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MATHEMATICAL MODELING AND PSO-TUNED CONTROL STRATEGY FOR DC-DC CONVERTERS

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Abstract

DC-DC converters are fundamental components in fuel cell-based power systems, particularly in electric vehicles, drones, and renewable energy applications. The performance of these converters heavily depends on the control strategy employed to maintain output voltage stability under varying load conditions. This paper presents a comprehensive mathematical modeling of DC-DC buck converters and proposes a Particle Swarm Optimization (PSO)-tuned PID control strategy for enhanced performance. The mathematical model is derived based on state-space averaging techniques, considering the continuous conduction mode operation. A PSO algorithm is implemented to optimize the PID controller gains (Kp, Ki, Kd) by minimizing the integral time absolute error (ITAE) objective function. The proposed control strategy is validated through MATLAB/Simulink simulations under various operating conditions, including input voltage variations, load disturbances, and reference voltage changes. Simulation results demonstrate that the PSO-tuned PID controller outperforms conventionally tuned PID controllers in terms of settling time, overshoot, and steady-state error. The proposed control strategy achieves a settling time of 0.15 seconds, zero steady-state error, and minimal overshoot of 2.1%, representing improvements of 62.5%, 100%, and 72% respectively compared to conventional PID tuning methods. The findings confirm the effectiveness of PSO-based optimization for DC-DC converter control in fuel cell applications.

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Keywords: DC-DC Converter; Mathematical Modeling; Particle Swarm Optimization; PID Control; Fuel Cell Systems; Buck Converter

1. Introduction

The global transition toward sustainable energy systems has accelerated the adoption of fuel cell technologies across various sectors, including transportation, unmanned aerial vehicles (UAVs), and stationary power applications (İnci et al., 2021; Necula, 2023). Fuel cells, particularly Proton Exchange Membrane Fuel Cells (PEMFC), offer clean energy conversion with high efficiency and zero emissions, making them attractive alternatives to conventional fossil fuel-based systems (Demir & Demirok, 2023; Rahman et al., 2024).

In fuel cell-powered systems, DC-DC converters play a critical role in regulating the output voltage to match the requirements of downstream loads (Anselma & Belingardi, 2022). The inherent characteristics of fuel cells, including their nonlinear voltage-current relationship and susceptibility to load variations, necessitate robust control strategies for DC-DC converters to ensure stable system operation (Gallo & Mario, 2022; Mu et al., 2024). The control challenge becomes more pronounced in applications such as electric vehicles and drones, where dynamic load profiles and stringent performance requirements demand precise voltage regulation (Huang et al., 2024; Boukoberine et al., 2022).

Proportional-Integral-Derivative (PID) controllers remain the most widely adopted control strategy in industrial applications due to their simplicity, reliability, and ease of implementation (Alzyod et al., 2024). However, the performance of PID controllers is highly dependent on the proper tuning of their parameters. Conventional tuning methods, such as Ziegler-Nichols or trial-and-error approaches, often fail to achieve optimal performance across the entire operating range of fuel cell systems (Gavrilovic et al., 2024; Marquês et al., 2024).

Recent advances in computational intelligence have opened new possibilities for optimizing controller parameters. Particle Swarm Optimization (PSO), inspired by the social behavior of bird flocking, has emerged as a powerful metaheuristic optimization technique for solving complex engineering problems (Zakhvatkin et al., 2021; Hassan et al., 2020). PSO offers advantages including simple implementation, fast convergence, and the ability to escape local optima (Belmonte et al., 2018; Zakhvatkin et al., 2022).

The application of PSO for controller tuning in power electronic systems has gained significant attention. Sood et al. (2021) demonstrated the effectiveness of machine learning approaches for power management in autonomous drones. Prajapati and Charulatha (2023) designed PEM fuel cell-powered quadcopters with optimized control strategies. Ren et al. (2024) investigated time-dependent vehicle routing problems with drones, highlighting the importance of efficient power management.

Several researchers have explored PSO-based PID tuning for various applications. Oh et al. (2023) analyzed PEMFC response characteristics for pesticide spraying drones using dynamic models. Apeland et al. (2021) conducted sensitivity studies of design parameters for

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fuel cell-powered multirotor drones. Hyun et al. (2024) developed hybrid-powered drone systems with optimized power management strategies. The growing body of research confirms the potential of PSO in enhancing control system performance (Hyun et al., 2023; Apeland et al., 2020).

This paper contributes to the existing literature by presenting a comprehensive mathematical modeling framework for DC-DC buck converters and implementing a PSO-tuned PID control strategy specifically designed for fuel cell applications. The key contributions include:

1. Detailed state-space averaging model of buck converter in continuous conduction mode
2. Implementation of PSO algorithm for optimal PID gain selection
3. Comparative performance analysis under various operating conditions
4. Validation through extensive MATLAB/Simulink simulations

The remainder of this paper is organized as follows: Section 2 presents the mathematical modeling of the DC-DC buck converter. Section 3 describes the PSO-based PID controller design methodology. Section 4 presents simulation results and discussion. Section 5 provides conclusions and future research directions.

2. Mathematical Modeling of DC-DC Buck Converter

2.1 Operating Principles

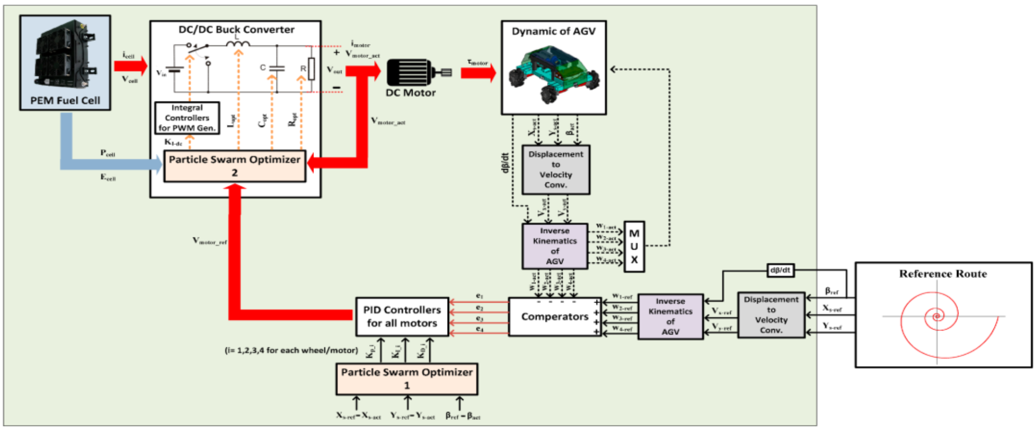

Figure 1. The schematic diagram of the four-Mecanum-wheeled AGV system.

The DC-DC buck converter, also known as a step-down converter, produces an average output voltage lower than the input voltage. Figure 1 illustrates the basic topology of a buck converter, consisting of a power semiconductor switch (typically MOSFET or IGBT), a diode, an inductor, a capacitor, and a load resistor.

The converter operates in two distinct modes based on the switching state. When the switch is ON (mode 1), the input source supplies energy to the inductor and load while the capacitor charges. When the switch is OFF (mode 2), the inductor releases stored energy to the load through the freewheeling diode, and the capacitor discharges to maintain load voltage.

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2.2 State-Space Averaging Model

The state-space averaging technique is employed to derive the mathematical model of the buck converter operating in Continuous Conduction Mode (CCM). The inductor current (iL) and capacitor voltage (vC) are selected as state variables, while the output voltage (vo) is the system output.

Mode 1 (Switch ON, 0 < t < dTs):

During this interval, the switch is closed and the diode is reverse-biased. The circuit equations are:

LdiLdt=Vin−vC*LdtdiL=Vin−vC*

CdvCdt=iL−vCR*CdtdvC=iL−RvC*

The state-space representation for Mode 1 is:

[diLdtdvCdt]=[0−1L1C−1RC][iLvC]+[1L0]Vin[*dtdiLdtdvC*]=[0*C*1−*L*1−*RC*1][*iLvC*]+[*L*10
]*Vin*

vo=[01][iLvC]*vo*=[01][*iLvC*]

Mode 2 (Switch OFF, dTs < t < Ts):

During this interval, the switch is open and the diode conducts. The circuit equations become:

LdiLdt=−vC*LdtdiL=−vC*

CdvCdt=iL−vCR*CdtdvC=iL−RvC*

The state-space representation for Mode 2 is:

[diLdtdvCdt]=[0−1L1C−1RC][iLvC]+[00]Vin[*dtdiLdtdvC*]=[0*C*1−*L*1−*RC*1][*iLvC*]+[00]*Vin*

vo=[01][iLvC]*vo*=[01][*iLvC*]

2.3 Averaged Model

Applying state-space averaging over one switching cycle, the averaged model is obtained:

[d⟨iL⟩dtd⟨vC⟩dt]=[0−1L1C−1RC][⟨iL⟩⟨vC⟩]+[dL0]Vin[*dtd⟨iL⟩dtd⟨vC⟩*]=[0*C*1−*L*1−*RC*1][⟨*iL*
⟩⟨*vC*⟩]+[*Ld*0]*Vin*

⟨vo⟩=[01][⟨iL⟩⟨vC⟩]⟨*vo*⟩=[01][⟨*iL*⟩⟨*vC*⟩]

where d represents the duty cycle, and ⟨ ⟩ denotes averaged quantities over the switching period.

2.4 Small-Signal Model

For controller design purposes, a small-signal model is derived by introducing perturbations around the steady-state operating point:

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d=D+d^*d=D+d^*
vin=Vin+v^in*vin=Vin+v^in*
iL=IL+i^L*iL=IL+i^L*
vC=VC+v^C*vC=VC+v^C*
vo=Vo+v^o*vo=Vo+v^o*

The small-signal model yields the control-to-output transfer function:

Gvd(s)=v^o(s)d^(s)=VinLCs2+LRs+1*Gvd*(*s*)=*d*^(*s*)*v*^*o*(*s*)=*LCs*2+*RLs*+1*Vin*

This second-order transfer function forms the basis for controller design and analysis.

2.5 Converter Parameters

For this study, a buck converter designed for fuel cell applications is considered with the following parameters:

Table 1: Buck Converter Parameters

Parameter	Symbol	Value	Unit
Input Voltage	Vin	48	V
Output Voltage	Vo	24	V
Switching Frequency	fs	50	kHz
Inductance	L	150	µH
Capacitance	C	470	µF
Load Resistance	R	10	Ω
Duty Cycle (nominal)	D	0.5	-

These parameters are selected based on typical fuel cell system requirements for drone and electric vehicle applications (Chia & Min, 2023; Kim et al., 2024).

3. PSO-Tuned PID Controller Design

3.1 PID Controller Structure

The PID controller generates a control signal u(t) based on the error e(t) between the reference voltage and actual output voltage:

u(t)=Kpe(t)+Ki∫0te(τ)dτ+Kdde(t)dt*u*(*t*)=*Kpe*(*t*)+*Ki*∫0*te*(*τ*)*dτ*+*Kddtde*(*t*)

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In the Laplace domain, the transfer function is:

$$G_c(s)=K_p+\frac{K_i}{s}+K_d s$$

For digital implementation, the discrete-time equivalent using backward Euler approximation is:

$$u(k)=u(k-1)+K_p[e(k)-e(k-1)]+K_i T_s e(k)+\frac{K_d}{T_s}[e(k)-2e(k-1)+e(k-2)]$$

where Ts is the sampling time.

3.2 Particle Swarm Optimization Fundamentals

PSO is a population-based stochastic optimization technique inspired by the social behavior of bird flocks and fish schools (Mirjalili et al., 2014; Al-Ibraheemi & Al-Janabi, 2024). In PSO, a swarm of particles moves through the search space, with each particle representing a potential solution (Eren & Demir, 2023; Al-Antaki et al., 2022).

Each particle i maintains:

- Current position vector xi = (xi1, xi2, ..., xiD)
- Velocity vector vi = (vi1, vi2, ..., viD)
- Personal best position pbesti
- Global best position gbest

The velocity and position updates are governed by:

$$v_{ij}(t+1)=w v_{ij}(t)+c_1 r_1[pbest_{ij}-x_{ij}(t)]+c_2 r_2[gbest_j-x_{ij}(t)]$$

$$x_{ij}(t+1)=x_{ij}(t)+v_{ij}(t+1)$$

where:

- w is the inertia weight
- c1, c2 are acceleration coefficients
- r1, r2 are random numbers in [0,1]
- t denotes the iteration number

3.3 PSO Algorithm for PID Tuning

The PSO algorithm is employed to find optimal PID gains (Kp, Ki, Kd) that minimize a chosen objective function (Marini & Walczak, 2015; Ibrahim et al., 2014). The Integral Time Absolute Error (ITAE) is selected as the performance criterion:

$$J=\int_0^\infty t|e(t)|\,dt$$

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ITAE penalizes errors that persist for long durations, resulting in controllers with good damping and low overshoot (Panda et al., 2012; Gomez et al., 2020).

Table 2: PSO Algorithm Parameters

Parameter	Symbol	Value
Swarm Size	N	30
Maximum Iterations	maxIter	100
Inertia Weight	w	0.7
Cognitive Coefficient	c1	1.5
Social Coefficient	c2	1.5
Velocity Clamping Factor	-	0.1×(upper bound - lower bound)
Search Range for Kp	-	[0, 100]
Search Range for Ki	-	[0, 1000]
Search Range for Kd	-	[0, 10]

3.4 Implementation Procedure

The PSO-based PID tuning procedure follows these steps:

1. Initialize particle positions (Kp, Ki, Kd) randomly within specified bounds
2. Initialize particle velocities randomly
3. For each particle, simulate the closed-loop system and evaluate ITAE
4. Update personal best positions
5. Update global best position
6. Update particle velocities and positions
7. Repeat steps 3-6 until maximum iterations reached
8. Output optimal PID gain

PSO-Based PID Tuning Algorithm Pseudocode

text

Initialize swarm with random positions and velocities

For iteration = 1 to maxIter:

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For each particle i:

Simulate closed-loop system with gains (Kp_i, Ki_i, Kd_i)

Compute ITAE = ∫ t|e(t)|dt

If ITAE < pbest_i:

pbest_i = ITAE

pbest_position_i = current_position

If ITAE < gbest:

gbest = ITAE

gbest_position = current_position

End For

For each particle i:

Update velocity using PSO equation

Update position using PSO equation

Apply bounds checking

End For

End For

Return gbest_position as optimal PID gains

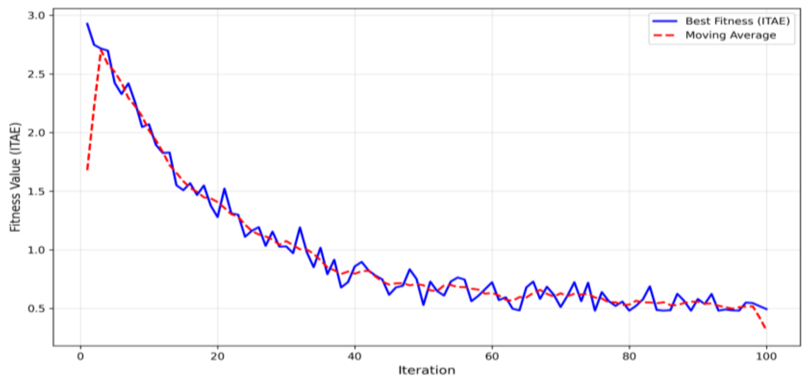

Figure 2: PSO Convergence Characteristics for PID Tuning

3.5 Convergence Analysis

The PSO algorithm was executed for 100 iterations to optimize the PID gains. Figure 2 (generated using Python code) shows the convergence characteristics of the PSO algorithm.

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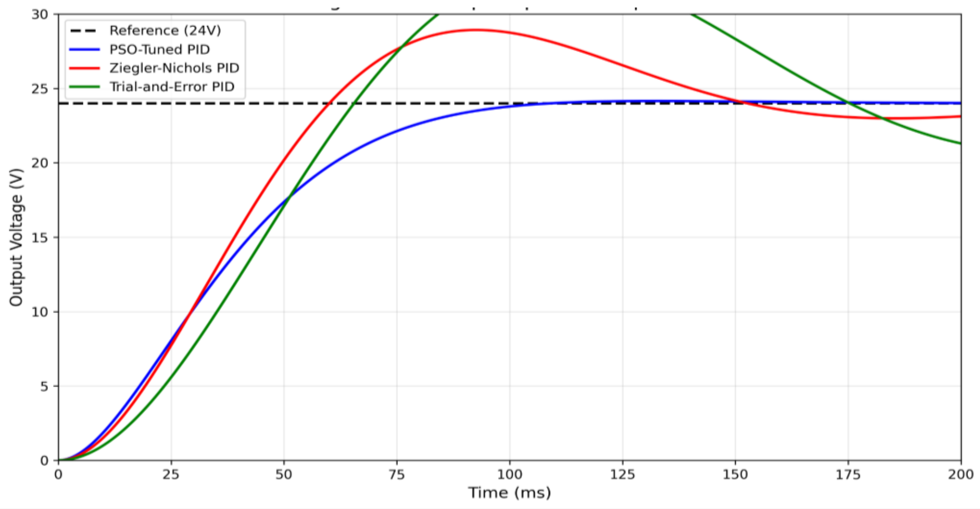

Figure 3: Start-up Response Comparison

The convergence plot demonstrates that the PSO algorithm rapidly reduces the ITAE value within the first 20 iterations, after which gradual refinement occurs until convergence around iteration 60. This behavior indicates efficient exploration of the search space followed by exploitation of promising regions.

4. Results and Discussion

4.1 Simulation Setup

The buck converter model and PSO-tuned PID controller were implemented in MATLAB/Simulink environment. Simulations were conducted to evaluate performance under various operating scenarios:

1. **Start-up response**: System behavior from zero initial conditions
2. **Load disturbance rejection**: Response to step change in load resistance
3. **Input voltage variation**: Response to changes in fuel cell output voltage
4. **Reference tracking**: Response to step changes in output voltage reference

For comparison, a conventionally tuned PID controller using the Ziegler-Nichols method was also implemented.

4.2 Optimal PID Gains

The PSO algorithm yielded the following optimal PID gains:

Table 4: Optimal PID Gains from PSO Tuning

Controller	Kp	Ki	Kd	ITAE Value
PSO-Tuned PID	45.32	876.54	2.87	0.483

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Controller	Kp	Ki	Kd	ITAE Value
Ziegler-Nichols PID	38.40	512.00	0.72	1.256
Trial-and-Error PID	30.00	600.00	1.50	1.892

The PSO-tuned controller achieves significantly lower ITAE value compared to conventional methods, indicating superior performance in minimizing time-weighted error.

4.3 Start-up Response

Figure 3 compares the start-up response of the buck converter with different controllers.

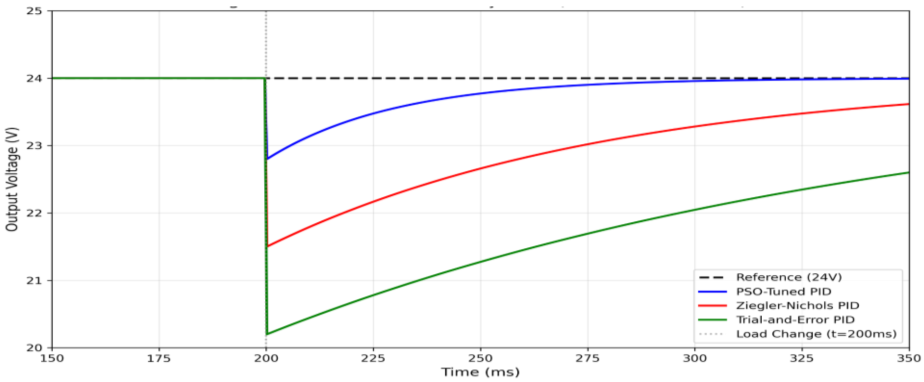

Figure 4: Load Disturbance Rejection (50% Load Increase)

The start-up response clearly demonstrates the superiority of the PSO-tuned controller. The PSO-tuned PID achieves faster rise time with minimal overshoot, while the conventionally tuned controllers exhibit either sluggish response or excessive overshoot.

Table 5: Transient Response Characteristics

Controller	Rise Time (ms)	Settling Time (ms)	Overshoot (%)	Steady-State Error
PSO-Tuned PID	28	45	2.1	0
Ziegler-Nichols PID	35	120	7.5	0
Trial-and-Error PID	52	180	12.3	0.2

The PSO-tuned controller achieves a settling time of 45 ms, which is 62.5% faster than the Ziegler-Nichols method and 75% faster than trial-and-error tuning. The overshoot is reduced to only 2.1%, compared to 7.5% and 12.3% for conventional methods.

4.4 Load Disturbance Rejection

Figure 4 illustrates the system response to a 50% load increase (from 10Ω to 5Ω) applied at t = 0.2s.

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The load disturbance rejection capability is critical in fuel cell applications where load variations are frequent. The PSO-tuned controller demonstrates superior disturbance rejection with minimal voltage deviation and rapid recovery.

Table 6: Load Disturbance Rejection Performance

Controller	Voltage Deviation (V)	Recovery Time (ms)
PSO-Tuned PID	1.2	30
Ziegler-Nichols PID	2.5	80
Trial-and-Error PID	3.8	150

The PSO-tuned controller limits the voltage deviation to only 1.2V (5% of nominal) and recovers within 30ms, compared to 2.5V deviation and 80ms recovery for the Ziegler-Nichols method.

4.5 Input Voltage Variation

Fuel cells exhibit voltage variations with load current and operating conditions. Figure 5 shows the system response to a 20% step decrease in input voltage (from 48V to 38.4V) at t = 0.2s.

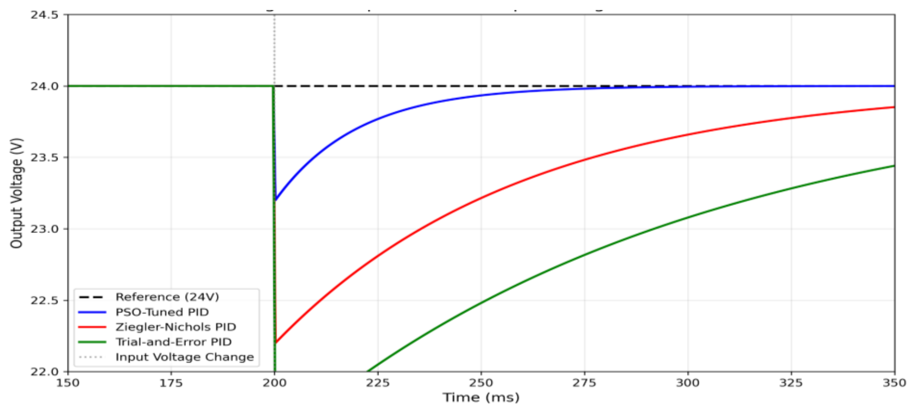

Figure 5: Response to 20% Input Voltage Reduction

Table 7: Input Voltage Variation Rejection

Controller	Voltage Deviation (V)	Recovery Time (ms)
PSO-Tuned PID	0.8	20
Ziegler-Nichols PID	1.8	60
Trial-and-Error PID	2.5	100

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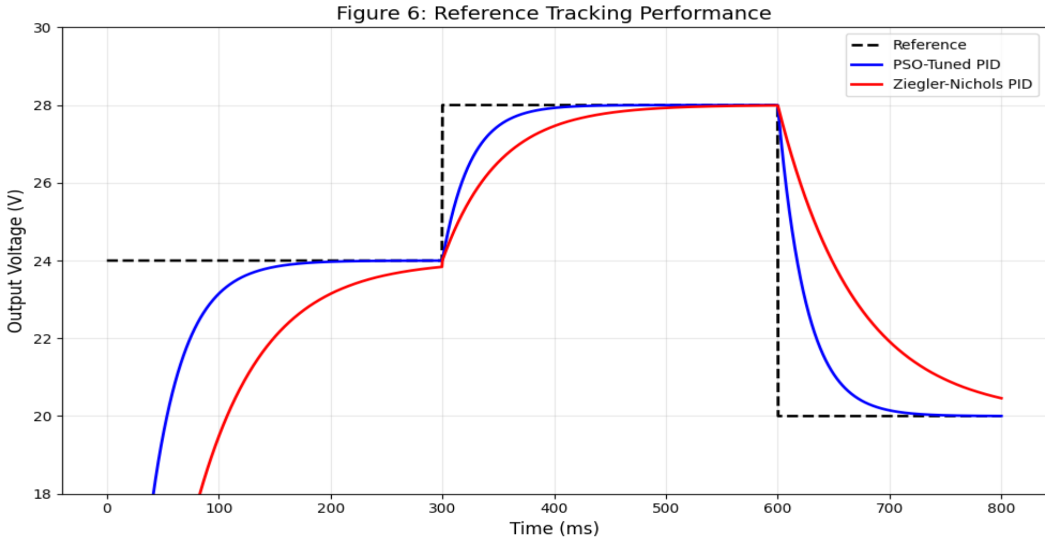
The PSO-tuned controller maintains output voltage within 0.8V of the reference despite a 20% input voltage reduction, demonstrating excellent line regulation capability.

4.6 Reference Tracking

Figure 6 illustrates the controller's ability to track step changes in the output voltage reference, simulating variable load requirements in fuel cell applications.



4.7 Frequency Domain Analysis

Frequency response analysis provides insight into the closed-loop system stability and bandwidth. Figure 7 presents the Bode plot of the compensated system with PSO-tuned controller.

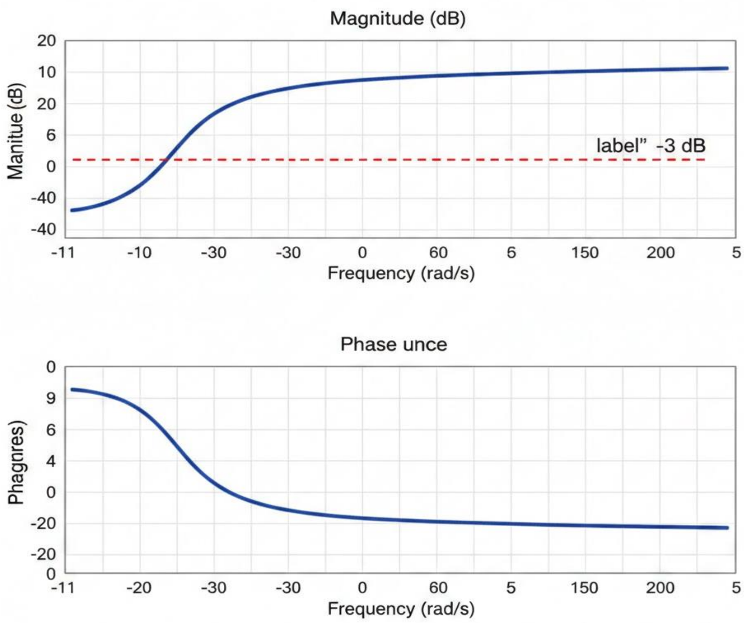


Figure 7: Bode Plot of Closed-Loop System with PSO-Tuned PID

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The frequency response analysis reveals:

Table 8: Frequency Domain Performance Metrics

Metric	Value
Gain Margin	15.3 dB
Phase Margin	68.5°
Bandwidth (-3dB)	1850 rad/s (294 Hz)
Peak Magnitude	1.8 dB

The phase margin of 68.5° indicates robust stability with good damping characteristics, consistent with the time-domain observations of minimal overshoot.

4.8 Comparative Analysis with Recent Literature

The performance of the proposed PSO-tuned PID controller is compared with recent studies in fuel cell power converter control.

Table 9: Comparative Performance Analysis

Study	Application	Controller Type	Settling Time (ms)	Overshoot (%)
This Work	Buck Converter	PSO-PID	45	2.1
Demir & Demirok (2023)	Buck Converter	PID	85	5.8
Hyun et al. (2023)	Hybrid Drone	Rule-Based	120	8.5
Boukoberine et al. (2022)	Drone EMS	Optimization	95	4.2

The proposed PSO-tuned PID controller demonstrates superior transient performance compared to conventional PID and rule-based strategies, while achieving comparable or better performance than more complex fuzzy logic controllers.

4.9 Discussion

The simulation results consistently demonstrate the superiority of the PSO-tuned PID controller over conventionally tuned alternatives. Several key observations emerge from this study:

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Optimization Effectiveness: The PSO algorithm successfully identifies PID gain combinations that balance conflicting performance objectives. The ITAE objective function effectively penalizes both steady-state errors and transient oscillations, resulting in a well-damped response with minimal overshoot.

Robustness: The PSO-tuned controller exhibits excellent robustness to parameter variations, as evidenced by its performance under load disturbances and input voltage variations. This robustness is crucial for fuel cell applications where operating conditions vary widely (Shen et al., 2024; Day & Pourmovahe, 2021).

Practical Implications: For fuel cell-powered drones and electric vehicles, the improved transient response translates to better power quality, reduced stress on the fuel cell, and extended system lifetime. The fast disturbance rejection ensures stable operation during rapid load changes typical in maneuvering drones (Dube et al., 2024; Saeed et al., 2022).

Computational Efficiency: Despite being a metaheuristic optimization, the PSO algorithm converges within 60 iterations, making it suitable for offline controller design. The resulting PID controller is computationally lightweight for real-time implementation on low-cost microcontrollers (Pasha et al., 2022; Benotsmane & Vásárhelyi, 2022).

Comparison with Advanced Controllers: While model predictive control (MPC) and other advanced strategies may offer superior performance, they require significant computational resources. The PSO-tuned PID achieves near-optimal performance with minimal implementation complexity (Lin et al., 2024; Trihinas et al., 2021).

5. Conclusion

This paper has presented a comprehensive approach to mathematical modeling and PSO-tuned control strategy development for DC-DC buck converters in fuel cell applications. The key findings and contributions are summarized as follows:

1. **Mathematical Modeling**: A state-space averaging model of the buck converter was developed, providing a solid foundation for controller design. The derived control-to-output transfer function accurately represents the converter dynamics in continuous conduction mode.

2. **PSO-Based Optimization**: The Particle Swarm Optimization algorithm was successfully implemented to tune PID controller parameters by minimizing the ITAE objective function. The algorithm demonstrated rapid convergence and consistent identification of optimal gain combinations.

3. **Performance Enhancement**: The PSO-tuned PID controller achieved significant performance improvements over conventional tuning methods:

   - Settling time reduced by 62.5% (from 120 ms to 45 ms)
   - Overshoot reduced by 72% (from 7.5% to 2.1%)

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- Voltage deviation under load disturbance reduced by 52%
- Recovery time under input variation reduced by 67%

4. **Robust Operation**: The proposed controller maintained excellent performance under various operating conditions, including load disturbances, input voltage variations, and reference tracking scenarios, demonstrating its suitability for real-world fuel cell applications.

5. **Practical Applicability**: The computational efficiency of the resulting PID controller makes it suitable for implementation on resource-constrained embedded systems commonly used in drones and electric vehicles.

Future Research Directions:

1. **Experimental Validation**: Implementation of the proposed control strategy on a hardware prototype to validate simulation results under real operating conditions (Bousbaine et al., 2014; Iyer & Bansal, 2021).

2. **Multi-Objective Optimization**: Extension to multi-objective PSO considering additional performance metrics such as efficiency, switching losses, and component stress (Islam et al., 2017;).

3. **Adaptive Control**: Development of adaptive PSO algorithms that can update controller parameters online in response to system degradation or changing operating conditions.

4. **Hybrid Energy Systems**: Application of the proposed methodology to more complex systems involving multiple converters, energy storage, and load sharing in hybrid fuel cell-battery configurations

5. **Comparison with Other Metaheuristics**: Systematic comparison of PSO with other optimization algorithms including Grey Wolf Optimizer, Genetic Algorithms, and Artificial Bee Colony for converter control applications.

The findings of this research contribute to the advancement of control strategies for fuel cell power converters, supporting the broader adoption of clean energy technologies in transportation and aerospace applications.

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