Implementation of Bio-inspired Algorithms in Designing Optimized PID controller for Cuk Converter for Enhanced Performance: A Software based Approach

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Abstract

This paper represents the idea of implementing bio-inspired algorithms in designing an optimized PID controller to investigate the stability and improve the performance of the closed-loop CUK converter. Bio-inspired algorithms (BIA) such as Firefly Algorithm (FA), Particle Swarm Optimization (PSO) and Artificial Bee Colony (ABC) are stochastic optimization techniques and have been increasingly applied to attain optimal solution for designing and optimizing power converters in current times. The closed-loop transfer function of the CUK converter has been developed by the State Space Average (SSA) technique. This paper assesses both the cases of converter stability when it is integrated with the conventional PID controller and the BIA-PID controllers (FA-PID, PSO-PID, ABC-PID) and eventually compares the outcomes from all the controllers. For examining the stability of the system, three objective functions (IAE, ITAE, and ISE) and various performance specifications such as percentage of overshoot, rise time, settling time, and peak amplitude are tabulated. MATLAB and Simulink are used to carry out the simulations meticulously. Hence, a comparative analysis is illustrated in this paper to state a clear-sighted evaluation of the performances.

Keywords: Cuk Converter, PID Controller, Bio-inspired Algorithm, Firefly Algorithm, Particle Swarm Optimization, Artificial Bee Colony

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1. Introduction

Bio-inspired algorithms (BIA) are nature-based algorithms pursuing artificial intelligence to execute optimized computation of complex and non-linear problems [1]. These algorithms are categorized according to their diverse inspirations and are cited as Genetic Algorithm, Ant Colony Optimization, Particle Swarm Optimization, Firefly Algorithm, Paddy Field Algorithm, Artificial Bee Colony Algorithm, Invasive Weed Colony Optimization, etc. which are witnessed to be implemented for optimizing the performance parameters in control systems, power systems, robotics, engineering, bioinformatics, computer networks, wireless networks, and many more areas [2-3]. These prominent search techniques have speedy adaptability and can outperform the traditional computational methods in terms of time and efficacy [4]. Among the BIAs, Firefly Algorithm (FA), Artificial Bee Colony (ABC), and Particle Swarm Optimization (PSO) are inspired by swarm intelligence (SI). SI is a multi-agent, decentralized system with coordinated motion and distributed consensus among the mass capable of satisfying tantamount objectives [5]. The swarm intelligence employed in the algorithms ensures that every autonomous agent learns from its surroundings through collaborative mannerisms analogous to swarm animals' etiquette and thereby attains optimized outcomes swiftly. For instance, Firefly Algorithm (FA) follows the interactive routine of the bio-luminescent fireflies to coordinate the exploration of the swarm members in the search space. Whereas social skills of swarm beings inspired the PSO algorithm to find suitable results through a random yet collaboratively developed motion of the individuals in the search space. Meanwhile, ABC complies with the foraging custom of honeybees to locate optimum solutions through constant evaluations of the food sources also referred to as solutions. Swarm intelligence attempts affluent exploitation of data which concentrates the search method within the vicinities of optimal solutions and simultaneously assists the procedure to escape from the confinement of the local minima materializing successful exploration of the search space [6].

One of the most popular application domains of the BIA is the power electronics domain. This paper aspires to investigate the respective implementation of the mentioned algorithms on a power converter system called Cuk. This power converter is a fourth-order system portraying non-linearity due to its switching attributes [7]. Therefore, regulating the output voltage of the converter becomes quite arduous. The converter consists of four reactive components (two inductors and two capacitors) which can build undesired resonances in the regulation circuit. Furthermore, the Pulse Width Modulation (PWM) control mechanism cannot guarantee closed-loop stability [8]. To compensate for the stated issues and to meet the steady-state and transient requirements, a Proportional Integral-Derivative (PID) controller is integrated with the Cuk converter. This feedback control procedure effectively stabilizes and provides a superior command over the close loop response by adjusting the PID gains through the trial-and-error method [9]. But this technique not only makes it challenging to select the appropriate set of PID regulator gains to reach the optimized result but also requires a substantial amount of time to do so. Thus, an artificial intelligence algorithm is fused with the control mechanism so that the control system can comprehend and improve its capacities to deliver a more stable and effective response [10].

An ample amount of literature exists on the successful executions of the Bio-Inspired Algorithms in the field of power converters professed by many researchers [11-20]. One of such promising instances of work has been witnessed with Machine learning (ML) algorithms [21-29], artificial intelligence [30-39], and different applications of ML in healthcare sectors [40-49], and so many other cases [50-59]. Similarly, in [60], the authors directed an investigative study on the ABC-controlled MPPT on a solar PV model involving Buck converter and compared it to the conventional P&O algorithm to generate power. The study manifested higher stability and power production from the system infused with ABC with a difference of 2.34 kW. Moreover, the authors of the journal [61] exhibited an experimental study on stability assessment of the Buck converter with the traditional PID controller and the Genetic Algorithm (GA) combined PID controller. The study confirmed better optimization of the performance parameters in the shape of 4.17% overshoot, settling time of 0.000538 seconds, and rise time of 0.0000504 seconds attained from the objective function IAE computed with the intelligent GA-PID algorithm. Furthermore, in [62], an extensive inspection was delivered on optimizing an interleaved DC-DC Boost converter (IBC) by incorporating PSO with a robust non-linear controller (RNC) to supervise the output of a fuel cell (FC). The PSO-RNC illustrated better responses with a distinct lowering of overshoot from 8.83 to 0.97 in the second overshoot while being confronted with variable load and variable input voltage. And finally, this paper intends to conduct an overall retrospection on the applicability of FA, PSO, and ABC algorithms on PID interlaced with the Cuk converter to realize its optimum product.

The paper illustrates the converter circuit design by the state-space averaging (SSA) process in Segment 2. A brief description of the Bio-Inspired Algorithms (FA, ABC, and PSO), the fitness functions, and BIA-PID application in the converter are presented in Segment 3. And ultimately simulations of the proposed control design, corresponding results, and overall stability analysis are depicted in Segment 4. MATLAB was used as a programming tool to carry out all the simulations. A model of the mentioned system is demonstrated through MATLAB Simulink.

2. Methodology

2.1. Circuit Analysis of Cuk Converter in CCM

Cuk converter can be defined as a series combination of buck-boost topology. This inverting converter decreases or increases the voltage level while operating in two different switching actions. It assembles some striking features such as high efficiency, flexibility in size, the capability of changing polarity, power factor pre-regulation, capacitive energy transfer, and many more. The circuit diagram of the Cuk converter is illustrated in Figure 1 which includes a dc voltage source (Vin), two inductors (L_1 and L_2) and two capacitors (C_1 and C_2) as energy storing elements, MOSFET as a switch (Q), a diode (D) as current flow controlling component and a resistor (R_0) as loading material. In CCM mode, the usage of capacitors is transferring energy from input to output portion and the current flowing through the inductors always has a finite value rather than zero.

Assuming V_{C1}, V_{C2} be the voltages across C_1 and C_2 respectively and I_{L1}, I_{L2} by the currents flowing through L_1 and L_2 respectively, the two switching modes (ON and OFF) are demonstrated in Figure 2(a) and Figure 2(b) []. During the ON switching action (while Q is on), I_{L1} increases while developing the magnetic field in the inductor L_1, the stored energy is transferred by the capacitor C_1 to the output side and the voltage V_{C1} sets off the diode (D) by reverse biasing it. During the OFF, switching action (while Q is off), the flow of I_{L1} is sustained by reversing the polarity, the diode (D) is forward biased and the capacitor C_1 is charged by utilizing the energy stored in the inductor L_1 and is transferred to the output portion of the circuit. The energy stored in the inductor L_2 and capacitor C_2 is used for the load current supply. The sum of the currents flowing through the inductors must be equal to zero in the steady state while keeping the assumption that the voltage across capacitor C_1 is constant. The ideal converter equation for the relationship between V_{in} and V_0 can be written as

$$\frac{V_{in}}{V_0} = \frac{d}{1-d} \tag{1}$$

Where the duty cycle is denoted by d and by controlling d, the value of output voltage can be controlled. The disturbances of the circuit can be ignored with the variation in the duty cycle by using a controller.

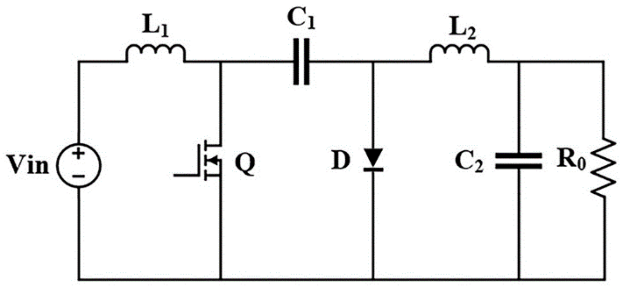

Figure 1. The circuit diagram of conventional Cuk converter

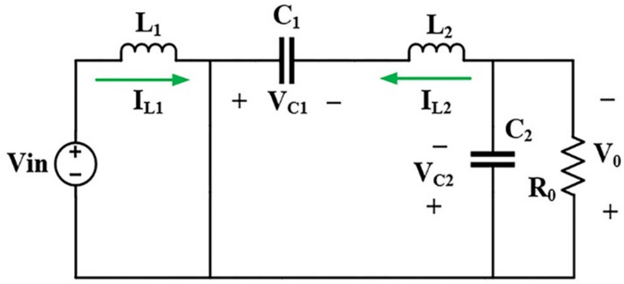

Figure 2 (a). Cuk Converter while operating in ON switching condition

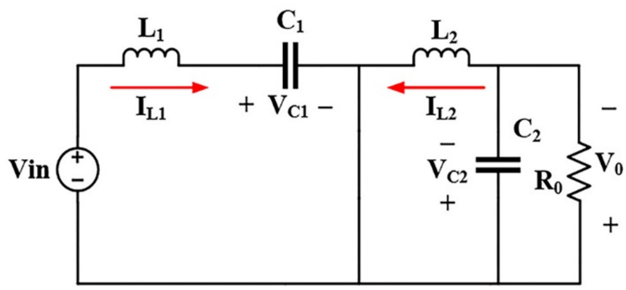

Figure 2 (b). Cuk Converter while operating in OFF switching condition

2.2. Mathematical Modeling of Cuk Converter

The dynamic modeling of any converter involves major difficulties rather than any other electrical system for having the property of changing the circuit outline concerning the position or the state of the switches used in the converter diagram. For solving this problem, the State-Space Averaging Technique is used because of addressing the circuit elements as time-weighted, and therefore, the approximation of a non-linear system to a linear system has become a common trend to follow. The State-space averaging method provides a different set of equations for each switching stage and a single equation is developed by making a linearly weighted average of each equation.

For the ON stage condition:

$$X' = A_1X + B_1V_{in} \qquad 0<t<dT \tag{2}$$

For OFF stage condition:

$$X' = A_2X + B_2V_{in} \qquad 0<t<(1\text{-}d)\,T \tag{3}$$

$$V_0 = C_1X \qquad \text{during interval dT} \tag{4}$$

$$V_0 = C_2X \qquad \text{during interval (1-d) T} \tag{5}$$

The resulting time-weighted and averaged equations can be written as,

$$X' = [A_1d + A_2(1-d)]X + [B_1d + B_2(1-d)]V_{in} \tag{6}$$

$$V_0 = [C_1d + C_2(1-d)]X \tag{7}$$

Considering CCM mode for a Cuk converter, two sets of equations are obtained according to the switching conditions. The differential equations are stated below:

When switch Q is ON,

$$\frac{dI_{L1}}{dt} = \frac{V_{in}}{L_1} \tag{8}$$

$$\frac{dI_{L2}}{dt} = \frac{1}{L_2}[V_{C1} - V_{C2}] \tag{9}$$

$$\frac{dV_{C1}}{dt} = -\frac{I_{L2}}{C_1} \tag{10}$$

$$\frac{dV_{C2}}{dt} = \frac{1}{C_2}\left[I_{L2} - \frac{V_{C2}}{R_0}\right] \tag{11}$$

When switch Q is OFF,

$$\frac{dI_{L1}}{dt} = \frac{1}{L_1}\left[V_{in} - V_{C1}\right] \tag{12}$$

$$\frac{dI_{L2}}{dt} = -\frac{V_{C2}}{L_2} \tag{13}$$

$$\frac{dV_{C1}}{dt} = \frac{I_{L1}}{C_1} \tag{14}$$

$$\frac{dV_{C2}}{dt} = \frac{1}{C_2}\left[I_{L2} - \frac{V_{C2}}{R_0}\right] \tag{15}$$

With the help of the above-mentioned differential equations, the weighted average matrices can be expressed as,

$$A_1 = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{1}{L_2} & -\frac{1}{L_2} \\ 0 & -\frac{1}{C_1} & 0 & 0 \\ 0 & \frac{1}{C_2} & 0 & -\frac{1}{R_0 C_2} \end{bmatrix} \tag{16}$$

$$A_2 = \begin{bmatrix} 0 & 0 & -\frac{1}{L_1} & 0 \\ 0 & 0 & 0 & -\frac{1}{L_2} \\ \frac{1}{C_1} & 0 & 0 & 0 \\ 0 & \frac{1}{C_2} & 0 & -\frac{1}{R_0 C_2} \end{bmatrix} \tag{17}$$

$$A = \begin{bmatrix} 0 & 0 & \frac{d-1}{L_1} & 0 \\ 0 & 0 & \frac{d}{L_2} & -\frac{1}{L_2} \\ \frac{1-d}{C_1} & -\frac{d}{C_1} & 0 & 0 \\ 0 & \frac{1}{C_2} & 0 & -\frac{1}{R_0 C_2} \end{bmatrix} \tag{18}$$

$$B_1 = B_2 = B = \begin{bmatrix} \frac{1}{L_1} \\ 0 \\ 0 \\ 0 \end{bmatrix} \tag{19}$$

$$C_1 = C_2 = C = \begin{bmatrix} 0 & 0 & 0 & 1 \end{bmatrix} \tag{20}$$

$$E_1 = E_2 = E = \begin{bmatrix} 0 \end{bmatrix} \tag{21}$$

where, $A = A_1 d + A_2(1-d)$

$B = B_1 d + B_2(1-d)$

$C = C_1 d + C_2(1-d)$

$E = E_1 d + E_2(1-d)$

3. Study of Bio-inspired Algorithm (BIA)

3.1. Firefly Algorithm (FA)

FA is a metaheuristic algorithm that has shown effectiveness in the field of optimizing non-linear, continuous, and complex designs in recent years [60]. Fireflies are colonial insects with the special feature of the glowing abdomen that serves as a significant tool of interaction within their colony. Based on this natural phenomenon, this algorithm was proposed by Yang where the brightness of the fireflies is associated with acquiring better results of the problem. Being unisexual, attraction among fireflies occurs irrespective of their sex and is proportional to their brightness [61]. Hence, the value of the objective function is linked with the brightness of fireflies that is evaluated by assigning light intensity to each firefly based on their performance for optimization in this paper. Moreover, multiple iterations have been performed to ensure optimized solutions through the process of movement of the swarm population within the pre-specified exploration area. In addition, a damping factor along with the randomization factor has been applied to secure swifter convergence. Therefore, the search technique is trained to minimize the cost function to obtain optimal control parameters of the proposed system.

The equation to deduce the movement of each firefly in the algorithm is presented as such [61]:

$$d_i^{\tau+1} = d_i^{\tau} + \rho(d_j^{\tau} - d_i^{\tau}) + \sigma e \quad (22)$$

$$\rho = \rho_0 * \exp(-\eta * (h_{ij})^2) \quad (23)$$

Here, d represents the displacement of the firefly at different periods. The co-efficient of attraction is denoted by ρ and σ indicates the randomization factor. The co-efficient of light absorption is represented by η and e symbolizes the vector consisting of random values obtained from uniform distribution at time τ, which defines the range of search space. Table 1 shows the pseudocode of FA with the steps for finding out the optimum result.

Table 1 Pseudocode of FA

Step 1:	Objective function: f(e), where ‘e’ defines values of error functions (IAE, ITAE, ISE)
Step 2:	Define decision variables number along with lower and upper bound
Step 3:	Specify the maximum iteration number (maxit) and swarm size (ns)
Step 4:	Set up a primary population of fireflies, di . (i = 1, 2, 3,…, ns)
Step 5:	Generate light intensity ‘LI’ to connect it with f(e)
Step 6:	Assign absorption coefficient, η.
Step 7:	While (t < maxit)
Step 8:	For i = 1 : ns
Step 9:	For j = 1 : ns
Step 10:	If ($L_{Ij} > L_{Ii}$)
Step 11:	Alter attractiveness with distance h via exp(-ηh); move fireflies i towards j
Step 12:	Assess new solutions and enhance light intensity
Step 13:	End if
Step 14:	End for j
Step 15:	End for i
Step 16:	Identify the present best solution
Step 17:	End while
Step 18:	Visualization of result after post-processing

3.2. Particle Swarm Optimization (PSO)

In the perspective of applications, Particle Swarm Optimization (PSO) is very effective to solve non-differentiable and multi-peak optimization problems, particularly in scientific and engineering researches [62]. The high accuracy and fast convergence speed of the algorithm ascertain the significant solution required in various controlling processes. The main feature of the PSO algorithm is stimulated by the cooperative nature of the swarms of flocks. PSO algorithm ensures the best fitness value by the iterative method. A group of random particles is assigned and the reflection of combination decision is portrayed through tracing the best fitness function [63]. After every iteration, the velocity is updated following by three factors-the velocities of the previous iteration, the particle best solution (pbest), and the global best solution (gbest). The displacement of their position is upgraded depending on the particles’ own best and swarms’ optimal position. This process is continued until the best fitness function is determined. Among the conditions of the termination criteria, attainment of maximum iteration or minimum error is mostly observed. The velocity and displacement equation according to the algorithm can be stated as:

$$V_i^{\tau+1} = WV_i^{\tau} + C_1 rand_1(P_i - d_i^{\tau}) + C_2 rand_2(G - d_i^{\tau}) \quad (24)$$

$$d_i^{\tau+1} = d_i^{\tau} + V_i^{\tau+1} \quad (25)$$

Here, W indicates the inertial weight, rand1 and rand2 are arbitrary numbers between the range (0, 1), C_1, and C_2 represent acceleration constants. Here, Table 2 shows the pseudocode for the steps relating to PSO.

Table 2 Pseudocode of PSO

Step 1:	Objective function: f(e), where ‘e’ defines values of error functions (IAE, ITAE, ISE)
Step 2:	Define decision variables number along with lower and upper bound
Step 3:	Specify PSO parameters such as Maximum iteration number (maxit), swarm size (ns), Inertia, Acceleration constants
Step 4:	For i = 1: ns
Step 5:	Set the value of d_i within admissible range
Step 6:	Set the value of V_i within admissible range
Step 7:	If f(Pfinest(i)) > f(Gfinest(i))
Step 8:	Gfinest(i) = Pfinest(i)
Step 9:	End if
Step 10:	End for i
Step 11:	While (t < maxit)
Step 12:	For i = 1: ns
Step 13:	Evaluate particle’s velocity, Vi
Step 14:	Evaluate particle’s position, di
Step 15:	If f(di) > f(Pfinest(i))
Step 16:	Pfinest(i) = di ; Particle’s best position

Step 17:	End if
Step 18:	f(Pfinest(i)) > f(Gfinest(i))
Step 19:	Gfinest(i) = Pfinest(i) ; Swarm's best position
Step 20:	End if
Step 21:	End for i
Step 22:	End while
Step 23:	Visualization of result after post-processing

3.3. Artificial Bee Colony (ABC)

The ABC algorithm is one of the most straightforward and competent optimization algorithms under the discipline of swarm intelligence and it has displayed promising performance in computing complex and non-linear problems. This algorithm follows the food locating pattern of the honey bee colony to search for potential solutions and is executed by three categories of bees. The algorithm engages the employed bees to locate the food sources in the search space where each food source symbolizes one possible solution with 'D' optimized parameters. The fitness of the solutions depends on the nectar quantity in the food sources and the probability of the solutions is computed in terms of the fitness. This information is stored and shared by the employed bees with the onlooker bees where the latter select the candidate solutions by assessing their fitness. Some solutions do not display progress after going through the preconceived cycles referred to as the limit. Those are omitted from the search space and the employed bees converting to scout bees randomly create new food locations. The greedy selection mechanism is deployed to store the best solution with the optimum factors. This sequence is iterated till a predetermined number of cycles called Maximum Cycle Number (MCN) is completed. This stochastic algorithm implements optimization by balancing a few regulating parameters only. The relevant equations are stated below:

$$d_{ij} = x_{ij} + \varphi_{ij}(x_{ij} - x_{kj}); \quad (26)$$

where j∈1, 2, …., N

$$P_i = \frac{FIT_i}{\sum_{i=1}^{N} FIT_i} \quad (27)$$

$$x_i^{j(new)} = x_{\min}^j + rand()\left(x_{\max}^j - x_{\min}^j\right) \quad (28)$$

Here, N is the population. d denotes the new candidate solution and x represents the initially developed solutions. υ is the random amount between -1 to 1. P expresses the probability of solution with respect to fitness and FIT expresses the fitness of solution. x_i j(new) is the new food source produced by scout bees. And finally, rand () generates arrays of random numbers whose elements are uniformly distributed in the interval (0, 1). In case of Table 3, pseudocode of ABC is explained and gathered in e suitable manner. Through this, the comparison can be easily distinguished with PSO, FA as well as ABC and the working principles can also be modified accordingly with the applications of the desired ones.

Table 3 Pseudocode of ABC

Step 1:	Objective function: f(e), where 'e' defines values of error functions (IAE, ITAE, ISE)
Step 2:	Define decision variables number along with lower and upper bound
Step 3:	Specify the maximum iteration number (maxit) and colony size, onlooker bees (ns)
Step 4:	Create Initial colony
Step 5:	While (t < maxit)
Step 6:	For i = 1 : ns ; #Recruited bees
Step 7:	Find new bee position, evaluation and comparison
Step 8:	End for i
Step 9:	Calculate fitness values and selection probabilities
Step 10:	For j = 1 : ns ; # Onlooker Bees
Step 11:	Select Source Site (Roulette Wheel Selection)
Step 12:	Find new bee position, evaluation and comparison
Step 13:	End for j
Step 14:	If an employed bee converts to scout bee; #Scout Bee
Step 15:	Replace Pi with a new random solution
Step 16:	End if
Step 17:	Update best solution ever found
Step 18:	End while
Step 19:	Visualization of result after post-processing

3.4. BIA-PID Controller

Fitness functions are a mathematical expression that quantifies the system's performance for optimization. In this paper, three fitness functions (IAE, ITAE, and ISE) are assessed to demonstrate competent regulation of the non-linear, close-loop, PID integrated power converter system [64]. Through the investigating approach, satisfactory outputs are observed by decreasing the value of error functions. Hence, adequate control over the system outcome is attained by manipulating the fitness functions.

$$IAE = \int_0^{\tau} |e(t)| dt \quad (29)$$

$$ITAE = \int_0^{\tau} t \cdot |e(t)| dt \quad (30)$$

$$ISE = \int_0^{\tau} e(t)^2 dt \quad (31)$$

PID controller exhibits the mechanism of controlling process variables by using control loop feedback. In this paper, a PID controller is adjoined with a Cuk converter system to provide a better-regulated output voltage along with a thorough evaluation on stabilizing the non-linearity of the closed-loop power converter system by locating the suitable controller constants K_P, K_I, and K_D [65].

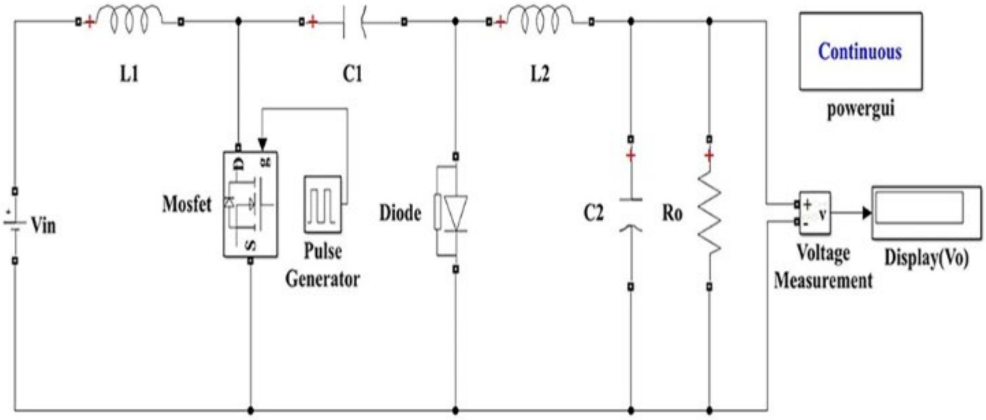

Figure 3. Simulink Model of Cuk Converter

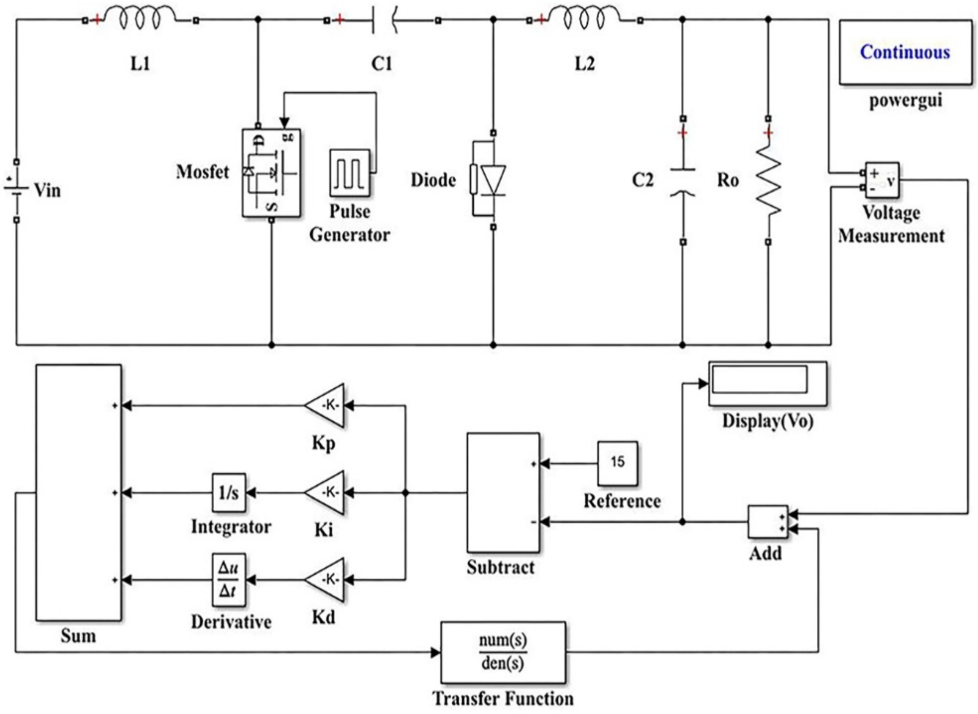

Figure 4. Simulink Model of PID Implemented Cuk Converter

However, prolonged operational time and unsatisfactory tuning of the PID parameters are observed for a conventional PID controller. Hence, metaheuristic swarm intelligence FA, ABC, and PSO are employed with the existing control technique individually [66-67]. These algorithms compute the best locations of the swarm agents within the search space through multifarious iterations, generating best suited PID constants for optimizing the collective system. Afterward, these optimized PID parameters are utilized to estimate the fitness functions of the system in the shape of cited error functions (IAE, ITAE, and ISE). Consequently, superior values of performance parameters such as overshoot percentage, settling time, rise time, and peak amplitude of step responses are affirmed by policing the procured fitness functions. This enables an extensive stability inspection of the collective system and delivers a distinguished regulation of the prevalent system response.

4. Results

The necessary simulations are performed in MATLAB and Simulink to obtain a comprehensive insight into the stability of the Cuk converter. Hence, the proposed parameters of the Cuk converter are tabulated in Table 4.

Table 4 Parameters of Cuk Converter

Parameter	Symbol	Value
Voltage (input)	V_{in}	15 V
Switching Frequency	fs	20 kHz
Duty Cycle	d	0.50
Inductor	L_1 L_2	117 μH 50.4 μH
Capacitor	C_1 C_2	1 mF 3 mF
Load Resistance	R_o	5 Ω
Voltage (output)	V_o	14.26 V

Furthermore, the Simulink model of Cuk converter is designed and illustrated in Figure 3 form which the open-loop transfer function of the system is generated which is given below.

$$\frac{-3.364x10^{-3}s^3-2.362x10^{-4}s^2-2.488x10^{-7}s-5.355x10^{-11}}{s^4+1.795x10^{-2}s^3+1.439x10^{-4}s^2+1.564x10^{-7}s+5.648x10^{-11}}$$

Afterward, a PID controller is added with the open-loop system which is depicted in Figure 4 and hence, the closed-loop transfer function is obtained. In Table 5, the output parameters of Cuk converter is manifested. We can have an idea about the gain values of k_P, k_I and k_D for Cuk converter and also the performance parameters are shown.

Table 5 Outputs of Cuk Converter

Attribute	Symbol	Values
Gain Values	K_P	-211.25
	K_I	-8.41
	K_D	-21.63
Performance Parameters	%OS	8.72
	Tr (seconds)	2.50
	Ts (seconds)	23.7
	Peak Amplitude	1.09

The step response of the closed-loop system with conventional PID controller is observed in Figure 5 where the overshoot was 8.72%. To reduce this initial overshoot, the PID parameters are tuned with bio-inspired algorithms and hence, the stability of the converter is witnessed with BIA-PID controllers.

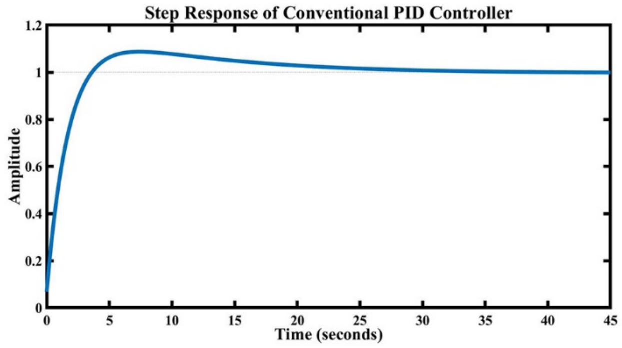

Figure 5. Step Response of Conventional PID Controller.

4.1 FA-PID

At first, Firefly Algorithm (FA) is implemented for optimizing the gain values of the PID Controller. The parameters of FA are given in Table 6.

Table 6 Parameters of Firefly Algorithm

Parameter	Symbol	Value
Mutual Coefficient	α	0.2
Attraction Coefficient	β	2
Light Absorption Coefficient	γ	1
Swarm Size	-	100

Table 7 Outputs Parameters of FA-PID Controller

Attribute	Symbols	Values		
		IAE	ITAE	ISE
Gain Values	K_P	-498.47	-495.75	-497.08
	K_I	-0.047	-0.05	-2.82
	K_D	-400	-397.69	-398.71
Performance Parameter	%OS	1.91	1.95	2.18
	Tr (sec)	2.52	2.44	2.49
	Ts (sec)	19.6	19.1	21.7
	Peak Amplitude	1.02	1.02	1.02

In case of Table 7, we see that the output parameters of FA-PID controller is shown and manifested. Value of k_I is decreased with respect to traditional one while k_P and k_D are increased if we want to compare with the state-of-the-art method.

Performance Parameter	Tr (sec)	2.49	1.90	2.33
	Ts (sec)	21.3	14.8	20.5
	Peak Amplitude	1.02	1.02	1.02

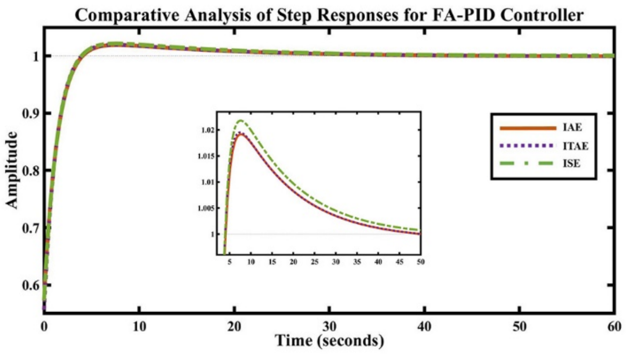

Figure 6. Comparative Analysis of Step Responses for FA-PID Controller.

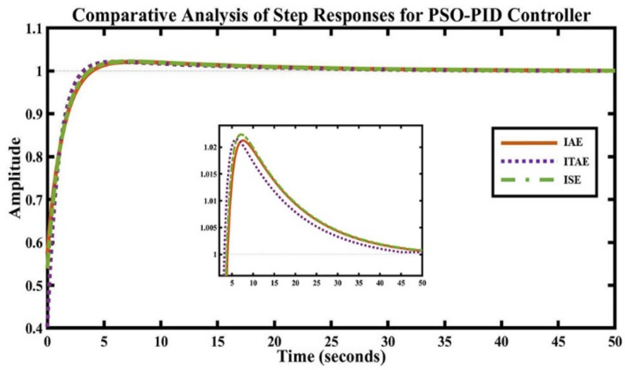

Figure 7. Comparative Analysis of Step Responses for PSO-PID Controller.

Hence, rigorous simulation of FA-PID controller is performed by utilizing the error functions IAE, ITAE, and ISE for attaining optimum values of k_P, k_I, and k_D. The corresponding responses of FA-PID controller for fitness functions IAE, ITAE, and ISE are tabulated in Table 4 and presented graphically in Figure 6.

4.2 PSO-PID

Secondly, Particle Swarm Optimization (PSO) is applied for the purpose of achieving optimized values of the PID controller.

Table 8 Parameters of Particle Swarm Optimization

Parameter	Symbol	Value
Acceleration Constants	C_1	2
	C_2	2
Inertia	W_{max}	0.9
	W_{min}	0.2
Swarm Size	-	100

Table 9 Outputs Parameters of PSO-PID Controller

Attribute	Symbols	Values		
		IAE	ITAE	ISE
Gain Values	K_P	-500	-500	-500
	K_I	-2.33	-0.0001	-2.8966
	K_D	-400	-200.62	-347.47
	%OS	2.12	2.15	2.24

The parameters of PSO are mentioned in Table 8 and the optimum gain values, as well as performance parameters of the PSO-PID controller, are enlisted in Table 9. Value of k_I is decreased only a small amount with respect to traditional one while k_P and k_D are slightly increased if we want to compare with the state-of-the-art method. Hence, Figure 7 represents a comparative analysis of step responses for different fitness functions.

4.3 ABC-PID

Lastly, Artificial Bee Colony (ABC) is employed to attain optimum values of the PID controller for the same population size and iteration number as FA and PSO. The parameters of the ABC algorithm are mentioned in Table 10.

Table 10 Parameters of Artificial Bee Colony Algorithm

Parameter	Values
Number of Onlooker Bees	1 per cycle
Number of Employed Bees	50% of Swarm Size
Number of Scout Bees	50% of Swarm Size
Swarm Size	100

Table 11 Outputs Parameters of ABC-PID Controller

Attribute	Symbols	Values		
		IAE	ITAE	ISE
Gain Values	K_P	-487.05	-349.39	-562.15
	K_I	-19.73	-3.11	-26.89

	K_D	-1386.9	-303.30	-548.76
Performance Parameter	%OS	2.50	3.13	3.29
	Tr (sec)	4.43	2.94	2.39
	Ts (sec)	33.5	25.8	23.0
	Peak Amplitude	1.03	1.03	1.03

A comparative analysis of the step responses for various fitness functions in terms of ABC-PID controller is depicted in Figure 8. In Table 11, the optimum gain values along with performance parameters of the ABC-PID controller are tabulated. Number of Onlooker Bees, employed bees, scout bees and swarm size are the parameters which are clearly depicted over here with the value 1 per cycle, 50% of swarm size, 50% of swarm size and 100 respectively.

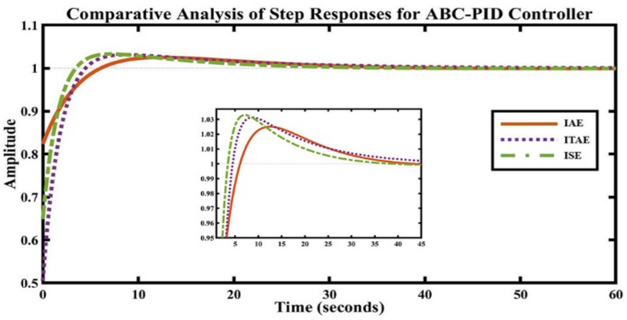

Figure 8. Comparative Analysis of Step Responses for ABC-PID Controller.

4.4. Comparative Analysis

From the data of Table 7 and Table 8, it is apparent that IAE gives a lower percentage of overshoot compared to ITAE and ISE for both FA-PID and PSO-PID. However, ITAE takes lesser time than IAE and ISE for both the settling time and the rise time. Yet, all the fitness function provides the same value of peak amplitude for both FA-PID and PSO-PID. For ABC-PID, IAE also provides a smaller percentage of overshoot than ITAE and ISE enlisted in Table 9. Despite that smaller time is taken by ITAE for the rise time and ISE for the settling time. Hence, it is evident that IAE provides a better result for all the BIA-PID controllers in terms of the percentage of overshoot.

Table 15 Comparative Analysis among All Algorithms

Attribute	Controllers		
	FA-PID	PSO-PID	ABC-PID
Best Performing Fitness Function	IAE	IAE	IAE
Percentage of Overshoot (%OS)	1.91	2.12	2.50
Rise Time, Tr (s)	2.52	2.49	4.43
Settling Time, Ts (s)	19.6	21.3	33.5
Peak Amplitude	1.02	1.02	1.03

In Table 15, performance parameters for IAE of FA-PID, PSO-PID, and ABC-PID are tabulated as a means to overserve comparative analysis and find the desirable BIA-PID controller. In order to compare model performance with fewer features, a baseline was established using all 81 features. The study employed five standalone machine learning models, two stacked regression models, and one voting regression model. Initially, default hyperparameters were used for training the models. Subsequently, hyperparameter optimization was conducted using the Random-Search CV algorithm to find the best combinations [68]. The resulting optimal hyperparameter configurations for each model can be found in Table 6.

5. Conclusion

In this paper, the bio-inspired metaheuristic algorithms-FA, PSO, and ABC are implemented on the PID controller of the close-loop feedback model of the Cuk power converter to overcome the dynamic and transient nature of the system. An analytical comparison among the results from the algorithms and a comprehensive stability inspection of the entire system is demonstrated in detailed manner. This paper illustrates the models for the Cuk power converter and PID integrated Cuk converter design simulated in MATLAB SIMULINK. In the result and simulation section, stability investigation of our system is conducted based on performance parameters of step responses. From assessing the tabulated data and figures, it is apparent that the best-optimized step response in the context of the percentage of overshoot is achieved from the objective function IAE of FA-PID layout with the smallest percentage of overshoot at 1.91. The optimal rise time of 1.90 seconds is obtained from the ITAE of the PSO-PID model which is the least among all the design results. The smallest settling time is 14.8 seconds which is procured from the ITAE of the PSO-PID design. And the minimum peak amplitude is 1.02 which is generated by both FA-PID and PSO-PID models. Finally, it can be easily concluded that all the BIA-PID control schemes delivered better outcomes in maintaining a steady voltage output in the converter system compared to the conventional PID control system.

Conflict of Interest

Authors do not have any conflict of interest.

Data Availability

The simulation data used to support the findings of this study are included within this article.

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References

[1] X. Fan, W. Sayers, S. Zhang, Z. Han, L. Ren, H. Chizari: Review and classification of bio-inspired algorithms and their applications. *Journal of Bionic Engineering*, 17, (2020), 611-631.

[2] A. Isaac, H. K. Nehemiah, A. Isaac, A. Kannan: Computer-Aided Diagnosis system for diagnosis of pulmonary emphysema using bio-inspired algorithms. *Computers in Biology and Medicine*, Elsevier, 124, (2020).

[3] M. M. Nishat, F. Faisal, M. A. Hoque, "Modeling and Stability Analysis of a DC-DC SEPIC Converter by Employing Optimized PID Controller Using Genetic Algorithm," *International Journal of Electrical & Computer Sciences*, 19(01), (2019), 1-7.

[4] P. S. Nayak, T. A. Rufzal: Performance analysis of feedback controller design for induction motor soft-starting using bio-inspired algorithms. *2018 International Conference on Power, Instrumentation, Control and Computing (PICC)*, (2018).

[5] G. Beni: Swarm intelligence. *Complex Social and Behavioral Systems: Game Theory and Agent-Based Models*, Springer, (2020).

[6] K. Hussain, M. N. Salleh, S. Cheng, Y. Shi: On the exploration and exploitation in popular swarm-based metaheuristic algorithms. *Neural Computing and Applications*, 31(11), (2019), 7665-7683.

[7] Ata Jahangir Moshayedi, Jinsong Li, Nima Sina, Xi Chen, Liefa Liao, Mehdi Gheisari, Xiaoyun Xie, "Simulation and Validation of Optimized PID Controller in AGV (Automated Guided Vehicles) Model Using PSO and BAS Algorithms", *Computational Intelligence and Neuroscience*, vol. 2022, Article ID 7799654, 22 pages, 2022. https://doi.org/10.1155/2022/7799654

[8] A. J. Moshayedi, A. Shuvam Roy, S. K. Sambo, Y., Zhong, and L. Liao, "Review On: The Service Robot Mathematical Model", *EAI Endorsed Trans AI Robotics*, vol. 1, p. e8, Feb. 2022

[9] A. J. Moshayedi, A. Abbasi, L. Liao and S. Li, "Path planning and trajectory tracking of a mobile robot using bio-inspired optimization algorithms and PID control," *CIVEMSA*, 2019, pp. 1-6, doi: 10.1109/CIVEMSA45640.2019.9071596.

[10] D. Pathak, G. Sagar, P. Gaur: An Application of Intelligent Non-linear Discrete-PID Controller for MPPT of PV System. *Procedia Computer Science*, 167(16), (2020), 1574-1583.

[11] M. M. Nishat, F. Faisal, M. A. M. Oninda and M. A. Hoque, "Modeling Simulation and Performance Analysis of SEPIC Converter Using Hysteresis Current Control and PI Control Method", *2018 Int. Conf. on Inv. in Science Engg. and Tech. (ICISET)*, pp. 7-12

[12] M. M. Nishat, F. Faisal, M. Rahman and M. A. Hoque, "Modeling and Design of a Fuzzy Logic Based PID Controller for DC Motor Speed Control in Different Loading Condition for Enhanced Performance", *1st Int. Conf. on Advances in Science Engg. and Robotics Tech. (ICASERT)*, pp. 1-6, 2019.

[13] A. A. Mehadi, M. M. Nishat, F. Faisal, A. R. H. Bhuiyan, M. Hussain and M. A. Hoque, "Design Simulation and Feasibility Analysis of Bifacial Solar PV System in Marine Drive Road Cox's Bazar", *International Conference on Science & Cont. Technology (ICSCT)*, pp. 1-6, 2021.

[14] A. A. Mehadi, M. A. Chowdhury, M. M. Nishat, F. Faisal and M. M. Islam, "A software-based approach in designing a rooftop bifacial PV system for the North Hall of Residence IUT", *Clean Energy*, vol. 5, no. 3, pp. 403-422, 2021.

[15] F. Faisal, M. M. Nishat and M. R. Mia, "An Investigation on DC Motor Braking System by Implementing Electromagnetic Relay and Timer", *International Conference on Electrical Computer and Communication Engineering*, pp. 1-6, 2019.

[16] M. M. Nishat, M. R. K. Shagor, H. Akter, S. A. Mim, F. Faisal, M. M. Nishat, et al., "An Optimal Design of PID controller for DC-DC Zeta converter using Particle Swarm Optimization", *23rd International Conference on Comp. and Info. Tech. (ICCIT)*, pp. 1-6, 2020.

[17] M. D. Rahman, F. Faisal, M. M. Nishat and M. R. K. Shagor, " Design and Analysis of Passive LC 3 Component Boost Converter ", *2021 IEEE Madras Section Conference (MASCON)*, pp. 1-6, 2021.

[18] M. R. K. Shagor, A. J. Mahmud, M. M. Nishat, F. Faisal, M. H. Mithun and M. A. Khan, "Firefly Algorithm Based Optimized PID Controller for Stability Analysis of DC-DC SEPIC Converter", *12th UEMCON*, pp. 0957-0963, 2021

[19] A. A. Mehadi et al., "Design simulation and analysis of monofacial solar pv panel based energy system for university residence: a case study", *IOP Conf. Series: Mater. Sci. and Eng.*, vol. 1045, no. 1, pp. 012011, 2021.

[20] F. Faisal, M. Rahman and F. B. Hashem, "*Speed control of dc motor using Self-tuned fuzzy PID controller*", Diss. Department of EEE, IUT, OIC, Gazipur-1704, Bangladesh, 2015.

[21] F. Faisal and M. M. Nishat, "An Investigation for Enhancing Registration Performance with Brain Atlas by Novel Image Inpainting Technique using Dice and Jaccard Score on Multiple Sclerosis (MS) Tissue," *Biomed. and Pharm. J.,* vol. 12, no. 3, pp. 1249-1262, 2019

[22] M. M. Nishat, et al., "An Investigative Approach to Employ Support Vector Classifier as a Potential Detector of Brain Cancer from MRI Dataset," *ICECIT*, pp. 1-4, doi: 10.1109/ICECIT54077.2021.9641168

[23] M. A. A. R. Asif *et al.*, "Performance Evaluation and Comparative Analysis of Different ML Algorithms in Predicting Cardiovascular Disease," *Engineering Letters,* vol. 29, no. 2, pp. 731-741, 2021

[24] M. M. Nishat *et al.*, "A Comprehensive Analysis on Detecting Chronic Kidney Disease by Employing Machine Learning Algorithms," *EAI Endorsed Transactions on Pervasive Health and Technology*, vol. 18, no. e6, 2021, doi: 10.4108/eai.13-8-2021.170671.

[25] M. R. Farazi, F. Faisal, Z. Zaman and S. Farhan, "Inpainting multiple sclerosis lesions for improving registration performance with brain atlas," *MediTec*, pp 1-6, doi: 10.1109/MEDITEC.2016.7835363.

[26] M. A. A. R. Asif *et al.*, "Computer Aided Diagnosis of Thyroid Disease Using Machine Learning Algorithms," *ICECE*, 2020, pp. 222-225, doi: 10.1109/ICECE51571.2020.9393054

[27] M. M. Nishat and F. Faisal, "An Investigation of Spectroscopic Characterization on Biological Tissue," *iCEEiCT*, 2018, pp. 290-295, doi: 10.1109/CEEICT.2018.8628081

[28] F. Faisal, et al., "Covid-19 and its impact on school closures: a predictive analysis using machine learning algorithms," *ICSCT*, 2021, pp. 1-6, doi: 10.1109/ICSCT53883.2021.9642617

[29] A. A. Rahman *et al*., "Detection of Epileptic Seizure from EEG Signal Data by Employing Machine Learning Algorithms with Hyperparameter Optimization," *BioSMART*, 2021, pp. 1-4, doi: 10.1109/BioSMART54244.2021.9677770.

[30] M. M. Nishat, et al., "Detection of Parkinson's Disease by Employing Boosting Algorithms," *ICIEV and icIVPR*, pp. 1-7, 2021, doi: 10.1109/ICIEVicIVPR52578.2021.956410.

[31] Nishat, M. M., et al. "Detection of Autism Spectrum Disorder by Discriminant Analysis Algorithm," *BIM,* pp. 473-482, Springer, Singapore, 2022 doi: 10.1007/978-981-16-6636-0_36

[32] A. A. Rahman, et al., "Detection of Mental State from EEG Signal Data: An Investigation with Machine Learning Classifiers," *KST*, pp. 152-156, 2022, doi: 10.1109/KST53302.2022.9729084.

[33] M. R. Rahman, S. Tabassum, E. Haque, M. M. Nishat, F. Faisal and E. Hossain, "CNN-based Deep Learning Approach for Microcrack Detection of Solar Panels," *2021 3rdInt. Conf. on STI 4.0*, 2021, pp. 1-6, doi: 10.1109/STI53101.2021.9732592.

[34] Nishat, M. M., et al. "A Comprehensive Investigation of the Performances of Different Machine Learning Classifiers with SMOTE-ENN Oversampling Technique and Hyperparameter Optimization for Imbalanced Heart Failure Dataset," *Scientific Programming*, https://doi.org/10.1155/2022/3649406.

[35] Nishat, M. M, Faisal, F., Mahbub, M. A., Mahbub, M. H., et al., "Performance Assessment of Different Machine Learning Algorithms in Predicting Diabetes Mellitus". *Biosc.Biotech.Res.Comm*.,14(1), 2021 doi: http://dx.doi.org/10.21786/bbrc/14.1/10.

[36] F. Faisal, "Image Inpainting to Improve the Registration Performance of Multiple Sclerosis (MS) Patient Brain with Brain Atlas," Diss. Department of EEE, IUT, OIC, Gazipur-1704, Bangladesh, 2016.

[37] M. M. Nishat *et al*., "Performance Investigation of Different Boosting Algorithms in Predicting Chronic Kidney Disease," *2020 2nd Int. Conf. on STI 4.0*, pp. 1-5, 2020, doi: 10.1109/STI50764.2020.9350440

[38] M. Islam, M. Tabassum, M. M. Nishat, F. Faisal and M. S. Hasan, "Real-Time Clinical Gait Analysis and Foot Anomalies Detection Using Pressure Sensors and Convolutional Neural Network," *ICBIR*, 2022, pp. 717-722, doi: 10.1109/ICBIR54589.2022.9786472

[39] I. J. Ratul, A. A. Monsur, B. Tabassum, A. M. Ar-Rafi, M. M. Nishat and F. Faisal, "Early risk prediction of cervical cancer: A machine learning approach," *ECTI-CON,* 2022, pp. 1-4, doi: 10.1109/ECTI-CON54298.2022.9795429.

[40] A. Al–Monsur, M. R. Kabir, A. M. Ar–Rafi, M. M. Nishat and F. Faisal, "Covid-EnsembleNet: An Ensemble Based Approach for Detecting Covid-19 by utilising Chest X-ray Images," *AIIoT*, 2022, pp. 351-356, doi: 10.1109/AIIoT54504.2022.9817237.

[41] I. A. Jahan, et al., "Accident Detection and Road Condition Monitoring Using Blackbox Module," *ICUFN*, 2022, pp. 247-252, doi: 10.1109/ICUFN55119.2022.9829589.

[42] A. A. Rahman *et al*., "Perceived Stress Analysis of Undergraduate Students during COVID-19: A ML Approach," *MELECON*, 2022, pp. 1129-1134, doi: 10.1109/MELECON53508.2022.9843081.

[43] F. Faisal, M. M. Nishat and M. A. M. Oninda, "Spectroscopic Characterization of Biological Tissue using Quantitative Acoustics Technique," *iCEEiCT*, doi: 10.1109/CEEICT.2018.8628146

[44] Z. K. Eisham *et al.,* "Chimp optimization algorithm in multilevel image thresholding and image clustering," *Evolving Systems,* 2022. https://doi.org/10.1007/s12530-022-09443-3.

[45] F. Faisal, M. A. Salam, M. B. Habib, M. S. Islam and M. M. Nishat, "Depth estmation from Video using Computer Vision and Machine Learning with Hyperparameter Optimization," *ICSSA,* 2022, pp. 39-44, doi: 10.1109/ICSSA54161.2022.9870961.

[46] S. Hassan *et al*., "Comparative Analysis of Machine Learning Algorithms in Detection of Brain Tumor," *IBDAP*, 2022, pp. 31-36, doi: 10.1109/IBDAP55587.2022.9907433. IEEE, 2022

[47] I. J. Ratul *et al.*, "Survival Prediction of Children Undergoing Hematopoietic Stem Cell Transplantation Using Different MLCs by Performing Chi-Square Test and Hyperparameter Optimization: A Retrospe. Analysis", *CMMM*, https://doi.org/10.1155/2022/9391136.

[48] T. Hasan, et al., "Employment of Ensemble Machine Learning Methods for Human Activity Recognition", *Journal of Healthcare Engineering*, vol. 2022, https://doi.org/10.1155/2022/6963891.

[49] M. R. Kabir, et al., "Procuring MFCCs from Crema-D Dataset for Sentiment Analysis using DL Models with Hyperparameter Tuning," *RAAICON*, pp. 50-55. doi: 10.1109/RAAICON54709.2021.9929975.

[50] M. K. Mahadi *et al*., "Machine Learning Assisted Decision Support System for Prediction of Prostate Cancer," *ECTI-CON*, 2023, pp. 1-5, doi: 10.1109/ECTI-CON58255.2023.10153167.

[51] A. A. Rahman, M. R. Kabir, R. H. Ratul, F. A. Shams, M. M. Nishat and F. Faisal, "An Efficient Analysis of EEG Signals to Perform Emotion Analysis", *4th Int. Conf. on Artificial Intelligence, Robotics and Control (AIRC 2023)*, Cairo, Egypt, IEEE, accepted, in press

[52] F. Faisal, M. M. Nishat, K. R. Raihan, A. Shafiullah and S. Ali, "A Machine Learning Approach for Analyzing and Predicting Suicidal Thoughts and Behaviors," *ICUFN,* 2023, pp. 43-48, doi: 10.1109/ICUFN57995.2023.10201075.

[53] F. A. Shams, R. H. Ratul, A. I. Naf, S. S. H. Samir, M. M. Nishat, F. Faisal and M. A. Hoque, "Investigation on Machine Learning Based Approaches for Estimating the Critical Temperature of Superconductors", *AIRoSIP*, IEEE 2023, accepted, in press

[54] I. J. Ratul, M. M. Nishat, F. Faisal, S. Sultana, A. Ahmed, M A. A. Mamun, "Analyzing Perceived Psychological and Social Stress of University Students: A Machine Learning Approach", *Heliyon*, 9(6), E17207, doi: 10.1016/j.heliyon.2023.e17307.

[55] M. N. S. Shahi, et al., "Automated Vehicle Access and Exit Control: A Smart Parking Management System using Finite State Machine in VHDL," *RI2C*, doi: 10.1109/RI2C56397.2022.9910305.

[56] F. Faisal, et al., "Ex-Vivo Design of pH meter To Analyze Nutrients Feature Assessment for Economic Domestic Purpose," *ITC-CSCC*, 2022, pp. 637-640, doi: 10.1109/ITC-CSCC55581.2022.9895032.

[57] A. Shafiullah, F. Faisal, R. H. Badhon, S. Ali, M. M. Nishat, M. R. Muttaqi and M. A. Billah, "Detection of Skin Cancer: A Deep Learning Approach," *20th Int. Conf. on Ubiquitous Intelligence and Computing (UIC 2023)*, Portsmouth, UK, IEEE, accepted, in press

[58] N. Sakib, Z. B. Saif, M. T. Hasan, M. Adnan, F. Faisal, M. M. Nishat, et al., "EEG-Driven Age Prediction: Advancements in Machine Learning Models", *ICE3IS*, IEEE 2023, accepted, in press.

[59] Z. B. Saif, N. Sakib, M. Adnan, M. T. Hasan, M. M. Nishat, F. Faisal, et al., "Sensorimotor Activity Patterns using Machine Learning: Assessing the Impact of Auditory Timing Perception and Comparing Different Algorithms", *ICRAIE*, IEEE 2023, accepted, in press

[60] C. Olivares-Rodríguez, T. Castillo-Calzadilla, O. Kamara-Esteban: Bio-inspired approximation to MPPT under real irradiation conditions. *International Symposium on Intelligent and Distributed Computing*, pp. 107-118, Springer, Cham, (2018).

[61] M. M. Nishat, F. Faisal, A. J. Evan, M. M. Rahaman, M. S. Sifat, H. F. Rabbi: Development of Genetic Algorithm (GA) Based Optimized PID Controller for Stability Analysis of DC-DC Buck Converter. *Journal of Power and Energy Engineering*, 8(9), (2020), 8-19.

[62] S. Abdelmalek, A. Dali, M. Bettayeb, A. Bakdi: A new effective robust nonlinear controller based on PSO for interleaved DC–DC boost converters for fuel cell voltage regulation. *Soft Computing*, 24(22), (2020), 17051-17064.

[63] D. Kumar, B.R. Gandhi, R.K. Bhattacharjya: Firefly Algorithm and Its Applications in Engineering Optimization. *Nature-Inspired Methods for Metaheuristics Optimization*, pp. 93-103. Springer, Cham, 2020.

[64] G. F. Gomes, J.V.P. Pereira: Sensor placement optimization and damage identification in a fuselage structure using inverse modal problem and firefly algorithm. *Evolutionary Intelligence*, 13(4), (2020), 571-591.

[65] M. A. Saleh, M. Soliman, H. H. Ammar, M. A. Shalaby: Modeling and control of 3-omni wheel Robot using PSO optimization and Neural Network. *International Conference on Control, Automation and Diagnosis (ICCAD)*, (2020).

[66] G. Marimuthu, M. G. Umamaheswari: Analysis and Design of Single Stage Bridgeless Cuk Converter for Current Harmonics Suppression Using Particle Swarm Optimization Technique. *Electric Power Components and Systems*, 47(11-12), (2019), 1101-1115.

[67] N. Paliwal, L. Srivastava, M. Pandit: PSO-based PID controller designing for LFC of single area electrical power network. *Nature Inspired Optimization for Electrical Power System*, pp. 43-54. Springer, Singapore, 2020.

[68] V. B. Kumar, G. Charan, Y. V. P. Kumar: Design of robust PID controller for improving voltage response of a cuk converter. *Innovations in Electrical and Electronic Engineering*, pp. 301-318. Springer, Singapore, 2021.