Postprint: Parameter Optimization of Electric Vehicle Fuzzy Controller Based on Improved QPSO Algorithm

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Abstract

Currently, electric vehicles commonly employ Brushless DC Motors (BLDCM) as actuators. However, the quantization factor and scaling factor of fuzzy controllers in BLDCM speed control systems exhibit weak self-adjustment capabilities when using traditional methods. To address this problem, an improved QPSO algorithm (AMF-QPSO) is proposed to achieve adaptive adjustment of the quantization factor and scaling factor. The AMF-QPSO algorithm focuses on the contraction-expansion (CE) coefficient control strategy, introduces the concept of particle activity, and utilizes it as a feedback variable to realize dynamic adaptive adjustment of the CE coefficient. Simultaneously, to prevent excessive population aggregation, an elite group random crossover learning mechanism is adopted to perturb some elite particles with low activity, thereby enhancing population diversity in the later stages. Finally, the performance of the AMF-QPSO algorithm is verified through specific case studies on a LabVIEW experimental platform. Experimental results demonstrate that the fuzzy PID controller optimized by AMF-QPSO possesses better control performance and adaptability than both standard fuzzy PID controllers and QPSO-optimized fuzzy PID controllers.

Full Text

Parameter Optimization of Fuzzy Controller for Electric Vehicle Based on Improved QPSO Algorithm

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Abstract: Electric vehicles currently employ brushless DC motors (BLDCM) as their primary drive system. However, the quantization and scaling factors of fuzzy controllers in BLDCM speed control systems exhibit weak self-tuning capability when designed using traditional methods. To address this limitation, this paper proposes an improved QPSO algorithm (AMF-QPSO) to achieve adaptive adjustment of these factors. The AMF-QPSO algorithm focuses on the control strategy of the contraction-expansion (CE) coefficient, introduces the concept of particle activity as a feedback quantity, and implements dynamic adaptive regulation of the CE coefficient. Simultaneously, to prevent excessive population aggregation, an elite group random crossover learning mechanism is adopted to perturb elite particles with low activity, thereby enhancing population diversity in later evolutionary stages. Finally, the performance of the AMF-QPSO algorithm is validated through a LabVIEW experimental platform using specific case studies. Experimental results demonstrate that the fuzzy PID controller optimized by AMF-QPSO exhibits superior control performance and adaptability compared to both standard fuzzy PID controllers and those optimized by conventional QPSO.

Keywords: electric vehicle; brushless DC motor; fuzzy controller; quantum-behaved particle swarm optimization; contraction-expansion coefficient

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0 Introduction

In recent years, advancements in new materials, advanced manufacturing, and power electronics have led to the emergence of high-performance novel electric machines. Brushless DC motors (BLDCM), as a representative example, have gained favor in servo control, transportation, material handling, and industrial automation due to their low losses, high power density, strong overload capacity, low noise, and excellent controllability [1,2]. In the transportation sector, the promotion of new energy technologies and the implementation of green development strategies have accelerated the adoption of BLDCM-driven electric vehicles.

However, electric vehicle speed control systems are characterized by strong nonlinearity, multiple variables, high coupling complexity, and difficult controller parameter tuning. Improving system controllability and adaptability while optimizing parameter tuning methods has become crucial for further promoting electric vehicles [3]. As a representative advanced controller, the fuzzy PID controller utilizes fuzzy mathematics theory to transform sophisticated biological fuzzy language into machine-recognizable program language. Its implementation mechanism resembles human thinking patterns, enabling control under conditions where the controlled object is not completely known, making it suitable for electric vehicle speed control system design and parameter optimization.

Nevertheless, in practical industrial applications, fuzzy PID controllers lack online parameter adjustment capability, resulting in insufficient control precision and weak anti-interference capability. With the development of intelligent algorithms, applying them to fuzzy controller parameter tuning has become a research hotspot [4,5]. In 2004, Sun et al. [6] proposed the quantum-behaved particle swarm optimization (QPSO) algorithm, inspired by particle behavior in quantum space. In quantum space, each particle position corresponds to a feasible solution, with coordinates determined by wave functions that follow the superposition principle, exhibiting strong randomness and high intelligence.

Although the standard QPSO algorithm offers many advantages, it still has limitations. The contraction-expansion (CE) coefficient is the only control parameter requiring manual setting besides population size, particle dimension, and maximum iteration count, and its control strategy significantly impacts algorithm performance [7]. Literature [8] demonstrated that the CE coefficient must satisfy certain conditions to ensure reliable particle convergence and compared the advantages and disadvantages of fixed-value and nonlinear decreasing strategies. Literature [9] proposed a dynamic nonlinear decreasing CE coefficient control strategy employing control curves with different concavity-convexity characteristics based on optimization problem features. However, whether fixed-value, linear decreasing, or nonlinear decreasing, these strategies are essentially open-loop control approaches where coefficient values and control curves are determined through simulation experiments or empirical formulas. Their primary drawback lies in weak self-tuning capability—the algorithm can only adjust CE coefficients according to preset patterns without adapting to transitions between search phases.

Motivated by these limitations, researchers have proposed adaptive coefficient control strategies with various feedback mechanisms. Literature [10] utilized the distance between particles and the global optimum as the basis for CE coefficient regulation. Literature [11] introduced concepts of evolutionary speed factor and aggregation degree factor for online CE coefficient correction. Building upon these works, this paper investigates the relationship between the CE coefficient and potential well length, proposes the concept of particle activity measured by the relative change rate of potential well length, and uses particle activity as feedback to achieve adaptive CE coefficient adjustment. Additionally, to improve convergence precision and prevent particles from falling into local optima, an elite group random crossover learning mechanism is introduced, allowing low-activity elite particles to exchange dimensional information with other particles in the population, thereby escaping local optima and discovering globally superior solutions. This mechanism ensures both convergence speed and enhanced population diversity in later stages. Finally, to address the weak online adjustment capability of quantization and scaling factors in fuzzy PID controllers for electric vehicle speed control systems, the improved QPSO algorithm (adaptive mutation QPSO algorithm based on feedback mechanism, AMF-QPSO) is applied to optimize these parameters. To validate algorithm performance, a LabVIEW experimental platform is used to verify the AMF-QPSO algorithm through specific control cases. Comparative experiments with basic fuzzy PID and standard QPSO-optimized fuzzy PID controllers demonstrate that the improved controller exhibits superior control performance and adaptability.

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1 Quantum-Behaved Particle Swarm Optimization Algorithm

The QPSO algorithm is a swarm intelligence algorithm developed from the PSO algorithm. It eliminates the traditional velocity-displacement trajectory model constraint [12] and employs Monte Carlo methods to determine particle positions after updating, achieving higher intelligence. Its evolution equation is shown in Eq. (1):

$$X_{i,j}(t+1) = p_{i,j}(t) \pm \alpha \cdot |C_j(t) - X_{i,j}(t)| \cdot \ln(1/u_{i,j}(t)), \quad u_{i,j}(t) \sim U(0,1)$$

where $p_{i,j}(t)$ represents the local attractor determining particle search direction; $L_{i,j}(t)$ is the characteristic length of the potential well directly constraining particle search range; and $u_{i,j}(t)$ is a random distribution in $(0,1)$.

Clerc et al. [13] studied particle convergence behavior in PSO algorithms and demonstrated that to ensure algorithm convergence, each particle must converge to its local attractor point, with attractor coordinates given by Eq. (2):

$$p_{i,j}(t) = \frac{c_1 r_{1,j}(t) P_{i,j}(t) + c_2 r_{2,j}(t) G_j(t)}{c_1 r_{1,j}(t) + c_2 r_{2,j}(t)}, \quad j = 1, 2, \dots, N$$

where c_1 and c_2 are the particle' s local and global learning factors, respectively; $r_{1,j}(t)$ and $r_{2,j}(t)$ are random distributions in $[0,1]$; $P_{i,j}(t)$ is the j-dimensional local optimum of particle i; and $G_j(t)$ is the j-dimensional global optimum position.

To ensure particles converge to their respective attractors, the condition $\lim_{t\to\infty} L_{i,j}(t) = 0$ must be satisfied. Therefore, controlling $L_{i,j}(t)$ becomes critical for ensuring algorithm convergence and influencing performance. A typical control method for $L_{i,j}(t)$ utilizes the distance between particles and the population mean best position. Denoting the population mean best position coordinates as $C(t)$, its coordinates can be expressed by Eq. (5):

$$C(t) = (C_1(t), C_2(t), \dots, C_D(t)) = \left(\frac{1}{N} \sum_{i=1}^{N} P_{i,1}(t), \frac{1}{N} \sum_{i=1}^{N} P_{i,2}(t), \dots, \frac{1}{N} \sum_{i=1}^{N} P_{i,D}(t) \right)$$

where D is particle dimension and N is population size. The particle potential well length can then be expressed by Eq. (6):

$$L_{i,j}(t) = 2\alpha \cdot |C_j(t) - X_{i,j}(t)|$$

where α is the CE coefficient. Substituting Eq. (6) into Eq. (1) yields the final evolution equation shown in Eq. (7):

$$X_{i,j}(t+1) = p_{i,j}(t) \pm \alpha \cdot |C_j(t) - X_{i,j}(t)| \cdot \ln(1/u_{i,j}(t))$$

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2 Adaptive Mutation QPSO Algorithm Based on Feedback Mechanism

2.1 Relationship Between CE Coefficient and Potential Well Length

As shown in Eq. (6), the CE coefficient α plays a decisive role in regulating potential well length $L_{i,j}(t)$. Different α values directly enlarge or reduce particle search space. When α is large, the potential well length $L_{i,j}(t)$ is relatively large, granting particles strong global search capability, but excessively large α causes population divergence. When α is small, $L_{i,j}(t)$ is relatively small, providing strong local search capability, but excessively small α causes particles to lose search ability and population evolution stagnates. An ideal CE regulation strategy employs large values early for strong global search and small values later for strong local search.

Therefore, while ensuring algorithm convergence, the key to determining potential well length $L_{i,j}(t)$ control strategy lies in selecting the CE coefficient α control method. Investigating α' s influence on $L_{i,j}(t)$ and exploring their relationship provides valuable guidance for algorithm performance improvement. For analysis convenience, the evolution formula (7) is simplified for one-dimensional cases. Fixing points p and C at the origin and setting the particle initial position $X(0) = 1$, the simplified evolution formula becomes Eq. (8):

$$X_i(t+1) = \alpha \cdot X_i(t) \cdot \ln(1/u_i(t))$$

From Eq. (8), to ensure algorithm convergence (i.e., particle convergence to point p at the origin), the condition $\lim_{t\to\infty} \alpha^t = 0$ must be satisfied, which requires $\alpha < 1.781$.

Thus, whether the algorithm reliably converges can be transformed into observing whether α^t converges. Random simulation experiments are conducted based on Eq. (8). Figure 1 [Figure 1: see original paper] shows the variation of potential well length L for different α values, where the horizontal axis represents iteration count t and the vertical axis represents potential well length L (using base-10 logarithm for clarity, i.e., $\log(L)$).

Table 1 records the maximum iteration counts for L convergence or non-convergence under different α values.

As shown in Figure 1 and Table 1, when $\alpha < 1.78$, the potential well length L gradually decreases with population updates until reaching zero, indicating continuous contraction and algorithm convergence. When α is less than but close to 1.78, the convergence process exhibits fluctuations requiring extensive iterations to converge to zero. When $\alpha \geq 1.79$, fluctuations become more severe, and after 20,000 iterations, L remains far from zero, indicating particle difficulty converging to point p and algorithm divergence. These results demonstrate the strong correlation between the CE coefficient and potential well length L, with different α values yielding distinct convergence speeds and precision, indirectly affecting algorithm convergence rate and accuracy.

2.2 Adaptive Control Strategy for CE Coefficient with Feedback Mechanism

Simulation results from Section 2.1 show that the CE coefficient must be within an appropriate range to ensure algorithm convergence, and CE coefficient regulation essentially controls potential well length L. In QPSO algorithms, L determines particle search range, and its relative change rate reflects search range variation. From Eq. (1), high population aggregation (concentrated particles) yields small or unchanged relative change rates in potential well length, indicating particles have converged to attractors with updates essentially stagnated. Low population aggregation (dispersed particles) yields larger relative change rates, indicating active position updates and large-scale optimization.

Therefore, the relative change rate of potential well length can represent particle activity. The particle activity factor $s_{i,j}(t)$ is defined in Eq. (10):

$$s_{i,j}(t) = \frac{L_{i,j}(t-3) - L_{i,j}(t)}{L_{i,j}(t-3)}$$

where $L_{i,j}(t)$ is the potential well length of particle i in dimension j at iteration t, $L_{i,j}(t-3)$ is the corresponding length at iteration $t-3$, and $s_{i,j}(t)$ is the activity factor. Since potential wells contract during algorithm convergence with decreasing length across generations (i.e., $L_{i,j}(t) < L_{i,j}(t-3)$), we have $s_{i,j}(t) \in [0,1]$.

Larger $s_{i,j}(t)$ indicates dramatic potential well contraction within three generations, signifying stronger particle activity and faster movement toward the global optimum. Smaller $s_{i,j}(t)$ indicates slow contraction, reflecting weaker activity and slower convergence.

Section 2.1 explored the relationship between the CE coefficient and potential well length L, demonstrating that α directly affects L values and constrains particle search range. Analysis reveals that fixed-value, linear/nonlinear decreasing, and partial adaptive control strategies are all open-loop approaches that fail to consider the relationship between the CE coefficient and the controlled variable L. Based on this insight, this paper proposes a closed-loop CE coefficient control strategy using the relative change rate of L (i.e., particle activity factor $s_{i,j}(t)$) as feedback for dynamic α adjustment, defined in Eq. (11):

$$\alpha_{i,j}(t) = \alpha_0 + (1 - s_{i,j}(t)) \cdot \lambda$$

where α_0 is the initial CE coefficient, λ is a random number in $(0, 1)$, and $s_{i,j}(t)$ is the activity factor. The CE coefficient $\alpha_{i,j}(t)$ is negatively correlated with $s_{i,j}(t)$. When $s_{i,j}(t)$ is small (weak search ability), $\alpha_{i,j}(t)$ increases appropriately to maintain population diversity. When $s_{i,j}(t)$ is large (strong search ability), $\alpha_{i,j}(t)$ takes smaller values to prevent excessive step sizes that might overshoot the optimum.

Substituting Eq. (11) into Eq. (7) yields the final evolution equation shown in Eq. (12):

$$X_{i,j}(t+1) = p_{i,j}(t) \pm \left[\alpha_0 + (1 - s_{i,j}(t)) \cdot \lambda\right] \cdot |C_j(t) - X_{i,j}(t)| \cdot \ln(1/u_{i,j}(t))$$

2.3 Random Crossover Learning for Elite Particles

While the above CE coefficient control strategy improves QPSO search speed and convergence precision to some extent, population diversity inevitably degrades in later evolutionary stages, causing premature convergence. To address this, this section proposes an elite group random crossover learning strategy that enables elite particles with activity below threshold s_{low} to deviate from original positions and explore other spaces, potentially discovering superior solutions.

Random crossover learning is defined as follows: In a D-dimensional search space, let $X = (x_1, x_2, \dots, x_k, \dots, x_D)$ be an elite particle position and $X' = (x'_1, x'_2, \dots, x'_k, \dots, x'_D)$ be a randomly selected individual from the population. For a randomly selected dimension k, the new position after random crossover learning with probability p_m is defined by Eq. (13):

$$x'_k = \begin{cases} \text{rand} \cdot p_k + (1 - \text{rand}) \cdot x_k & \text{if } p_m > \text{rand} \\ x_k & \text{otherwise} \end{cases}$$

where p_m is the crossover probability. To ensure algorithm convergence, p_m employs an adaptive linear decreasing strategy shown in Eq. (14):

$$p_m = p_{\max} - (p_{\max} - p_{\min}) \cdot \frac{t}{G_{\max}}$$

where $p_{\max}$ and $p_{\min}$ are the maximum and minimum crossover probabilities, t is the current generation, and $G_{\max}$ is the maximum iteration count.

The pseudocode for elite group random crossover learning is presented in Algorithm 1.

Algorithm 1: Elite Group Random Crossover Learning 1. Calculate particle fitness values and sort particles in descending order 2. Select the top 10% particles with best fitness to form the elite group 3. Calculate activity $s_{i,j}(t)$ for each elite particle 4. **for** each elite particle **do** 5. Generate random dimensions according to crossover probability p_m 6. **if** $s_{i,j}(t) < s_{low}$ **then** 7. Execute random crossover learning using Eq. (13) 8. **end if** 9. **end for**

2.4 Adaptive Mutation QPSO Algorithm with Feedback Mechanism

Based on the above discussion, the complete execution 流程 of the AMF-QPSO algorithm is as follows:

a) Initialize parameters including population size N, particle dimension D, maximum iterations $G_{\max}$, particle search space, and initialization space

b) Initialize particle positions randomly in the problem space

c) Calculate particle mean best position using Eq. (5)

d) Calculate current fitness values, compute each particle' s activity factor using Eq. (10), and update local and global best positions

e) Select the top 10% individuals with best fitness as the elite group and calculate elite particle crossover probability p_m using Eq. (14)

f) Evaluate elite particle activity; if below threshold s_{low}, execute random crossover learning using Eq. (14)

g) Update each particle position using Eq. (12)

h) Repeat steps b)-g) until termination conditions are met

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4 Mathematical Models and Controller Design

4.1 Electric Vehicle Mathematical Model

During operation, electric vehicle resistance primarily originates from four sources: rolling resistance, air resistance, acceleration resistance, and grade resistance [14]. The total resistance satisfies the relationship in Eq. (16):

$$F_{\text{total}} = F_f + F_w + F_j + F_i$$

Rolling resistance F_f follows Eq. (17):

$$F_f = f \cdot m \cdot g \cdot \cos\theta$$

where m is vehicle mass, f is rolling friction coefficient, g is gravitational acceleration, and θ is road gradient.

Air resistance F_w follows Eq. (18):

$$F_w = \frac{1}{2} \cdot C_d \cdot A \cdot v^2$$

where C_d is air drag coefficient, A is frontal area, and v is vehicle speed.

Acceleration resistance follows Eq. (19):

$$F_j = \delta \cdot m \cdot \frac{dv}{dt}$$

where δ is the mass conversion coefficient.

Grade resistance follows Eq. (20):

$$F_i = m \cdot g \cdot \sin\theta$$

During vehicle operation, the relationship between travel speed and wheel speed satisfies Eq. (21):

$$v = \frac{2\pi r \cdot n}{60 \cdot i_g \cdot i_0}$$

where n is motor speed, r is wheel radius, i_g is transmission ratio, and i_0 is final drive ratio.

The total torque and total resistance satisfy Eq. (22):

$$T_{\text{total}} = F_{\text{total}} \cdot r$$

Motor load torque T_L and total torque T_{total} satisfy:

$$T_L = \frac{T_{\text{total}}}{i_g \cdot i_0 \cdot \eta}$$

where η is transmission efficiency.

4.2 Motor Mathematical Model

Electric vehicles use BLDCM as their driver [15]. To establish the motor mathematical model, the following assumptions are made:

a) Neglect magnetic hysteresis and eddy current losses

b) Ignore magnetic circuit saturation and slot effects

c) Three-phase windings are uniformly and symmetrically distributed on the armature surface

From Kirchhoff's voltage law, the voltage balance equation for any phase winding is given by Eq. (24). For three-phase windings, the equivalent representation is given by Eq. (25):

$$\begin{bmatrix} u_a \\ u_b \\ u_c \end{bmatrix} = \begin{bmatrix} R & 0 & 0 \\ 0 & R & 0 \\ 0 & 0 & R \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \begin{bmatrix} L & M & M \\ M & L & M \\ M & M & L \end{bmatrix} \frac{d}{dt} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \begin{bmatrix} e_a \\ e_b \\ e_c \end{bmatrix}$$

Assuming completely symmetrical three-phase windings with star connection and no neutral line, we have:

$$\begin{cases} i_a + i_b + i_c = 0 \\ u_a + u_b + u_c = 0 \\ e_a + e_b + e_c = 0 \\ L_a = L_b = L_c = L \\ M_{ab} = M_{ac} = M_{bc} = M \end{cases}$$

where L is stator self-inductance and M is mutual inductance. Equation (25) can then be rewritten as:

$$\begin{bmatrix} u_a \\ u_b \\ u_c \end{bmatrix} = \begin{bmatrix} R & 0 & 0 \\ 0 & R & 0 \\ 0 & 0 & R \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \begin{bmatrix} L-M & 0 & 0 \\ 0 & L-M & 0 \\ 0 & 0 & L-M \end{bmatrix} \frac{d}{dt} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \begin{bmatrix} e_a \\ e_b \\ e_c \end{bmatrix}$$

From Eq. (27), the BLDCM equivalent circuit is shown in Figure 5 [Figure 5: see original paper].

Figure 5: BLDCM Equivalent Circuit Diagram

Under operating conditions, BLDCM induced electromotive force is proportional to speed and winding turns. Therefore, the armature winding back EMF formula can be expressed by Eq. (28):

$$E = n_p \cdot N_e \cdot \phi \cdot \alpha \cdot n = K_e \cdot n$$

where n_p is pole pairs, N_e is series turns per phase, ϕ is flux per pole, α is pole arc coefficient, n is motor speed, and K_e is back EMF coefficient.

The motor electromagnetic torque equation and motion equation are given by Eq. (29):

$$\begin{cases} T_e = \frac{e_a i_a + e_b i_b + e_c i_c}{\omega} = K_t \cdot i \\ J\frac{d\omega}{dt} = T_e - T_L - B \cdot \omega \end{cases}$$

For single-phase analysis, we obtain $T_e = K_t \cdot i$, where J is rotor inertia (g·cm²), B is damping coefficient, K_t is torque constant (Nm/A), ω is motor speed, and T_L is motor load torque (Nm).

Applying Laplace transform to the above equation set yields the BLDCM dynamic model shown in Figure 6 [Figure 6: see original paper].

Figure 6: BLDCM Dynamic Model Diagram

From Figure 6, the motor transfer function can be expressed by Eq. (30):

$$G(s) = \frac{n(s)}{U(s)} = \frac{K_t}{(L-M)s+R} \cdot \frac{1}{Js+B} \cdot \frac{1}{1 + \frac{K_e K_t}{(L-M)s+R} \cdot \frac{1}{Js+B}}$$

4.3 Controller Design Based on AMF-QPSO Algorithm

Electric vehicles operate under complex conditions requiring frequent speed adjustments, making it difficult for traditional PID controllers to achieve desired performance. This paper adopts a fuzzy PID controller [16] with system structure shown in Figure 7 [Figure 7: see original paper].

Figure 7: BLDCM Speed Control System Based on Fuzzy Adaptive PID

The primary factors affecting controller performance are: (a) PID controller parameters K_p, K_i, K_d; and (b) quantization factors k_e, k_{ec} and scaling factor k_u. While fuzzy PID controllers possess certain adjustment capabilities for K_p, K_i, K_d, their inherent adaptive performance remains limited. To further optimize fuzzy controller performance, this section focuses on optimizing the quantization factors k_e, k_{ec} and scaling factor k_u using the AMF-QPSO algorithm to adapt to system parameter variations and enhance anti-interference and adaptive capabilities. The algorithm structure is shown in Figure 8 [Figure 8: see original paper].

Figure 8: AMF-QPSO Algorithm Optimizing Fuzzy PID

If the controlled variable error e and its change rate ec serve as system inputs, with basic domains $[e_L, e_H]$, $[ec_L, ec_H]$, and output variable u basic domain $[u_L, u_H]$, the fuzzy domains are determined by Eq. (31):

$$\begin{cases} e_f = \{-N_i, \dots, 0, \dots, N_i\} \\ ec_f = \{-N_j, \dots, 0, \dots, N_j\} \\ u_f = \{-N_k, \dots, 0, \dots, N_k\} \end{cases}$$

The quantization factors k_e, k_{ec} and scaling factor k_u are then determined by Eq. (32):

$$k_e = \frac{N_i}{e_H - e_L}, \quad k_{ec} = \frac{N_j}{ec_H - ec_L}, \quad k_u = \frac{u_H - u_L}{N_k}$$

Environmental factors and parameter errors often cause deviations between theoretical and actual values, resulting in strong system performance randomness and parameter sensitivity. Therefore, practical applications require empirical adjustments. This section addresses this challenge by employing the AMF-QPSO algorithm to optimize the tuning process of quantization factors k_e, k_{ec} and scaling factor k_u in the fuzzy PID controller, enabling adaptation to system parameter changes and enhancing anti-interference and adaptive performance.

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5 Experimental Platform and Results Analysis

5.1 Experimental Platform Construction

Actual electric vehicle speed control systems involve complex hardware and software operating conditions. For laboratory research convenience, the hardware system employs a small BLDCM manufactured by Maxon Company to simulate electric vehicle motors. Detailed parameters are listed in Table 5 . The inverter circuit is built around ST' s dedicated integrated chip L6235.

Table 5: Brushless DC Motor Parameters

Parameter	Value
Rated Voltage/U	(value)
Rated Power/P	(value)
Rated Speed/n	(value)
Rated Torque/T	(value)
Phase Inductance/L	1.6×10 H
Phase Resistance/R	0.51 Ω
Back EMF/KE	$1.47×10^{3}$
Torque Constant/KT	5.54×10 $Kg \cdot m^2$
Rotor Inertia/J	(value)

Parameter	Value

The software design utilizes ActiveX technology to integrate LabVIEW and MATLAB. LabVIEW primarily completes data acquisition and processing, system fitting, and connects with MATLAB for executing the AMF-QPSO algorithm and comparison algorithms. The entire experimental platform framework is shown in Figure 9 [Figure 9: see original paper].

Figure 9: Experimental Platform System Block Diagram

The system comprises two main components: the AMF-QPSO algorithm execution unit and the Simulink simulation unit. The AMF-QPSO algorithm is implemented via S-Function in MATLAB. Particle dimension is set to 3, representing two quantization factors and one output factor, with population size 20 and maximum iterations 500. Other control parameters reference Section 3.1. The fuzzy PID controller and BLDCM control system are built using Simulink toolbox, where the fuzzy PID controller uses BLDCM speed error e and its change rate ec as inputs, with adjustment quantities ΔK_p, ΔK_i, ΔK_d as outputs. The fuzzy set is {NB, NM, NS, ZE, PS, PM, PB}. Variable basic domains and fuzzy domains are shown in Table 4 . Fuzzy rules follow literature [17], with triangular membership functions and "if⋯then" rule format, using centroid method for defuzzification.

Table 4: Fuzzy Adaptive PID Controller Parameters

Parameter	Basic Domain	Fuzzy Domain	Quantization/Scaling Factor
e	[-100, 100]	[-6, 6]	6/100
ec	[-10 , 10]	[-6, 6]	6/10
u	[-0.01, 0.01]	[-6, 6]	0.01/6

To balance system dynamic and static characteristics while ensuring steady-state error approaches zero, the fitness function is determined by Eq. (33) to maintain overshoot σ and settling time t_s within small ranges:

$$\text{fitness} = k_1 \int_0^{\infty} e(t)dt + k_2\sigma + k_3 t_s$$

where k_1, k_2, k_3 are weighting coefficients determined by actual system performance priorities.

5.2 Controller Dynamic Performance Analysis

To verify controller dynamic performance, a unit step signal serves as the test input. Traditional fuzzy PID (Fuzzy), QPSO-optimized fuzzy PID (QPSO-Fuzzy), and AMF-QPSO-optimized fuzzy PID (AMF-QPSO-Fuzzy) algorithms are executed sequentially on the MATLAB platform. LabVIEW calls MATLAB processes via ActiveX, acquires actual motor operating status through a data acquisition card (DAQ), constructs the electric vehicle speed control system model based on Sections 4.1 and 4.2, and outputs PWM control signals to the inverter circuit. System output response curves are observed on the host computer interface, with experimental results shown in Figure 10 [Figure 10: see original paper].

Figure 10: Step Response Curves Under Different Control Strategies

To quantitatively compare controller performance advantages, performance indicators including steady-state error, overshoot, and settling time under unit step input are calculated, with results shown in Table 6 .

Table 6: Performance Indicators Under Unit Step Input

Control Strategy	Steady-State Error (%)	Overshoot (%)	Settling Time (s)
Fuzzy	1.0006	1.0010	1.0014
QPSO-Fuzzy	1.0018	1.0022	(value)
AMF-QPSO-Fuzzy	(value)	(value)	(value)

The experimental data from Figure 10 and Table 6 demonstrate that controllers optimized by QPSO and AMF-QPSO algorithms outperform traditional fuzzy PID controllers in steady-state error, overshoot, and settling time. Although the AMF-QPSO-optimized controller exhibits higher complexity resulting in slightly slower rise time compared to the QPSO-optimized controller, it demonstrates absolute superiority in steady-state error, overshoot, and settling time.

To further verify anti-interference and adaptive performance of the AMF-QPSO-optimized fuzzy PID controller, a square wave signal with amplitude 1 is applied to simulate periodic interference during electric vehicle operation. Experimental results are shown in Figure 11 [Figure 11: see original paper], with detailed views in Figure 12 [Figure 12: see original paper].

Figure 11: Square Wave Response Curves Under Different Control Strategies

Figure 12: Detailed Square Wave Response Curves

Figures 11 and 12 show that although the AMF-QPSO-optimized fuzzy PID controller responds slightly slower than the QPSO-optimized controller, it exhibits absolute advantages including smaller overshoot, higher steady-state precision, and stronger anti-interference and adaptive capabilities.

5.3 Controller Speed Regulation Performance Analysis

Speed regulation performance is tested through a 0.4 s simulation via no-load and loaded experiments. The system starts under no-load conditions with a target speed of 1000 r/min. At $t = 0.1$ s, a sudden load $T_L = 0.03$ N·m is applied to simulate a 5° slope increase and corresponding grade resistance increase. At $t = 0.2$ s, speed is adjusted to 2000 r/min to simulate sudden acceleration. System speed response curves and torque response curves are shown in Figures 13-15 [FIGURE:13-15].

Figure 13: Speed Response Curves Under Different Control Strategies

Figure 14: Detailed Speed Response Curves

Figure 15: Torque Variation Under Different Control Strategies

Figure 13 shows that the AMF-QPSO-optimized controller outperforms traditional fuzzy PID and QPSO-optimized fuzzy PID controllers in speed regulation performance. Detailed advantages are illustrated in Figure 14:

- **Figure 14(a)** (No-load startup): The AMF-QPSO-optimized controller achieves optimal steady-state precision with error only 0.05%, though slightly slower than QPSO-optimized controller.
- **Figure 14(b)** (Sudden load at $t = 0.1$ s): Traditional fuzzy PID shows poor anti-interference capability, struggling to restore pre-load speed. QPSO-optimized controller responds quickly but exhibits large speed and torque fluctuations. AMF-QPSO-optimized controller, while slightly slower, achieves high precision with minimal fluctuations and strong anti-interference capability.
- **Figure 14(c)** (Speed adjustment at $t = 0.2$ s): Traditional fuzzy PID responds slowest with steady-state error and 0.3% overshoot. QPSO-optimized controller responds fastest but also shows steady-state error and 0.3% overshoot. AMF-QPSO-optimized controller, though requiring 0.075 s, achieves minimal overshoot (0.025%) with virtually no steady-state error.

In summary, the AMF-QPSO-optimized fuzzy PID controller leverages the algorithm' s efficient and precise global search performance to quickly adjust control parameters to optimal values, adapting to system parameter changes, reducing steady-state error, avoiding speed jitter, and improving system control performance and anti-interference capability.

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6 Conclusion

This paper analyzed the relationship between the CE coefficient and potential well length, proposed the concept of particle activity measured by potential well length relative change rate, and utilized particle activity as feedback for adaptive CE coefficient adjustment. Simultaneously, to prevent severe diversity loss in later evolutionary stages and avoid premature convergence, an elite group random crossover learning mechanism was proposed, allowing low-activity elite individuals to randomly exchange dimensional information with other population members, enhancing population diversity and accelerating later-stage search speed and convergence precision.

To validate algorithm performance, the AMF-QPSO algorithm was applied to optimize fuzzy controller parameters in electric vehicle speed control systems. Using LabVIEW as the experimental platform, comparative experiments with traditional fuzzy PID and QPSO-optimized fuzzy PID controllers demonstrated that the AMF-QPSO-optimized controller exhibits excellent response speed, control precision, and strong adaptive/self-tuning capability against system disturbances, holding significant importance for electric vehicle speed controller optimization.

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Note: Figure translations are in progress. See original paper for figures.