the maximum power from the PV panel. The performance of the PV panel varies with changes in ambient temperature and solar irradiance. Therefore, the MPPT algorithm determines the reference voltage extracted from the PV panel to ensure maximum efficiency. Current-voltage and power-voltage curves illustrating the panel's performance under varying temperature and irradiance conditions are presented in Figures 2 and 3.

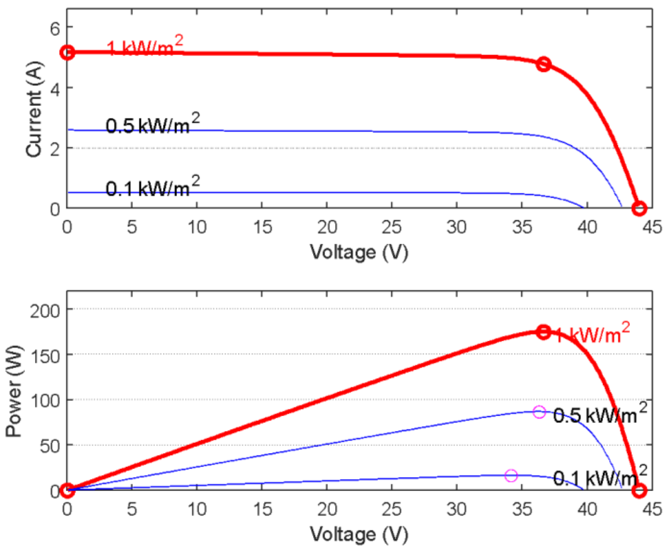

Figure 2: At 25°C and irradiance levels of 100, 500, and 1000 W/m², the current-voltage (I-V) and power-voltage (P-V) characteristic curves of the panel

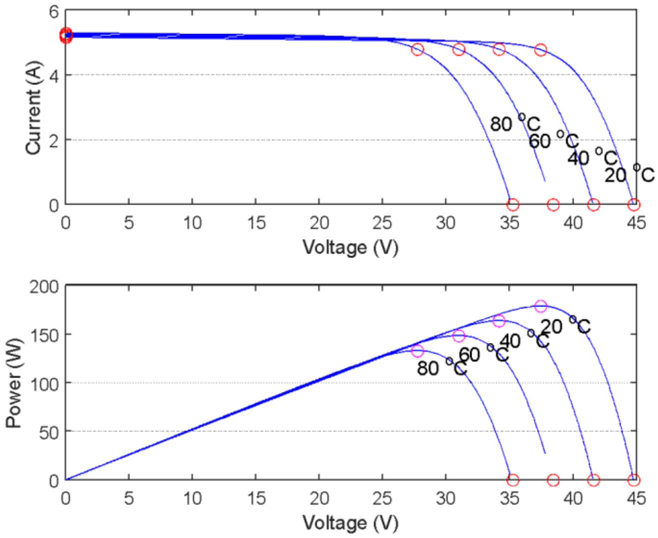

Figure 3: Current-Voltage graph and Power-Voltage characteristic curve of the panel at 1000 W/m² irradiance and ambient temperature of 20°C-80°C

2.4 Buck Boost Converter

A buck-boost converter is a versatile DC-DC converter that can produce an output voltage that is either lower or higher than its input voltage. This ability makes it a popular choice in power electronics, especially for applications like PV systems, where the input voltage from a solar panel can fluctuate. When the connected load requires a voltage that is either above or below the PV panel's output, a buck-boost converter can efficiently step the voltage up or down to meet the load's requirements. The topology of a buck-boost converter is shown in Figure 4. In Figure 4, L, C, SW, V_{dc}, R_{load}, and V_o are filter inductance, filter capacitance, power switch, DC input voltage, load resistance, and output voltage, respectively. I_L represents the inductor current, and D denotes duty cycle (Vatansever & Kuyu, 2019).

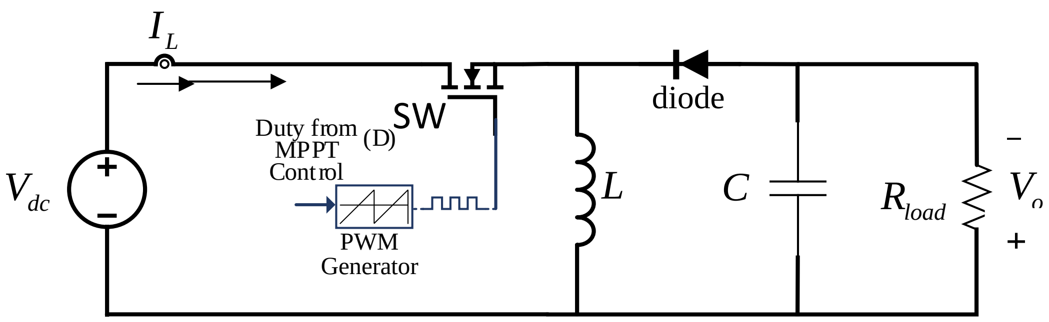

Figure 4: A buck-boost converter topology

A boost converter can operate in one of three modes, which are determined by the behavior of the inductor's current. In discontinuous conduction mode (DCM), the inductor current falls to zero before the next pulse from the PWM controller. In continuous conduction mode (CCM), the inductor current remains above zero at all times. The third mode, boundary conduction mode (BCM), occurs when the inductor current reaches zero at the exact moment the next PWM pulse is applied. The relationship between the buck-boost converter's input voltage and output voltage is determined by its operating mode. While Boundary Conduction Mode (BCM) is considered a special case of Continuous Conduction Mode (CCM)—and their functions are treated as identical—this paper specifically considers the converter's behavior in CCM. The transfer function for this mode is detailed in Equation 11.

$$\frac{V_o}{V_{dc}} = \frac{D}{1-D} \tag{11}$$

To ensure the buck-boost converter operates in Continuous Conduction Mode (CCM), the minimum required filter inductance (L_{min}) is calculated using Equation 12. To achieve specific ripple levels in the inductor current (ΔI_L) and output voltage (ΔV_o) for a given operating point, the filter inductance and capacitance are determined using Equations 13 and 14, respectively. The full set of boost converter parameters, based on these calculations, is provided in Table 2.

$$L_{min} = \frac{R_{load}}{2f_{sw}} \tag{12}$$

$$L = \frac{V_{dc}D}{\Delta I_L f_{sw}} \tag{13}$$

$$C = \frac{V_O D}{\Delta V_O R_{load} f_{sw}} \tag{14}$$

3 PI Controller Design for Buck-Boost Converter Connected to PV Panel with AHA and CO Optimization Methods

The performance of a solar panel varies depending on the intensity of sunlight reaching the panel and the ambient temperature. In this study, a buck-boost converter was connected to the panel's output to ensure the panel operates at the maximum reference voltage determined by the MPPT, which adjusts according to the panel's changing maximum operating point. A PI controller was implemented to regulate the converter's operation according to a specified performance criterion (Mühürcü et al., 2017). Figure 5 illustrates the overall system structure. Specifically, the AHA and CO methods were employed to optimize the PI controller's performance based on a defined objective function.

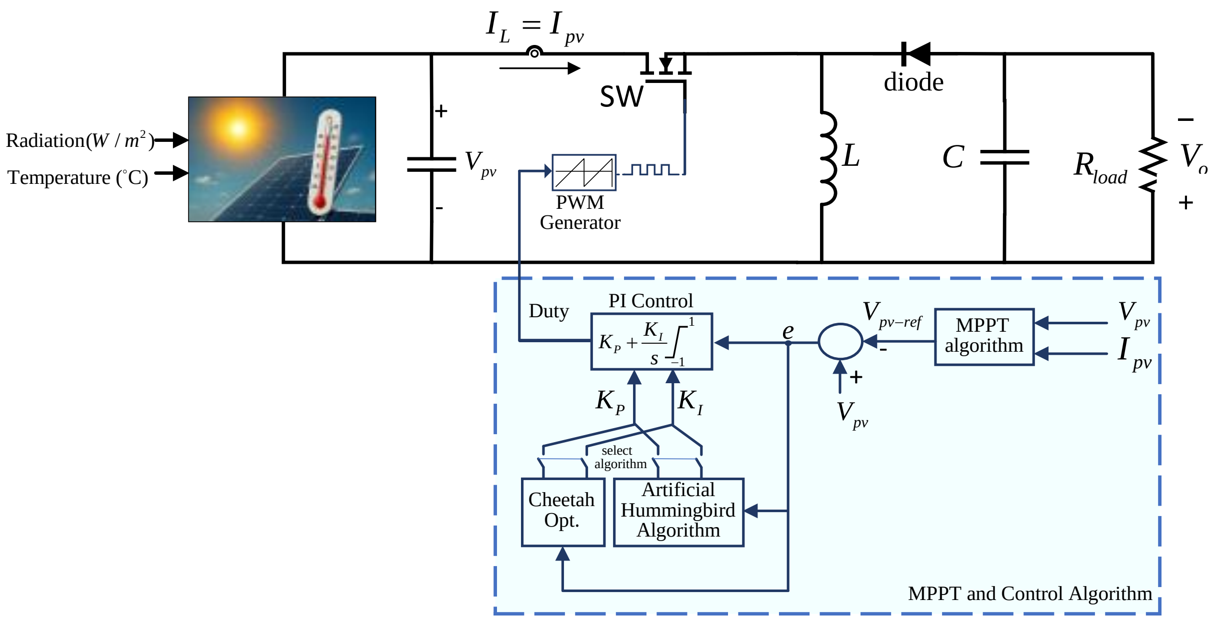

Figure 5: The complete system: the buck-boost converter topology and control algorithm

To control the system, the AHA and CO algorithms must perform optimization according to a specific performance criterion. In this study, the Integral of ITSE criterion in Equation 15 was chosen. This objective criterion is given in Equation 11.

$$ITSE = \int_0^{10} \left(V_{PVref} - V_{PV}\right)^2 t dt \tag{15}$$

The parameters of the buck boost AHA and CO algorithms used in the study are given in Table 2.

Table 2: *Parameters of Buck Boost Converter and AHA and CO algorithm*

Buck Boost Converter		**CO**		**AHA**	
Parameter	**Value**	**Parameter**	**Value**	**Parameter**	**Value**
L	1000×10^{-6} H	Swarm size (n)	10	Swarm size (n)	10
C	470×10^{-6} F	(Max_iter)	10	(Max_iter)	10
R	9	Number of searches agenets in a group (m)	2	Number of searches agenets in a group (m)	-
Switching Frequency	20 kHz	Number of Variables	2	Number of Variables	2
Ipv_{mmp}	4.78 A	(LB)	0	(LB)	0
Vpv_{mmp}	36.63 V	(UB)	10	(UB)	10
Integral limits	[-1, 1]				

In this study, the temperature and solar radiation values changing over time are given in Figure 6. When these values are applied in Figure 6, the PV panel produces a voltage value according to the radiation falling on it and the ambient temperature.

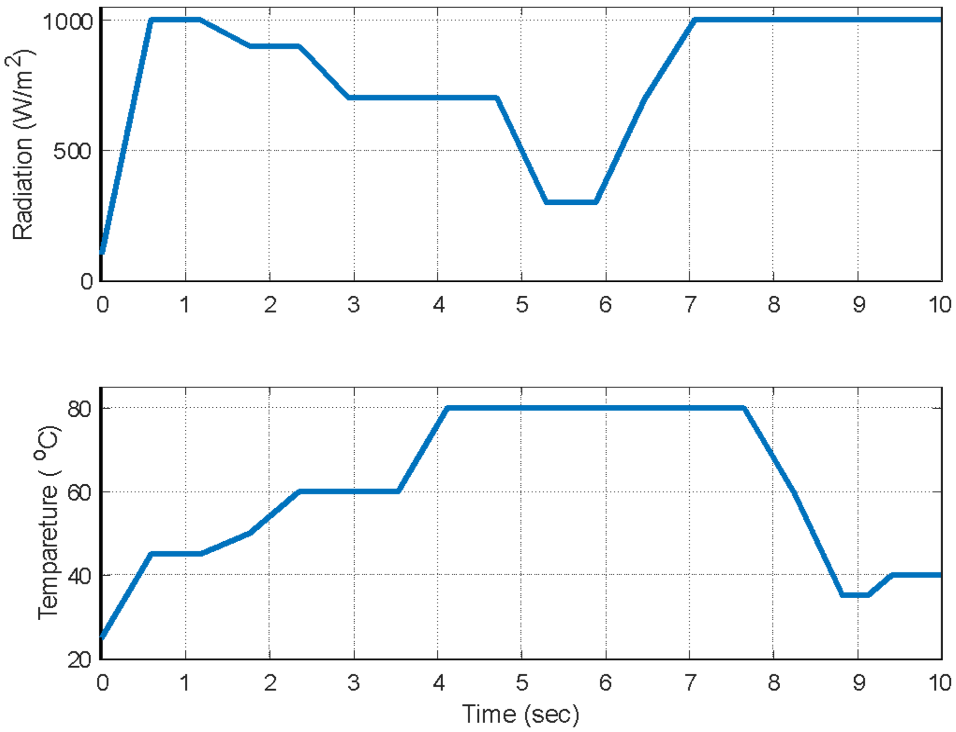

Figure 6: Variation of solar radiation and temperature over time

The desired operating point for maximum power extraction from the panel. The reference voltage generated by the MPPT is applied to the input of the buck-boost converter. Consequently, the buck-boost converter regulates the panel voltage based on this reference voltage. This regulation requires generating a control signal according to a specific performance criterion. To achieve this, a controller was designed to produce the control signal. In this study, two different algorithms were employed to design the PI controller. ITSE performance was used as the design criterion.

In order to perform the studies, a computer with 11th Gen Intel(R) Core (TM) i7-11800H @ 2.30GHz (2.30 GHz), 64 Bit, 32 GB RAM was used. The study was conducted using MATLAB 2022. In order to compare the performance of the AHA and CO algorithms, the algorithms were run independently 30 times. As a result of these experiments, the minimum, mean and standard deviations were calculated in order to compare the performances of the algorithms. The obtained values are given in Table 3. The results for the lowest objective criterion values produced by the algorithms as a result of these experiments are given in Table 3. The lowest value of the AHA algorithm was obtained as Kp=0.0575024432219904 and Ki=5.45217861944446. The controller parameters for the lowest objective criterion value of the CO algorithm were obtained as Kp=0.0285528443568747 and Ki=9.69715176673759. In addition, box plots are given in Figure 7 for a better understanding of the results. When the results are examined, it is seen that the AHA algorithm produces better results.

Table 3: Results of the optimization algorithm

	Min.	Average	Standard deviation	Average time
CO	10210.0782030664	10682.9724293460	96.6397968421406	260.441269176667
AHA	10002.3886137881	10014.6727064433	32.4168310287990	2049.88273525333

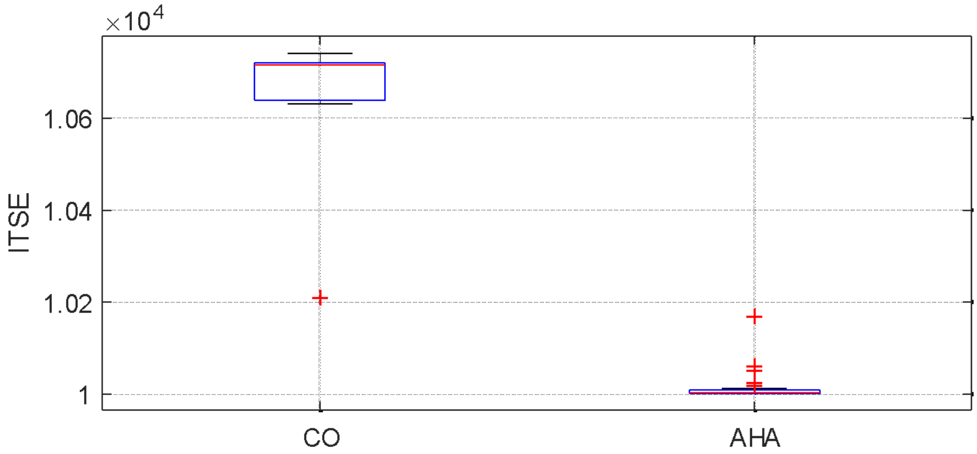

Figure 7: Boxplot of the Best ITSE Performance

The parameters and objective criterion values obtained as a result of the optimization are presented graphically in Table 4. As can be seen from this table, the AHA algorithm produced better results. On the other hand, the objective criterion obtained when the system was run was obtained over time, as shown in Figure 8.

Table 4: ITSE values produced as a result of the control of the PI controller of the controlled Boost converter

	AHA-PI	CO-PI
Controller	Kp=0.0285528443568747 Ki=9.69715176673759	Kp=0.0575024432219904 Ki=5.45217861944446
Objective Function	1.000238861378809e+04	1.021007820306643e+04

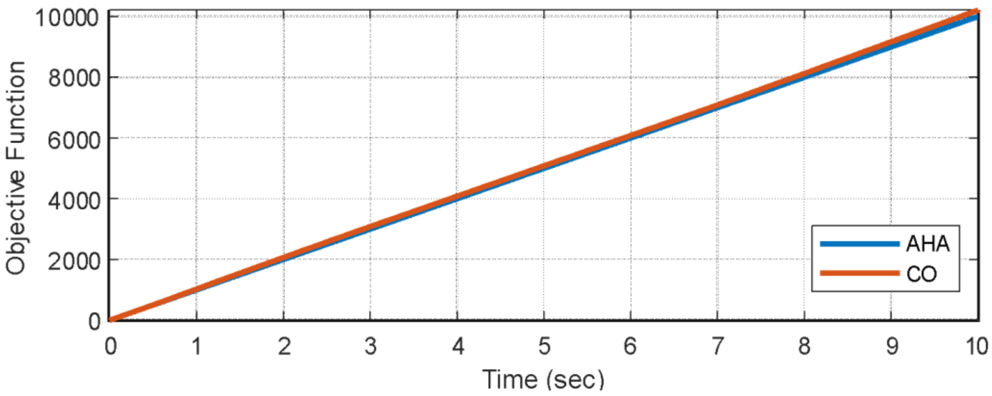

Figure 8: Objective criterion values produced as a result of the control of PI controllers designed with AHA and CO

The PV panel voltage obtained for maximum operation under varying irradiance and temperature conditions when the system was started is shown in Figure 9. As can be seen, the controller parameters determined with the AHA algorithm resulted in less PV panel variation. The control signal required to achieve this is shown in Figure 10. The AHA-PI controller provides a smooth, stable control signal, while the CO-PI controller is highly oscillatory. This stability in the AHA's control effort directly leads to the lower voltage ripple. The output voltage of the buck-boost converter is also shown in Figure 11. This graph shows that the buck-boost converter circuit operates as a buck under some conditions and a boost under others to track maximum power. The power values drawn from the panel when the system was started are shown in Figure 12. As can be seen from this graph, the controller designed with AHA drew higher and more stable power from the panel on average. This contributed to increased system efficiency.

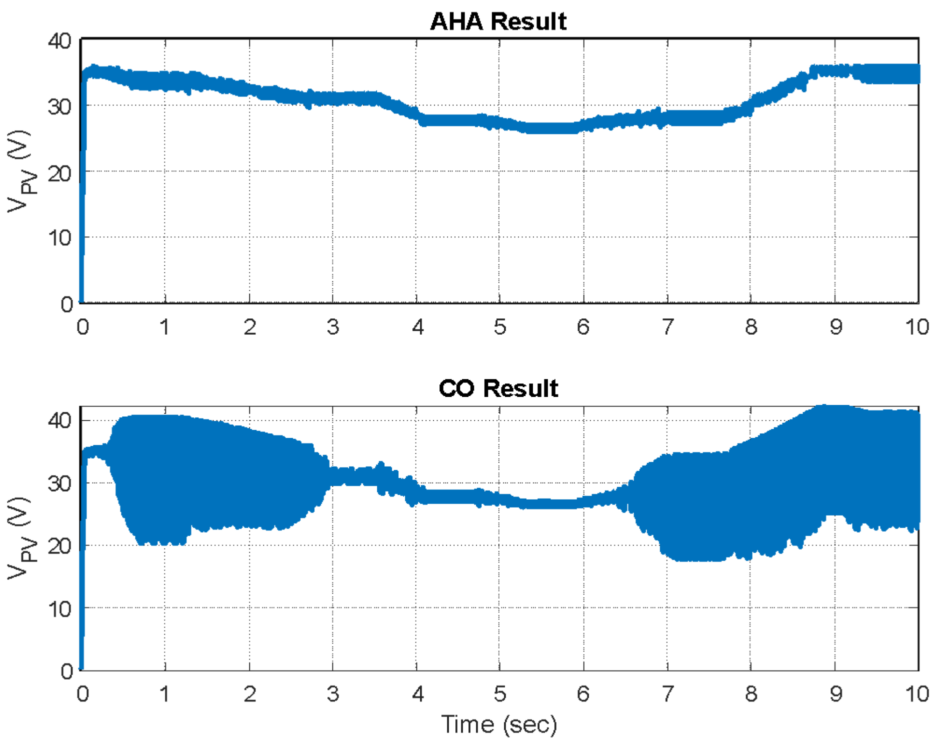

Figure 9: The voltage values on the panel are controlled by the controllers' buck boost converter

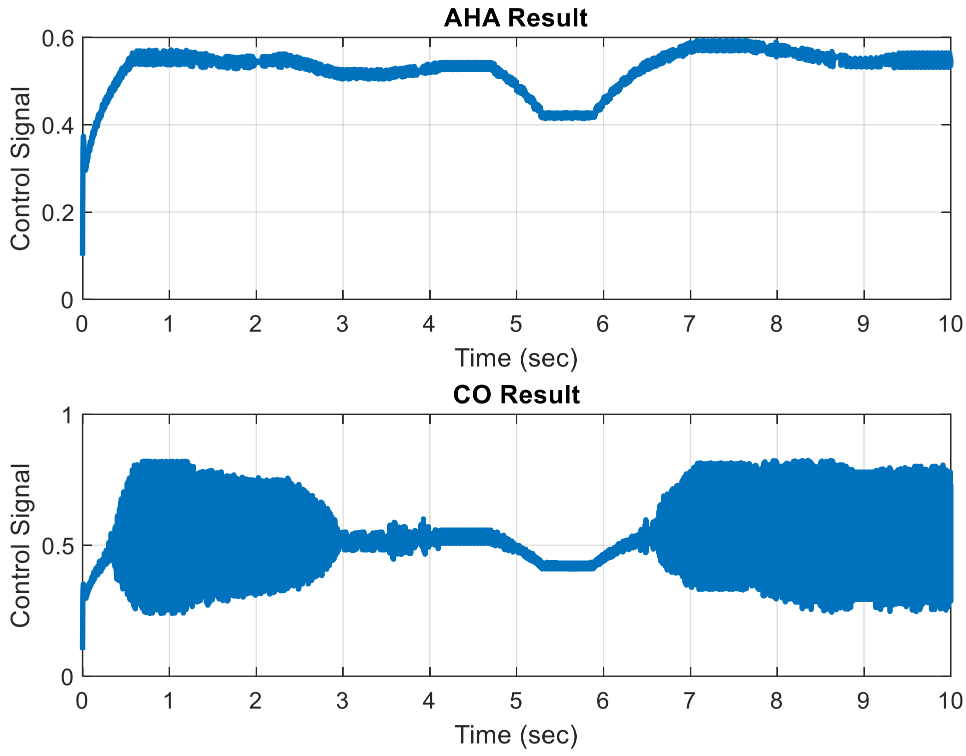

Figure 10. The control signal generated by the controllers

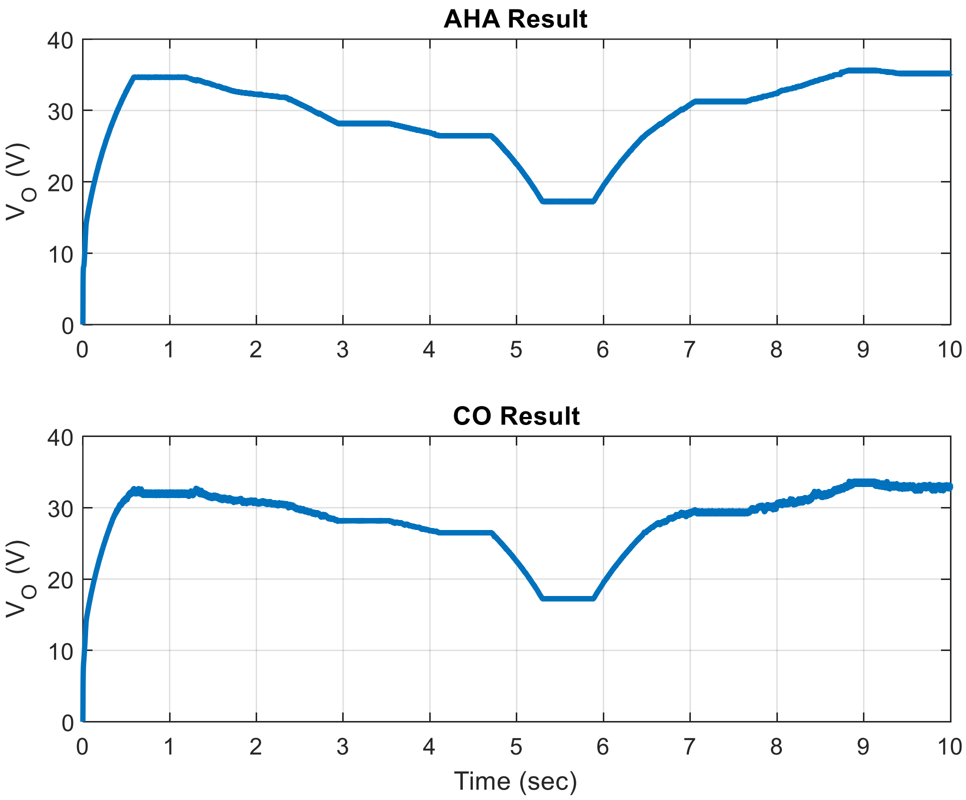

Figure 11: Output voltage values of the controllers' buck boost converter

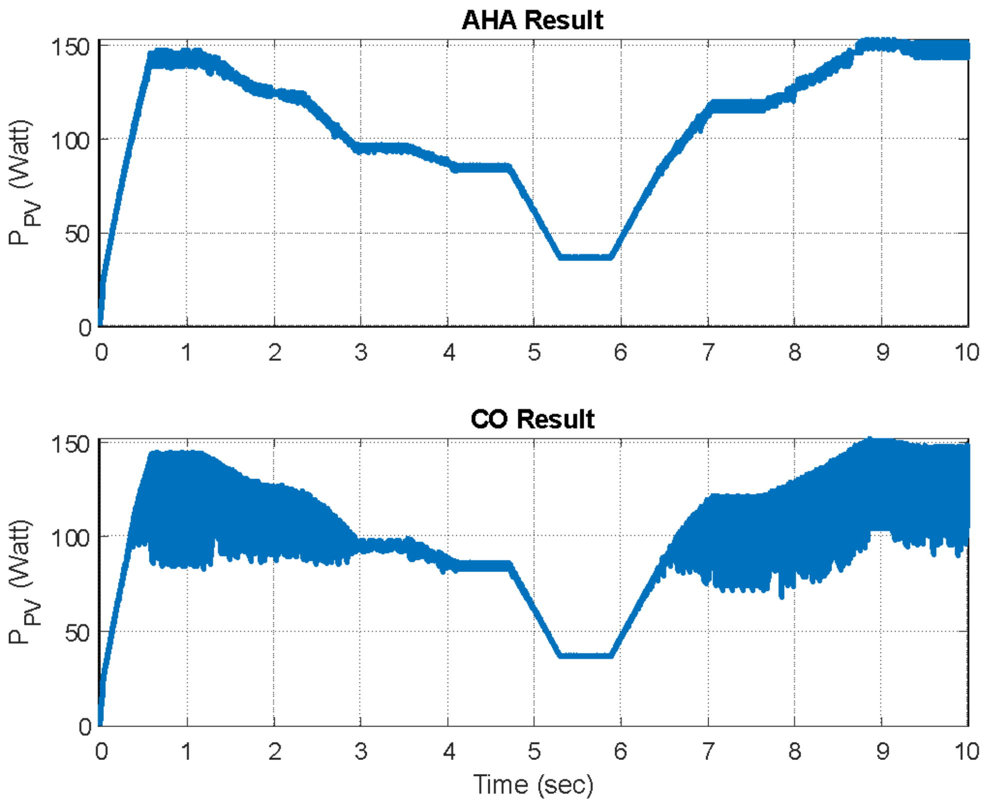

Figure 12: The power graph that the controllers draw from the panel by controlling the boost converter

4 Conclusions

This study aims to determine the optimum PI controller parameters for a DC-DC buck-boost converter connected to solar PV panels. To achieve this, MPPT was implemented under variable temperature and irradiance conditions using the recently proposed AHA and CO algorithms, minimizing the ITSE performance criterion. Both methods enhanced the dynamic behaviour of the buck-boost converter by optimizing the PI controller gain parameters, enabling the system to track power stably and rapidly in both boost and step-down modes. The results show that controllers optimized with both the AHA and CO algorithms significantly reduced the ITSE value and increased the average power output from the PV panel. Both methods improved the system's dynamic response and reduced electrical stress on components by minimizing voltage and current fluctuations, thereby increasing the converter's reliability and service life. However, the controller optimized with the AHA algorithm performed slightly better than the CO algorithm in terms of the ITSE criterion and average power generation. In this context, while both algorithms provide effective solutions, the AHA algorithm can be considered a prominent alternative for enhancing the efficiency and overall performance of PV-based buck-boost converters. This comparative investigation of AHA and CO algorithms for optimizing PI controller parameters in a PV-based buck–boost converter has not been previously reported in the literature. Unlike conventional optimization studies, this work provides a detailed dynamic evaluation under varying environmental conditions and demonstrates the effectiveness of two recently developed metaheuristic algorithms within the same control framework. Therefore, the study contributes to the literature by offering a novel comparative perspective and a validated methodological framework for intelligent optimization of converter-based renewable energy systems.

5 Declarations

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5.3 Competing Interests

There is no conflict of interest in this study.

5.4 Authors' Contributions

Murat Erhan ÇİMEN: Conceptualization, Methodology, Software, Investigation, Data Curation, Formal Analysis.

Ali KUYUMCU: Methodology, Investigation, Data Curation, Validation, Formal Analysis, Visualization.

Kadir Yasin SUNCA: Investigation, Formal Analysis, Writing – Original Draft, Writing – Review & Editing.

Yaprak YALÇIN: Supervision, Review & Editing.

Akif AKGÜL: Supervision, Review & Editing.

Ali Fuat BOZ: Supervision, Review & Editing.

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