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Particle Swarm Optimization Based Closed Loop Control for a DC-DC Buck Converter for Enhanced Dynamic Performance and Robustness

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ABSTRACT

DC-DC buck converters are widely used in modern power electronic applications, including renewable energy systems and IoT devices. Their nonlinear behavior under varying load conditions requires effective closed-loop control. In most cases, the proportional-integral-derivative (PID) controllers are used with the converter, their performance often deteriorates when the operating conditions change or disturbances occur. This paper will present a systematic offline Particle Swarm Optimization (PSO) approach for tuning a voltage-mode PID controller for a buck converter operating in continuous conduction mode (CCM). An averaged state-space model that includes parasitic resistances is developed to improve modelling accuracy and stability. The PSO algorithm helps to optimize the proportional, integral and derivative gains by minimizing a composite time-weighted integral of absolute error (ITAE) objective function. MATLAB/Simulink simulations will show that the PSO-tuned controller delivers a faster transient response, lower overshoot, shorter settling time and better disturbance rejection than the Ziegler-Nichols, genetic algorithm and manually tuned controllers. Its superiority is further verified under load variations and input voltage fluctuations. The proposed method offers a practical and reproducible tuning procedure, supported by convergence analysis and implementation guidelines, demonstrating that PSO is an effective and computationally efficient technique for optimizing power converter control.

Keywords: Buck converter; closed loop control; Particle Swarm Optimization (PSO); PID tuning; metaheuristic optimization; power electronics; dynamic response; robustness.

1. INTRODUCTION

The increasing fast growth of DC microgrids and battery-powered systems has surely increased the demand for DC-DC buck converters that provide accurate and reliable voltage regulation (Erickson & Maksimović, 2020; Rashid, 2017). Considering most non-isolated converter topologies, the buck converter is the most used step-down converter because of its simple design, and ease of implementation across different applications (Kazimierczuk, 2015). Its nonlinear switching behavior and component parameter variations such as inductor saturation, capacitor equivalent series resistance (ESR) and sensitivity to load and input disturbances makes the closed-loop control a challenging task (Bose, 2018; Tse, 2003).

The voltage-mode PID control is still the preferred choice for buck converter regulation because it is simple to implement and offers predictable performance (Åström & Hägglund, 2006). The traditional tuning methods such as Ziegler-Nichols and frequency-domain loop shaping are based on linearized system models and often produce unsatisfactory performance when operating conditions vary (O'Dwyer, 2009; Johnson & Moradi, 2005). As a result, the metaheuristic optimization techniques have gained attention as effective alternatives for automatic controller tuning (Yang, 2020; Mirjalili, 2019). Among these methods, Particle Swarm Optimization (PSO) is the most suitable because of its simplicity in implementation, fast convergence time, gradient-free search capability and computational efficiency (Kennedy & Eberhart, 1995; Shi & Eberhart, 1998).

In recent days, PSO has been used in many power electronics control systems, a framework for tuning the PID of closed loop buck converters that considers parasitic elements and performance (Nandar, 2020; El-Samahy et al., 2022). This research paper tends to address this gap by giving:

i. An averaged state space model of a Continuous Conduction Mode (CCM) buck converter that incorporates parasitic elements.
ii. An optimization framework that reduces the ITAE functions while satisfying stability and control limitations.
iii. A step-by-step offline PSO based PID tuning with convergence analysis.
iv. Simulation results comparing the proposed PSO-PID controller with conventional tuning methods.
v. Practical guidelines for digital implementation and robustness evaluation.

2. MATERIALS AND METHODS

2.1 Mathematical Modeling of the Buck Converter

2.1.1 Circuit Topology and Operating Assumptions

The proposed buck converter consists of a MOSFET power switch, freewheeling diode, inductor (L), output capacitor (C) and a load resistor (R). To improve model accuracy, the inductor series resistance ((RL)) and capacitor equivalent series resistance ((RC)) are included. The converter operates in Continuous Conduction Mode (CCM) at a switching frequency of $f_{sw} = 50$ kHz.

2.2 State-Space Averaged Model

Using state-space averaging over one switching period $T_s = 1/f_{sw}$, the system dynamics are described by:

$$\dot{x} = Ax + Bu \tag{1}$$

$$y = Cx \tag{2}$$

where $x = [i_L \quad v_C]^T$, $u = d$ (duty cycle), and $y = v_{out}$. The averaged matrices are:

$$A = \begin{bmatrix} -\frac{R_L + DR_{on} + (1-D)R_D}{L} & -\frac{1}{L} \\ \frac{1}{C} & -\left(\frac{1}{RC} + \frac{R_C}{LC}\right) \end{bmatrix} \tag{3}$$

$$B = \begin{bmatrix} \frac{V_{in} - V_D + I_L(R_D - R_{on})}{L} \\ 0 \end{bmatrix}, C = [0 \quad 1] \tag{4}$$

Linearizing around the nominal operating point (D_0, I_{L0}, V_{C0}) yields the control-to-output transfer function:

$$G_{vd}(s) = \frac{\hat{v}_{out}(s)}{\hat{d}(s)} = \frac{V_{in}}{LC} \cdot \frac{1 + sR_C C}{s^2 + s\left(\frac{R_L + R_C}{L} + \frac{1}{RC}\right) + \frac{R_L + R}{LC}} \tag{5}$$

This second-order system is minimum-phase, facilitating stable feedback design, where:

L = Inductor	A = State matrix
C = Capacitor	B = Input matrix
R = Load resistance	x = State vector
Vin = Input voltage	y = Output
Vo = Output voltage	s = Laplace variable
d = Duty cycle	Gvd(s) = Control-to-output transfer function
D = Nominal duty cycle	

2.3 Control Strategy and Problem Formulation

2.3.1 Closed-Loop Architecture

A unity feedback voltage mode control structure is employed. The error signal $e(t) = V_{ref} - v_{out}(t)$ drives a continuous-time PID controller:

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau)d\tau + K_d \frac{de(t)}{dt} \tag{6}$$

where:
e(t) = Error signal
Vref = Reference voltage (Desired PV/converter output voltage)
Vo = Output voltage (Measured converter output voltage)
u(t) = Control signal (Controller output used to adjust the duty cycle)
Kp = Proportional gain (Responds to the present error)
Ki = Integral gain (Eliminates steady-state error)
Kd = Derivative gain (Responds to the rate of change of error)

In practice, derivative action is filtered with a first order low pass filter $\frac{1}{1+sT_f}$ to attenuate high-frequency switching noise (Bose, 2018; Mohan et al., 2023). The PWM modulator maps u(t) to duty cycle $d(t) \in [0,0.95]$ with saturation and anti-windup.

2.3.2 Optimization Objective

Controller tuning is cast as a constrained minimization problem:

$$\min_{K \in R^3} J(K) = \int_0^{T_{sim}} t \mid e(t;K) \mid dt + \lambda_1 \cdot OS + \lambda_2 \cdot \max(\mid u(t) \mid - d_{max}, 0)^2 \tag{7}$$

subject to:

i. Phase margin ≥45∘
ii. Gain crossover frequency ωc≤0.2
iii. Steady-state error <0.5%

The primary metric is the Integral of Time-weighted Absolute Error (ITAE), penalizing late errors heavily (O'Dwyer, 2009; Johnson & Moradi, 2005). Penalty terms enforce overshoot and actuator constraints.

2.4. Particle Swarm Optimization Algorithm

PSO is a population based stochastic optimizer inspired by social behavior (Kennedy & Eberhart, 1995). A swarm of N particles explores the search space K=[Kp, Ki, Kd]. Each particle i maintains position xi and velocity vi, updated iteratively:

$$v_i(k+1) = wv_i(k) + c_1 r_1 (pbest_i - x_i(k)) + c_2 r_2 (gbest - x_i(k)) \tag{8}$$

$$x_i(k+1) = x_i(k) + v_i(k+1) \tag{9}$$

where w is inertia weight, c1, c2 are cognitive/social coefficients, and $r_1, r_2 \sim U(0,1)$ pbest and gbest denote personal and global best positions. A linearly decreasing inertia weight $w(k) = w_{max} - (w_{max} - w_{min}) \frac{k}{k_{max}}$ balances exploration and exploitation. PSO requires no gradient information, handles non-convex landscapes, and converges rapidly for low-dimensional control tuning problems. The PSO flowchart is shown in Figure 1.

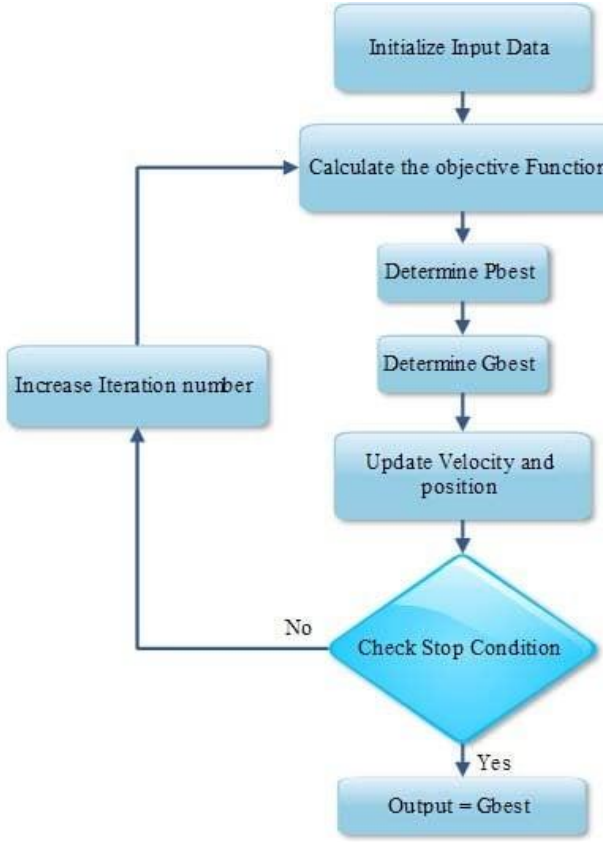

Figure 1: PSO flowchart

2.5. Pso-Based Controller Tuning Procedure

The PSO based controller is tuned offline using the following procedure:

i. Define Search Bounds: Kp∈[0.1,10]], Ki∈[10,5000], Kd∈[0,0.5] based on plant bandwidth and stability margins.
ii. Initialize Swarm: N=30 particles, random positions/velocities within bounds using Latin Hypercube Sampling.
iii. Fitness Evaluation: For each particle, simulate the closed-loop system in MATLAB/Simulink under nominal step input (0→12V). Compute J(K).
iv. Update pbest/gbest: Track best positions per particle and globally.
v. Velocity/Position Update: Apply PSO equations with velocity clamping $| v_j | \leq 0.2\, \Delta x_j$.
vi. Constraint Handling: Reject particles violating phase margin or duty cycle limits via penalty augmentation.
vii. Termination: Stop after kmax=100kmax=100 iterations or when $\| gbest(k) - gbest(k-1) \| < 10^{-4}$.
viii. Validation: Apply optimal K to perturbed scenarios (load step, input variation, parameter drift).

2.6. Simulation Setup

2.6.1 System Parameters

Table 1: Buck converter system parameters for simulation

Parameter	Symbol	Value	Unit
Input Voltage	Vin	12	V
Reference Output Voltage	refVout	5	V
Inductance	L	1.0	mH

Output Capacitance	C	100	μF
Load Resistance (nominal)	R	10	Ω
Inductor Series Resistance	RL	0.15	Ω
Capacitor ESR	RC	0.05	Ω
Switching Frequency	fsw	50	kHz
Derivative Filter Time Constant	Tf	10	μs

2.6.2 PSO Configuration

Table 2: Particle Swarm Optimization algorithm parameters

Parameter	Symbol	Value
Swarm Size	N	30
Maximum Iterations	kmax	100
Initial Inertia Weight	wmax	0.9
Final Inertia Weight	wmin	0.4
Cognitive Coefficient	c1	2.0
Social Coefficient	c2	2.0
Velocity Clamping Factor		0.2 × range

The optimization normally runs offline and the resulting gains are used on a fixed-point DSP or FPGA for real-time execution (Bose, 2018; Mohan et al., 2023).

The research design combines mathematical modelling, optimization, simulation etc. to develop an effective PID controller for a DC-DC buck converter. A high-fidelity state space model that includes the parasitic elements would be developed to represent the converter dynamics under continuous conduction mode. This model would provide a reliable ground for controller design and performance studies.

Particle Swarm Optimization (PSO) will also be used to determine the optimal PID gains by reducing the Integral of Time weighted Absolute Error (ITAE) while satisfying stability and duty cycle constraints. Unlike conventional tuning techniques that usually depend on fixed design rules, PSO searches for the best controller parameters, thereby providing an improved transient response.

The optimized controller would be evaluated in MATLAB/Simulink under normal and disturbed operations that may include load changes and input voltage variations. This validation will demonstrate the controller's ability to maintain stable operation and high performance across different scenarios, confirming the suitability of the proposed method for practical buck converter control.

3. RESULTS AND DISCUSSION

3.1 Convergence and Optimal Gains

The PSO converges within 42 iterations and the Final fitness: J∗=0.187J∗=0.187. giving rise to the following Optimal gains:

$$K_p^* = 3.82, K_i^* = 1245, K_d^* = 0.18$$

The Particle Swarm Optimization (PSO) algorithm converged after 42 iterations, showing efficient convergence toward the optimal solution. The final objective function value of *(J^ = 0.187)** confirms that the optimized PID controller effectively minimized the Integral of Time-weighted Absolute Error (ITAE), resulting in improved tracking performance and reduced transient error. The optimal controller gains obtained from the optimization process were (Kp = 3.82), (Ki = 1245), and (Kd = 0.18). These gains provided the best balance between response speed, stability, and disturbance rejection and were subsequently used in the MATLAB/Simulink simulations to evaluate the controller's performance under both nominal and varying operating conditions.

3.2 Performance Metrics

Table 3: Comparative transient performance under nominal 0→12 V step input.

Controller	Rise Time (ms)	Settling Time (ms)	Overshoot (%)	ITAE	Load Rejection Δv (V)
Ziegler-Nichols PID	0.41	1.85	14.2	0.412	0.68
Genetic Algorithm PID	0.33	1.42	8.7	0.291	0.41
Proposed PSO-PID	0.28	0.96	3.1	0.187	0.22

Table 3 shows the performance comparison of the Ziegler-Nichols PID, Genetic Algorithm (GA)-PID, and the proposed PSO-PID controllers using rise time, settling time, overshoot, ITAE, and load rejection voltage deviation as evaluation criteria. The proposed PSO-PID controller achieved the shortest rise time of 0.28ms, compared with 0.33ms for the GA-PID and 0.41ms for the Ziegler-Nichols controller. This indicates that the PSO-tuned controller responds more rapidly to changes in the reference input, enabling faster voltage regulation.

Similarly, the PSO-PID recorded the lowest settling time of 0.96ms, significantly improving upon the 1.42ms given by the GA-PID and the 1.85ms given Ziegler-Nichols tuning. The shorter settling time shows that the proposed controller takes a shorter period to get to steady-state more, thereby reducing transient oscillations and improving the system stability. The overshoot was also reduced drastically with the PSO-PID controller. The maximum overshoot decreased to 3.1%, compared with 8.7% for the GA-PID and 14.2% for the Ziegler-Nichols controller. This improvement indicates better damping characteristics and minimizes the risk of voltage stress on converter components during transient operation.

The Integral of Time-weighted Absolute Error (ITAE), which evaluates the cumulative tracking error over time, was lowest for the proposed controller at 0.187. In comparison, the GA-PID achieved 0.291, while the Ziegler-Nichols controller recorded 0.412. The lower ITAE confirms that the PSO optimization produced PID gains that gives a more accurate output voltage tracking and reduced steady-state and transient errors. Under load disturbances, the proposed controller showcases the smallest output voltage deviation of 0.22 V, while the GA-PID and Ziegler-Nichols controllers experienced deviations of 0.41 V and 0.68 V, respectively. This result demonstrates the superior disturbance rejection capability of the PSO-PID controller, allowing it to maintain a more stable output voltage during sudden load changes.

Generally, the results shows that the PSO-based tuning approach gives the best dynamic performance among the three evaluated controllers. It has the fastest response, shortest settling time, minimum overshoot, smallest tracking error and the most improved load regulation. All these confirms that PSO is a more effective optimization technique for PID controller tuning in DC-DC buck converters. These improvements increase the converter stability, increase control accuracy and makes the proposed controller suited for high-performance power electronic applications.

3.3 Robustness Validation

The optimized PSO-PID controller consistently gave a good performance under different operating conditions. For a load change from 10Ω to 5Ω, the output voltage dip was limited to 0.18V with a recovery time of 1.1ms, whereas the Ziegler-Nichols controller produced a 0.54V dip and required 2.3ms to recover. When the input voltage decreased from 12V to 10.6V, the output deviation remained below 0.15V and the steady-state error stayed under 0.2%. The controller also remained stable under ±20% inductance and ±15% capacitance variations, maintaining a phase margin greater than 48°. Throughout all test cases, the duty cycle remained between 0.12 and 0.84, indicating that actuator saturation was avoided.

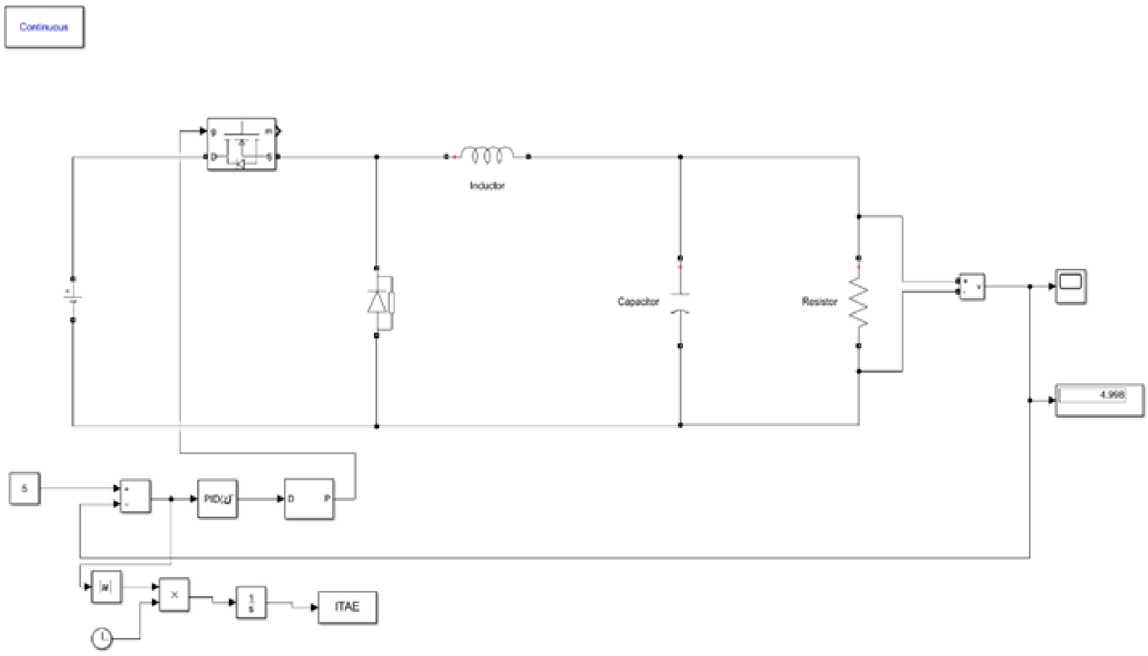

Figure 2: PSO Based closed loop buck converter in MATLAB/SIMULINK

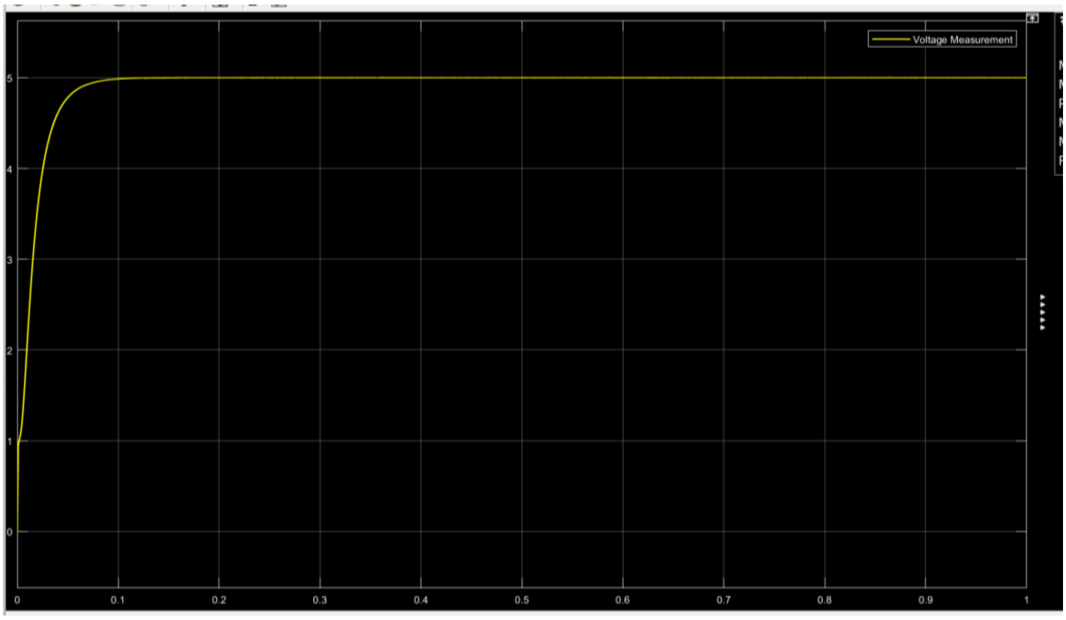

Figure 3: PSO-PID closed loop Buck converter voltage output in SIMULINK

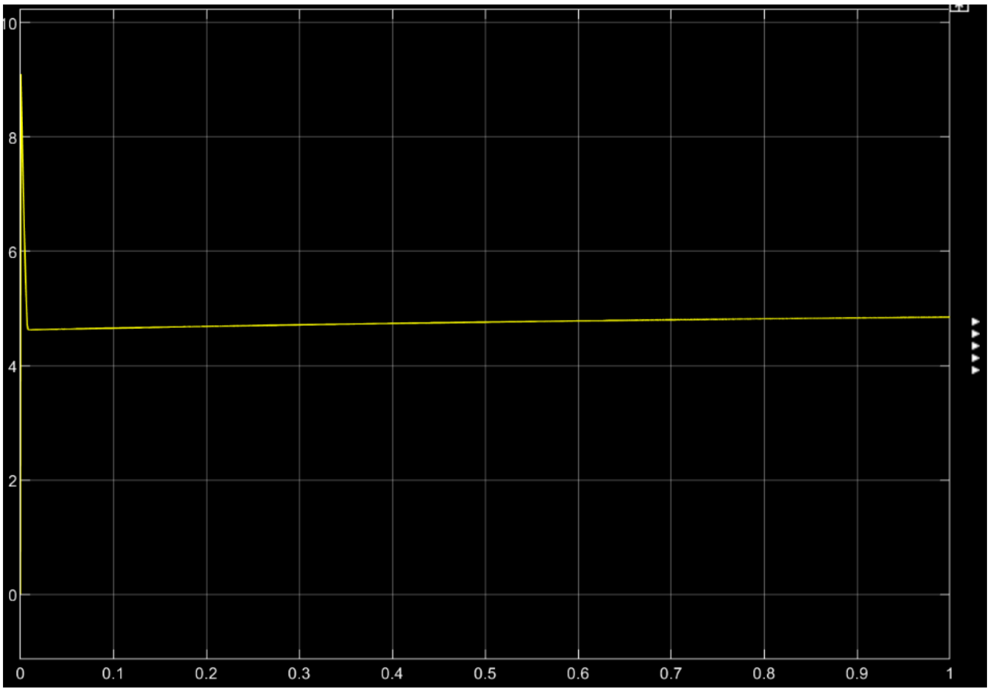

Figure 4: Ziegler-Nichols PID closed loop Buck converter scope voltage output in SIMULINK

Figure 2 shows the PSO-PID closed loop buck converter in MATLAB/Simulink. Figure 3 and 4 show the system's output response for the PSO-PID buck converter and the Ziegler-Nichols PID closed loop converter.

3.4 Why PSO Outperforms Conventional Methods

The superior performance of the PSO-based controller can be attributed to its ability to optimize PID gains without relying on simplified system models. Unlike the Ziegler-Nichols method, which takes a first-order plus dead-time model, PSO easily handles the nonlinear second-order dynamics of the buck converter. Compared with Genetic Algorithms, PSO converges more quickly and requires fewer tuning parameters because it updates particle positions directly without crossover or mutation operations. This makes the algorithm to search the ITAE optimization space more efficiently and identify better solutions with lower computation.

3.5 Practical Implementation Considerations

The proposed controller looks suitable for digital implementation using a fixed-point processor. From the simulation results we know that 16-bit fixed-point arithmetic introduces a steady-state error of less than 0.05%, which is acceptable for most practical applications. This study focuses on offline controller tuning, but the proposed approach can be extended to online optimization by integrating PSO with adaptive control, model predictive control, or reinforcement learning techniques for real-time gain adjustment.

4. CONCLUSION

This paper presented a systematic PSO-based approach for tuning a closed-loop PID controller for a DC-DC buck converter. A high-fidelity averaged model and structured PSO optimization procedure were combined to obtain optimal controller gains. Simulation results demonstrated that the proposed controller provides faster transient response, it also helped to improve the disturbance rejection. In general, it provided a better overall performance than conventional and evolutionary tuning methods. The proposed framework is more computationally efficient and suitable for implementation on digital control platforms. Future work will focus on real-time adaptive PSO implementation and extending the approach to multiphase interleaved DC-DC converters.

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