A novel PID controller for BLDCM speed control using dual fuzzy logic systems with HSA optimization

Tingting Wang1,2, Hongzhi Wang1,2, Chuhang Wang3,2 & Huangshui Hu2

In order to enhance the speed control performance of the brushless DC motor (BLDCM), a novel proportion integration differentiation (PID) is proposed in this paper by using dual fuzzy logic systems (FLSs) with harmony search algorithm (HSA) optimization, which is called DFPID-HSA. Firstly, the FLS1 in DFPID-HSA locks the three coefficients of the PID controller in an extensive range on the basis of the system error and error change rate. Then, the FLS2 is optimized by HSA (HSA-F2) to obtain the precise correction of the three coefficients. To get the optimal global harmony better, the improved dynamic adjustment mode is used for the pitch adjustment rate (PAR) and distance bandwidth (BW) in HSA, and the triple selection method is adopted in the composition harmony section to realize the global search. Finally, DFPID-HSA provides the optimal supply control signal to BLDCM so that it can control the speed effectively. Moreover, the stability of the system is analyzed by the pole, Lyapunov, and Nyquist determination methods. And the sensitivity analysis of DFPID-HSA is carried out under the condition of different motor's mechanical parameters to check its robustness. In addition, the superiority of DFPID-HSA is verified by MATLAB simulation and experiment platform.

Brushless direct current motor (BLDCM) has been successfully applied to electric vehicles1,2, aerospace3,4, photovoltaic water pumps5, and other industrial and agricultural fields due to its advantages such as good speed regulation performance, high power density, high reliability, and easy control6. Given the broad application of BLDCM, the research on its control problem is of great importance. In the face of the progress and development of science and technology, people's demand for motor control problems also increases day by day. For decades, experts and scholars have proposed various intelligent control strategies to obtain better control performance of motors7.

For BLDCM control systems, PID is one of the most classic control strategies. Generally, P (proportional), I (integral), and D (differential) can be make up many forms. For example, PI, PD, PID have been successfully implemented in the BLDCM's speed control8,9. Although the traditional PID structure can be easily implemented in the control system of the motor, its drawbacks, such as non-deterministic parameters and nonlinear problems, lead to the system being unable to achieve the optimal control effect. Therefore, many intelligent algorithms optimized PID controllers are put forward. Gobinath and Mu et al.10,11 adopt neural networks to optimize PID form controllers. Although the control performance is improved, the neural network training process is online or offline, with high computational complexity and slow response speed. Dat and Xie et al.12,13 use particle swarm optimization algorithm to optimize PID structure controllers, and the control performance is improved to a large extent. Still, it is difficult for the particle swarm algorithm to find the optimal solution through particle or individual iteration. Demirtas14 proposed the genetic algorithm to optimize the PI controller's gains, but its initial population is challenging to determine. However, fuzzy logic control does not require a precise system model, and only calculations ground on expert knowledge bases. Therefore, optimization methods ground on fuzzy logic control has better control effects than other algorithms in most cases15,16. For example, He et al.17 proposed a new fuzzy self-tuning PID optimal controller based on the analysis of the basic working principle of brushless dc motor. The controller output switches power MOSFET devices by changing the duty ratio of PWM control signal to realizes the speed control of brushless DC motor. Yin et al.18 designed a fuzzy parameter adaptive PI control algorithm based on the speed loop of brushless DC motor, which has good control effect and robustness and can ensure the stable operation of the system under under variable speed conditions.

1College of Mechatronic Engineering, Changchun University of Technology, Changchun 130012, China. 2College of Computer Science and Engineering, Changchun University of Technology, Changchun 130012, China. 3College of Computer Science and Technology, Changchun Normal University, Changchun 130032, China. *email: wangchuhang@ccsfu.edu.cn
The superiority of the fuzzy logic control optimization algorithm is obvious, yet its shortcomings are also inevitable. The definition of its knowledge rule base is not scientific, so its adjustment of PID parameters still needs to be optimized. In21, an ANFIS controller with fuzzy PID online supervision is adopted to realize speed control of BLDCM, which has good performance under various driving conditions. However, it still fluctuates slightly in the steady-state. Premkumar and Valdez et al.9,20 adopted using bat algorithm, particle swarm, and other group optimization algorithms to adjust the fuzzy PID controller adaptively. In22, the adaptive fuzzy neural network control algorithm is adopted to realize the speed tracking of the BLDCM drive system. Rubaai et al.22 adopted the genetic algorithm to optimize the scale factor of the output variable of the fuzzy PID controller. In23, a speed control method of BLDCM based on the genetic algorithm optimizing fuzzy PID membership function and rule base is proposed. All the above algorithms have better control effects than the traditional fuzzy PID control method, and they also have the limitations of the algorithm mentioned in the previous section. Harmony search algorithm (HSA) is a newly published heuristic global search algorithm, which has been successfully implemented in many combinatorial optimization solution problems24,25, such as solving continuous optimization problems26, solving unconstrained problems27, and also in field of motor28,29. It is shown that the harmony search algorithm has better performance than the genetic algorithm, simulated annealing algorithm, and tabu search algorithm, etc. In30, an optimization method combining harmony search algorithm with fuzzy logic is successfully proposed, and the superiority of the process is verified.

Based on the descriptions of the above algorithm mentioned, this paper proposes a novel PID controller using dual FLSs with HSA optimization called DFPID-HSA to enhance the various speed control performance of BLDCM. The major contributions of this paper are as follows.

1. DFPID-HSA adopts dual FLSs, in which the FLS1 locks the three coefficients of the PID controller in an extensive range on the basis of the system error and the error change rate. Then, the FLS2 is optimized by HSA (HSA-F2) to obtain the precise correction of the three coefficients.

2. To better obtain the optimal global harmony, the PAR and BW of HSA adopt the improved dynamic adjustment mode. In the composition harmony section, the triple selection method is used to achieve the optimal global search. Finally, DFPID-HSA provides the optimal control signal to BLDCM to realize the speed control of BLDCM.

3. The stability of the proposed controller is analyzed by the pole determination method, the Lyapunov determination method, and the Nyquist determination method. Then the system has been demonstrated to be closed-loop stable.

4. The performance indicators about steady-state, transient, and integral of DFPID-HSA are compared with the deep perceptron neural network optimized fuzzy PID controller (DPNN-FuzzyPID)30, the fuzzy logic PID controller optimized by genetic algorithm (GA-PID-FLC)31, the fuzzy logic PID controller based on particle swarm optimization (PSO-FuzzyPID)10, PID controller with fuzzy logic regulation (FuzzyPID)15, and conventional PID controller (PID) by Matlab. The superiority of DFPID-HSA in BLDCM speed control is verified. And the sensitivity analyses of DFPID-HSA are carried out under mechanical parameters variations of the motor to check its robustness.

5. The BLDCM drive system experimental platform is built. Under three experimental conditions, it is verified that DFPID-HSA still maintains its superiority and can achieve excellent control of the BLDCM, which proves the feasibility of the algorithm.

The electromotive torque generated by the stator winding is

\[ \epsilon_{x} = \epsilon_{x} + \epsilon_{y} + \epsilon_{w} \]

where, \( u_{x}, i_{x}, \epsilon_{x} (x = u, v, w) \) and \( R \) denotes the phase voltage, phase current, back electromotive force, and phase impedance of the stator windings, respectively. \( L \) and \( M \) represent the self-inductance and pairwise mutual inductance of the three-phase windings, respectively.

The electromagnetic torque generated by the stator winding is

\[ T_{e} = (\epsilon_{x}i_{x} + \epsilon_{y}i_{y} + \epsilon_{w}i_{w})/\omega_{m} \]

where, \( \omega_{m} \) and \( T_{e} \) represent the mechanical angular speed and electromagnetic torque of the BLDCM, respectively.
The equation of motion of the BLDCM is as follows:

\[ T_e = T_m + B \frac{d\omega_m}{dt} + J\omega_m \]  (3)

where, \( T_m \), \( B \) and \( J \) represent load torque, damping coefficient, and moment of inertia, respectively. Hence, the characteristic equation of BLDCM can be expressed as:

\[ \frac{s^2 + \frac{B}{J}s + \frac{T_m}{J}}{s + \frac{1}{R(s+1)}} = 0 \]

where, \( K_{emf} \) is the back electromotive force constant. Figure 1 is the equivalent circuit of BLDCM.

**Figure 1.** Equivalent circuit of BLDCM.

**Figure 2.** Block diagram of the speed control system for BLDCM.

| Parameters                  | Value       | Units       |
|-----------------------------|-------------|-------------|
| Stator phase resistance \( R \) | 2.875       | \( \Omega \) |
| Stator phase inductance \( L \)   | 0.0085      | \( H \)     |
| Flux linkage established by magnets \( \lambda \) | 0.175       | \( V\cdot s \) |
| Voltage constant            | 0.1466      | \( V/(r/\text{min}) \) |
| Torque constant             | 1.4         | \( N\cdot m/A \) |
| Moment of inertia \( I \)    | 0.0008      | \( (kg\cdot m^2) \) |
| Friction factor \( B \)      | 0.001       | \( N\cdot m/s/\text{rad} \) |
| Pole pairs \( P \)           | 4           | -           |
| Inverter gain \( K_w \)      | 500         | -           |
| Inverter time constant \( T_w \) | \( 5 \times 10^{-6} \) | s |

**Table 1.** Basic parameters of BLDCM.

The basic equations for the BLDCM are:

\[
\begin{align*}
  u_i(t) &= R i(t) + L \frac{d i(t)}{dt} + e_c(t) \\
  e_c(t) &= K_{emf} \omega_m(t) \\
  T_e(t) &= K_{emf} i(t) \\
  T_e(t) &= J \frac{d\omega_m(t)}{dt} + B\omega_m(t) + T_m
\end{align*}
\]  (4)

where, \( K_{emf} \) is the back electromotive force constant. Figure 2 is the block diagram of the speed control system for BLDCM. The proposed controller mainly realizes tracking control for the speed of the BLDCM. Table 1 gives the basic parameters of BLDCM and inverter. From the characteristic equation of the BLDCM given in Eq. (4), the transfer function model of the BLDCM is deducted as,
The transfer function model of the PWM inverter is given as,

\[ \frac{y(s)}{u_s(s)} = \frac{K_{emf}}{R(Ts + 1)(Js + B) + K_{emf}^2} \]  

(5)

The transfer function model of the PWM inverter is given as,

\[ \frac{u(s)}{u_s(s)} = \frac{K_w}{T_w s + 1} \]  

(6)

**Proposed DFPID-HSA controller**

Aiming at the speed control problem for BLDCM, this paper proposes an HSA optimized dual fuzzy logic systems-based PID controller called DFPID-HSA. The specific control system construction is given in Fig. 2. Firstly, the FLS1 in DFPID-HSA locks the proportional coefficient \( K_P \), integral coefficient \( K_I \), and differential coefficient \( K_D \) of PID controller in a wide range on the basis of the system error \( e \) and error change rate \( ec \). Then, the accurate correction value \( k_p' \), \( k_i' \), \( k_d' \) of \( K_P \), \( K_I \), \( K_D \) is obtained by HSA optimized FLS2. In order to get the optimal global harmony better, the PAR and BW in HSA adopt the improved dynamic adjustment mode, and the triple selection method is adopted in the composition harmony section to realize the optimal global search. Finally, DFPID-HSA provides the optimal control signal \( u(t) \) to BLDCM to realize the speed control.

According to the structure in Fig. 3, it is known that \( e = y - r \), \( ec = de/dt \), and the control signal \( u(t) \) can be given as

\[ u(t) = K_p e + K_i \int e dt + K_d \frac{de}{dt} \]  

(7)

where, \( K_p \), \( K_i \), and \( K_d \) in A are determined by the output parameters \( K_{P1}/K_{I1}/K_{D1} \) of FLS1 in DFPID-HSA, and the output parameters \( k_p'/k_i'/k_d' \) of HSA Optimized FLS2.

\[
\begin{aligned}
K_P &= K_{P1} + k_p' \\
K_I &= K_{I1} + k_i' \\
K_D &= K_{D1} + k_d'
\end{aligned}
\]  

(8)

**Fuzzy logic system.** The fundamental structure of the fuzzy logic system is given in the dashed box in Fig. 2, and it mainly consists of the below four parts:

- **Fuzzification**
  The role of fuzzification is to transform the precise input quantity into fuzzification quantity. The input contains external reference input, system output or state, etc.

- **Knowledge bases**
  The knowledge bases include the knowledge in the specific application field and the required control objectives. It mainly consists of two parts: databases and fuzzy control rule bases.

- **Fuzzy Inference engine**
  The fuzzy inference engine is the kernel of FLS, which has the inference capacity of simulating humans ground on fuzzy concepts. The inference process is ground on the implication relationship and inference rules in fuzzy logic.

- **Clarification**
  The role of clarification is to convert the fuzzy quantity (control quantity) got by fuzzy inference engine into the precise quantity of practical application control.
In DFPID-HSA, both FLS1 and FLS2 adopt dual-input dual-output Mamdani controllers. The fuzzification process of FLS1 and FLS2 is mainly to convert the actual values of the system speed error $e$ and error change rate $e\dot{c}$ into the corresponding fuzzy values according to the fuzzy domains and membership functions. The fuzzy domain of input and output variables in FLS1 is: $e, e\dot{c} = [-3, 3], K_{P1}, K_{I1}, K_{D1} = [0, 60]$; the fuzzy domain of input and output variables in FLS2 is: $e, e\dot{c} = [-1, 1], k_{f}, k_{d} = [0, 6]$. The fuzzy language set of FLS1 and FLS2 input variables is $\{NB, NM, NS, ZO, PS, PM, PB\} = \{\text{negative big}, \text{negative middle}, \text{negative small}, \text{zero}, \text{positive small}, \text{positive middle}, \text{positive big}\}$; The fuzzy language set of FLS1 and FLS2 output variables is $\{VS, MS, S, M, B, MB, VB\} = \{\text{very small}, \text{medium small}, \text{small}, \text{medium}, \text{big}, \text{medium big}, \text{very big}\}$.

Figure 4. Membership function of FLS1: (a) input variables (b) output variables.

Figure 5. Membership function of FLS2: (a) input variables (b) output variables.

The membership functions of input and output variables of FLS1 and FLS2 are shown in Figs. 4 and 5, respectively. In this paper, the membership functions mainly choose isosceles triangle type and Gaussian function type. The isosceles triangle has the advantages of being convenient for representation, simple for calculation, and fast for the response. The edge values of the fuzzy sets mainly adopt the Gaussian function, which makes its value smoother and more adaptive. The fuzzy rules of different output variables of FLS1 and FLS2 are shown in Table 2. The establishment of fuzzy rules refers to the experience of experts and is modified through multiple simulations. Specific fuzzy rules can be written in the following form:

- If $e = e_f$ and $e\dot{c} = e\dot{c}_f$, then $K_{P1} = K_{P1f}$ and $K_{I1} = K_{I1f}$ and $K_{D1} = K_{D1f}$;
- If $e = e_f$ and $e = e\dot{c}_f$ then $K_{P1f} = K_{Pf}$ and $K_{I1f} = K_{If}$ and $K_{D1f} = K_{Df}$; (i = 1, 2, 49; each variable representing 49 rules).

where, $e_f, e\dot{c}_f, K_{P1f}, K_{I1f}, K_{D1f}, K_{Pf}, K_{If}, K_{Df}$ represent the fuzzy language sets of $e, e\dot{c}, K_{P1}, K_{I1}, K_{D1}, K_{P}', K_{I}', K_{D'}$.

Taking $K_{P1}$ as an example, the membership degree of the first fuzzy rule of $K_{P1}$ is

$$\mu_{K_{P1}} = \mu_{NB}(e) * \mu_{NB}(e\dot{c})$$

where, "$*$" means to take the smaller, i.e.

$$\mu_{K_{P1}} = \min[\mu_{NB}(e), \mu_{NB}(e\dot{c})]$$

By analogy, the membership degrees of all fuzzy rules corresponding to $K_{P1}$ under different $e$ and $e\dot{c}$ can be obtained. According to the membership degree of each fuzzy rule, the fuzzy value of $K_{P1}$ can be obtained by Clarifying with the center of gravity method

$$K_{P1} = \frac{\sum_{f=1}^{49} \mu_{K_{P1f}}(K_{P1})K_{P1f}}{\sum_{f=1}^{49} \mu_{K_{P1f}}(K_{P1})}$$

where, $K_{P1f}$ is a real value on the domain $K_{P1} = [0, 60], \mu_{K_{P1f}}$ is the membership degree of corresponding fuzzy rules. Similarly, the fuzzy output value of $K_{I1}, K_{D1}, K_{P}', K_{I}', K_{D'}$ in each sampling period can be obtained.
Harmony search algorithm. Harmony Search Algorithm (HSA) is a heuristic algorithm put forward by Geem et al.\textsuperscript{37}, with strong global convergence. HSA is a simulation of the process by which musicians iteratively adjust the tones of various musical instruments to achieve the most beautiful harmony finally\textsuperscript{38,39}. The evolution speed of HSA is faster than that of intelligent algorithms such as the genetic algorithm and has fewer mathematical requirements. HSA mainly consists of five steps\textsuperscript{40,41} which are as follows:

1. Define problem and parameter values

   (1) This paper belongs to the problem of minimization, that is:
   \[
   \min f(X), \quad X = \{x_1, x_2, \ldots, x_n\} \in \mathbb{R}^n
   \]
   where, \(x_i \in X_i, \quad i = 1, 2, \ldots, n, \quad x_i \in [X_{i_{\min}}, X_{i_{\max}}]\)

   (2) Determine parameter values.

   - Harmony memory size (HMS): Size of the harmonic population.
   - Harmony memory considering rate (HMCR): Probability of taking a harmony voice from the existing population.
   - Pitch adjusting rate (PAR): Probability of adjusting the harmony voice.
   - Bandwidth (BW): Amplitude of pitch adjusting.
   - Times of creation (Tmax): Times of adjustment (iteration).

2. Obviously, a set of suitable parameters can enhance the algorithm’s ability to search for the global optimal or close to the optimal region and has a high convergence speed. Where the parameter BW is the distance bandwidth of continuous design variables. An enormous BW value is conducive to search the algorithm in an extensive range, and a small BW value is suitable for adjusting the optimal solution. To better obtain the objective optimization results, the BW value in this paper decreases dynamically with the increase of iteration times. The improved dynamic adjustment method is as follows:

   \[
   BW = BW_0 \times e^{-t/T_{\text{max}}}
   \]

   where, \(BW_0\) is the initial coefficient of pitch adjusting bandwidth, and \(t\) is the current times of iteration.

| \(e\) | NB | NM | NS | ZO | PS | PM | PB |
|------|----|----|----|----|----|----|----|
| Fuzzy rules for \(K_{i_0}/k_p\) | NB | VB | MB | MB | B  | B  | M  |
|      | NM | VB | MB | MB | B  | B  | M  |
|      | NS | MB | MB | MB | B  | M  | S  |
|      | ZO | MB | MB | MB | B  | M  | S  |
|      | PS | B  | B  | M  | S  | S  | MS |
|      | PM | B  | S  | S  | MS | MS | VS |
|      | PB | M  | S  | S  | MS | MS | VS |
| Table 2. | Fuzzy rules for different output variables of FLS1 / FLS2. |
PAR is the adjustment rate of the pitch. An enormous PAR value is conducive to transmitting the information of $x_i$ to the next generation, which enhances the local development capabilities of the algorithm near $x_i$. In contrast, a small PAR value capacitates the new harmony vector to expand the search range and increase the multiplicity of the harmony memory by disturbing the values of the corresponding dimensions in the harmony memory. As the times of iteration increase, it is closer to obtaining better harmony, so the probability of adjusting harmony should also be reduced. In this paper, an improved dynamic adjustment is adopted for PAR, as follows:

$$PAR = PAR_0 \times (1 - \frac{t}{T_{\text{max}}})$$  \hspace{1cm} (14)

where, $PAR_0$ and $t$ stand for the initial coefficient of pitch adjusting rate and the current times of iteration, respectively.

2. Initialization of harmony memory

HMS harmonies $X^1, X^2, \ldots, X^{HMS}$ are randomly created from the solution space of $X$ and put into the harmony memory. The matrix form of the harmony memory is:

$$HM = \begin{bmatrix} X^1 \\ X^2 \\ \vdots \\ X^{HMS} \end{bmatrix}$$  \hspace{1cm} (15)

$HM$ adopts external random values to prevent falling into local optimization or local convergence, as in Eq. (16)

$$x_i = x_{i_{\text{min}}} + (x_{i_{\text{max}}} - x_{i_{\text{min}}}) \times r_0$$  \hspace{1cm} (16)

where, $r_0$ is a random number between $[0, 1]$.

3. Generate a new harmony

Generate a random number $r_1$ between $[0, 1]$, compare with HMCR, If $r_1 < \text{HMCR}$, take a random harmony variable from the harmony memory, Otherwise, a random harmonic variable is created from the solution space; A harmony variable is got from the above. If the harmony variable is got from the harmony memory, it is necessary to adjust it to generate a random number $r_2$ between $[0, 1]$. If $r_2 < \text{PAR}$, adjust the resulting harmony variable on the basis of BW and get a new harmony variable, Otherwise, to avoid that the performance of the randomly generated harmony in the solution space is worse than that of the best harmony $x_{i_{\text{best}}}$ in $HM$, $x_{i_{\text{best}}}$ is used to replace the randomly generated harmony. Finally, we get a new harmony $x_{\text{new}}$:

$$x_{\text{new}} = \begin{cases} x_{i_{\text{old}}} \pm BW \times r_3, & r_1 < \text{HMCR} \cup r_2 < \text{PAR} \\ x_{i_{\text{best}}}, & r_1 < \text{HMCR} \cup r_2 \geq \text{PAR} \\ x_{i_{\text{min}}} + (x_{i_{\text{max}}} - x_{i_{\text{min}}}) \times r_0, & r_1 \geq \text{HMCR} \end{cases}$$  \hspace{1cm} (17)

where, $r_0, r_1, r_2$ and $r_3$ are random numbers between $[0, 1]$.

4. Update harmony memory

Evaluate $X_{\text{new}}$, i.e. $f(X_{\text{new}})$. If it is better than the one with the worst function value in $HM$, i.e. $f(X_{\text{new}}) < f(X_{\text{worst}})$, then $X_{\text{new}}$ will replace $X_{\text{worst}}$; Otherwise, no modification is made.

5. Determine the stop condition

Repeat steps (3) and (4) until the times of creation (iteration) reach $T_{\text{max}}$.

In this paper, HSA is used to optimize FLS2 to obtain the accurate correction value $kp'/ki'/kd'$ of FLS1 parameters. Since the BLDCM speed control system belongs to the problem of minimizing the error $e$, the cost function is defined as the Integral absolute error (IAE).

$$IAE = \int_0^t |e(t)|dt$$  \hspace{1cm} (18)

The constraints of optimization variables are as follows:

$$\begin{cases} 0 \leq kp' \leq 6 \\ 0 \leq ki' \leq 6 \\ 0 \leq kd' \leq 6 \end{cases}$$  \hspace{1cm} (19)

Then, the harmony memory is

$$HM = \begin{bmatrix} k_{p1}' & k_{i1}' & k_{d1}' \\ k_{p2}' & k_{i2}' & k_{d2}' \\ \vdots & \vdots & \vdots \\ k_{pHMS}' & k_{iHMS}' & k_{dHMS}' \end{bmatrix}$$  \hspace{1cm} (20)

The flow chart of the HSA-F2 algorithm is shown in Fig. 6, and the specific steps are shown in Table 3.
Stability analysis

This section analyzes the stability of the closed-loop system of the speed control for BLDCM based on the novel PID controller using dual fuzzy logic systems with HSA optimization. The pole determination method, Lyapunov determination method, and Nyquist determination method are used to verify the stability of the system. To test the stability, the transfer function of the closed-loop system needs to be used. Adopting bilinear transformation, the closed-loop transfer function of the optimized DFPID-HSA controlled BLDCM is provided in Eq. (21), where the transfer function of the proposed controller can be equivalent to

$$G_C(s) = \frac{5.864s^2 + 5255.61s + 397.286}{2.3 \times 10^{-9}s^4 + 4.6 \times 10^{-9}s^3 + 5.867s^2 + 5255.635s + 397.286}$$

(21)

Pole determination method. According to the analysis of the unit step response of the higher-order system, it is the dynamic component that affects the change of system output with time. Whether the dynamic component attenuates only depends on the sign of the closed-loop pole of the system. A necessary and sufficient condition for system stability: all poles of the closed-loop system are negative real numbers or conjugate complex numbers with negative real parts. In other words, all closed-loop nodes must distribute on the left half of the S-plane. Figure 7 lays out the pole-zero plot of the speed control system for the BLDCM based on DFPID-HSA. It is observed from the pole-zero plot that all the poles are on the left half of the S-plane, thus indicating that the system is stable.

Figure 6. The flow chart of HSA-F2.
(1) FLS2 parameter initialization (input dimension, output dimension, fuzzy rule number, and fuzzy rule base), HSA parameter initialization (HM, HMCr, PAR0, BW0, and Tmax).

(2) Define the cost function IAE.

(3) Generate the random variable as follows:
\[ t=0; \quad \% \text{Current times of iteration} \]

\[ \text{for } i=1 \text{ to } H \text{ do} \]
\[ \text{for } k=1 \text{ to } n \text{ do} \]
\[ x_i = x_{\text{min}} + (x_{\text{max}} - x_{\text{min}}) * \text{rand}(0,1) \quad \% \text{random variable } x_i \]

(4) Create new harmony as follows:
\[ \text{While } t<T_{\text{max}}: \]
\[ \text{PAR} = \text{PAR}_0 * (1 - t/T_{\text{max}}) \quad \% \text{PAR generation, as the times of iteration increases, PAR becomes smaller} \]
\[ \text{BW} = \text{BW}_0 * \exp(-t/T_{\text{max}}) \quad \% \text{BW generation, as the times of iteration increases, BW becomes smaller} \]

\[ \text{for } i=1 \text{ to } n \text{ do} \]
\[ r1 = \text{rand}(0,1); \]
\[ \text{if } (r1 < \text{HMCr}) \text{ then} \quad \% \text{memory consideration} \]
\[ x_{\text{new}} = x_{\text{best}} \]
\[ r2 = \text{rand}(0,1); \]
\[ \text{if } (r2 < \text{PAR}) \quad \% \text{pitch adjusting} \]
\[ r3 = \text{rand}(0,1); \]
\[ x_{\text{new}} = x_{\text{old}} + \text{BW} * r3 \]
\[ \text{end if} \]
\[ \text{else} \]
\[ x_{\text{new}} = x_{\text{min}} + (x_{\text{max}} - x_{\text{min}}) * \text{rand}(0,1) \]
\[ \text{end if} \]
\[ \text{end for} \]

(5) Update harmony memory as follows:
\[ x_{\text{max}} = \text{max}(HM) \]
\[ x_{\text{min}} = \text{min}(HM) \]
If \( f(X_{\text{new}}) < f(X_{\text{worst}}) \) then
\[ X_{\text{worst}} = X_{\text{new}} \]
\[ t = t + 1 \]
end while

Table 3. Specific steps of HSA-F2 algorithm.

On the basis of the Matlab command, the zero points (z), pole points (p) and gain (k) of the system are:
\[
\begin{align*}
z &= \begin{bmatrix} -896.1744 & -0.0756 \end{bmatrix} \\
p &= \begin{bmatrix} -1.8638 \times 10^5 & -0.1256 \times 10^5 & -0.0097 \times 10^5 & -0.0000 \end{bmatrix} \\
k &= [2.5496 \times 10^9]
\end{align*}
\] (22)

Lyapunov determination method. Lyapunov is a Russian mathematician who derived the famous stability criteria for linear and nonlinear systems. Lyapunov theorem points out that if there is a unique \( P = P^T > 0 \) satisfying Eq. (23) for any \( Q = Q^T > 0 \), then that system is asymptotically stable:
\[
A^T P + P A = -Q, \quad Q = Q^T, \quad Q = I (\text{Identity matrix})
\] (23)

where, \( Q \) stands for a any positive definite matrix.
To solve the discrete-time Lyapunov equation, the state-space model matrix of the system is required. According to Eq. (21), use the tf2ss() function to obtain the state-space model matrix $A$, $B$, $C$, $D$ of the speed control system for BLDCM based on DFPID-HSA,

$$ A = \begin{bmatrix} -0.0000 & -0.0026 \times 10^{12} & -2.2851 \times 10^{12} & -0.1727 \times 10^{12} \\ 0.0000 & 0 & 0 & 0 \\ 0 & 0.0000 & 0 & 0 \\ 0 & 0 & 0.0000 & 0 \end{bmatrix} $$

$$ B = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}^T $$

$$ C = \begin{bmatrix} 0 \\ 0.0025 \times 10^{12} \\ 2.2850 \times 10^{12} \\ 0.1727 \times 10^{12} \end{bmatrix} $$

$$ D = [0] $$

(24)

Utilize Eq. (23) to obtain the $P$ matrix and its eigenvalues $\lambda$, and determine whether $P$ is positive definite according to $\lambda$.

$$ \lambda = \begin{bmatrix} 5.1698 \times 10^9 \\ 2.3395 \times 10^{12} \\ 8.8436 \times 10^{10} \\ 3.8910 \times 10^7 \end{bmatrix} $$

Both $\lambda$ are positive, which proves that $P$ is positive definite, and Lyapunov criterion confirms that the speed control system of BLDCM based on DFPID-HSA is asymptotically stable.

**Nyquist determination method.** Suppose the open-loop transfer function of the system be $G_C(s)G(s)$. If the system is open-loop stable, the necessary and sufficient condition for the stability of the closed-loop system is that when $\omega$ by $0 \rightarrow \infty$, the open-loop Nyquist curve $G_C(j\omega)G(j\omega)$ of the system does not enclose point $(-1, j0)$, then the closed-loop system is stable. Otherwise, it is unstable.

The Nyquist diagram of the speed control system for BLDCM based on DFPID-HSA is obtained according to the nyquist() function in Matlab, see Fig. 8. It can be seen from the diagram that the system does not contain $(-1, j0)$ point. Therefore, this paper proposes that the DFPID-HSA-based BLDCM speed control system is closed-loop stable.

**Simulation analysis**

In order to verify the superiority of DFPID-HSA in BLDCM speed control, its performances are compared and analyzed with DPNN-FuzzyPID, GA-PID-FLC, PSO-FuzzyPID, FuzzyPID, and PID by MATLAB. The selection of relevant parameters in the comparison algorithms referred to the original literature, followed the selection rules of relevant data, and made reasonable adjustments in the test to ensure the fairness of comparison. The comparison performance indicators mainly include steady-state performance indicators: error (r/min, %), transient performance indicators: delay time, adjustment time, maximum overshoot/undershoot, oscillation, etc., integral performance indicators: Integral absolute error (IAE) criterion, Integral square error (ISE) criterion, Integrated time absolute error (ITAE) criterion, Integral time square error (ITSE) criterion.

The initialization of DFPID-HSA parameters is shown in Table 4, the selection of relevant parameters mainly refers to the experience of experts, and is modified and determined through many simulations. The convergence diagram of DFPID-HSA obtained by running the system based on the corresponding parameters is shown in Fig. 9. It can be seen that the optimal cost of DFPID-HSA is obtained when the iteration reaches 55.
Figure 8. Nyquist diagram of the speed control system for the BLDCM based on DFPID-HSA.

Table 4. Initialization parameters of DFPID-HAS.

| Elements              | Value   |
|-----------------------|---------|
| Search parameter number| 3       |
| HMS                   | 200     |
| HMCR                  | 0.98    |
| PAR0                  | 0.9     |
| BW0                   | 0.01    |
| Tmax                  | 80      |

Figure 9. Solution convergence for DFPID-HAS.

Table 5. The final optimized parameters of $K_p/K_i/K_d$.

| Algorithms/parameters | $K_p$ | $K_i$ | $K_d$        |
|-----------------------|-------|-------|--------------|
| PID                   | 16.6  | 0.013 | $0.1 \times 10^{-5}$ |
| FuzzyPID              | 25.1  | 3.00  | 0.10         |
| PSO-FuzzyPID          | 29.4  | 2.92  | 0.09         |
| GA-PID-FLC            | 34.5  | 3.01  | 0.10         |
| DPNFPII-FuzzyPID      | 40.2  | 3.21  | 0.09         |
| DFPID-HSA             | 71.7  | 5.42  | 0.08         |
The final optimized parameters $K_p/K_i/K_d$ of the four comparison algorithms are shown in Table 5. The integral performance indicators of the four algorithms are shown in Table 6, and the error signal performance indicator analyses are shown in Fig. 10. From the comparison of the error signal performance indicators, it can be seen that DFPID-HSA is the best.

Considering that uncertainties such as load changes and speed changes are prone to occur in the operation of the BLDCM system, the performance comparison and analysis of the four algorithms are carried out under the following three working conditions.

**No-load condition.** Under the no-load condition, the target speed of BLDCM is given to be 2000 r/min. The control system is operated according to different algorithms and obtain the comparison of speed response curves, as shown in Fig. 11. As can be seen from Fig. 11 that all the five algorithms can make the system reach the ideal speed, among which PID has an evident overshoot phenomenon. In contrast, FuzzyPID, PSO-FuzzyPID, GA-PID-FLC, DPNN-FuzzyPID, and DFPID-HSA have no evident overshoot phenomenon. The maximum overshoot MP% and oscillation times $N$ of the five algorithms meet the engineering requirements ($MP\% \leq 50\%$, $n \leq 1.5$). Still, DFPID-HSA has the shortest delay time and settling time, and the smallest steady-state error.

**Table 6.** Observed performance indices for error. $IAE = \int |e(t)| \, dt$, $ISE = \int e^2(t) \, dt$, $ITAE = \int t |e(t)| \, dt$, $ITSE = \int te^2(t) \, dt$.

| Algorithms/performance indicators | $IAE$ | $ISE$ | $ITAE$ | $ITSE$ |
|----------------------------------|------|------|------|------|
| PID                              | 18.38| $2.3327 \times 10^4$| 0.132| 92.52|
| FuzzyPID                        | 9.84 | $0.7962 \times 10^4$| 0.242| 17.73|
| PSO-FuzzyPID                    | 8.17 | $0.6285 \times 10^4$| 0.200| 12.07|
| GA-PID-FLC                      | 7.06 | $0.5357 \times 10^4$| 0.174| 8.91 |
| DPNN-FuzzyPID                   | 6.02 | $0.4493 \times 10^4$| 0.192| 6.39 |
| DFPID-HSA                       | 2.52 | $0.1740 \times 10^4$| 0.084| 1.02 |

**Figure 10.** Error signal performance indicator analyses: (a) $IAE$ (b) $ISE$ (c) $ITAE$ (d) $ITSE$. 
which shows that the control performance of DFPID-HSA is better. See Table 7 for the comparison of specific performance indicators.

**With-load condition.**

(1) Fixed load

The system target speed of 2000 r/min is given as above, and a 3Nm load interference is applied to the system at 0.1 s. The comparisons of speed response and performance indicators are obtained in the operating system, as shown in Fig. 12 and Table 8, respectively. It can be seen from Fig. 12 and Table 8, when
the load is added to the system, the undershoot of PID is the most obvious, and the volatility of FuzzyPID, PSO-FuzzyPID, GA-PID-FLC, DPNN-FuzzyPID, and DFPID-HSA is weak. Among them, the shortest settling time of DFPID-HSA is about 0.001 s, and the smallest steady-state error is 4.5 r/min. It can be seen that DFPID-HSA is obviously better than other algorithms in terms of anti-interference ability.

(2) Variable load

Next, there is a continuous sinusoidal signal load disturbance applied to the system, which is defined as

$$T_m = 20 \sin t, \ 0 \leq t \leq 0.2s.$$  

The comparison of the speed response and performance indexes under the operating system is shown in Fig. 13 and Table 9. From Fig. 13 and Table 9, it can be seen that the oscillation of PID is most obvious when the system is accompanied by sinusoidal signal load and causes severe steady-state errors. The fluctuation of FuzzyPID, PSO-FuzzyPID, GA-PID-FLC, and DPNN-FuzzyPID is weaker. Among them, DFPID-HSA has no obvious fluctuation phenomenon and still maintains the shortest settling time and the smallest steady-state error. It can be seen that DFPID-HSA has good robustness and anti-interference performance.

**Table 8.** The comparison of performance indicators under the fixed load condition.

| Controllers     | Transient performance indicators | Steady-state performance indicators |
|-----------------|----------------------------------|-------------------------------------|
|                 | Maximum undershoot (−Mp%) × 10^{-5} | Peak time (s) | Settling time (s) | Steady-state error (r/min) | Steady-state error (%) |
| PID             | 2342.13                           | 0.108                     | 0.060             | 9.5                          | 0.475                 |
| FuzzyPID        | 7.54                              | 0.121                     | 0.020             | 11.6                         | 0.580                 |
| PSO-FuzzyPID    | 12.31                             | 0.116                     | 0.017             | 9.9                          | 0.495                 |
| GA-PID-FLC      | 9.04                              | 0.116                     | 0.010             | 8.6                          | 0.430                 |
| DPNN-FuzzyPID   | 9.19                              | 0.115                     | 0.009             | 7.5                          | 0.375                 |
| DFPID-HSA       | 6.77                              | 0.100                     | 0.001             | 4.5                          | 0.225                 |

**Figure 13.** The comparison of speed response under the variable load condition.

**Table 9.** The comparison of performance indicators under the variable load condition.

| Controllers     | Transient performance indicators | Steady-state performance indicators |
|-----------------|----------------------------------|-------------------------------------|
|                 | Maximum overshoot (Mp%) | Delay time (s) × 10^{-3} | Settling time (s) | Steady-state error (r/min) | Steady-state error (%) |
| PID             | 0.95                             | 7.20                          | 0.085             | 21.0                         | 1.050                 |
| FuzzyPID        | –                                | 2.65                          | 0.050             | 11.6                         | 0.580                 |
| PSO-FuzzyPID    | –                                | 2.37                          | 0.046             | 10.2                         | 0.510                 |
| GA-PID-FLC      | –                                | 1.83                          | 0.040             | 8.6                          | 0.430                 |
| DPNN-FuzzyPID   | –                                | 1.52                          | 0.030             | 7.6                          | 0.380                 |
| DFPID-HSA       | –                                | 0.60                          | 0.015             | 4.3                          | 0.215                 |

**Speed changes condition.** Speed changes condition is a common situation in the operation of BLDCM, so it is essential to verify the control performance of DFPID-HSA under this working condition. First, the initial target speed of the BLDCM system is given at 2000 r/min in the no-load state, and the speed is increased
to 2500 r/min at 0.1 s, and then reduced to 2000 r/min again at 0.2 s. The corresponding comparison of speed response is shown in Fig. 14, and the comparison data of performance indicators are given in Table 10. It can be seen from Fig. 14 and Table 10, PID is still accompanied by an overshoot/undershoot phenomenon. FuzzyPID, PSO-FuzzyPID, GA-PID-FLC, DPNN-FuzzyPID, and DFPID-HSA have relatively good performance, but DFPID-HSA is optimal for the delay, settling, and steady-state error. Therefore, this proves the superiority of DFPID-HSA once again.

Mechanical parameters variation conditions. In view of the optimization control problem of DFPID-HSA in this paper, it is essential to analyze the sensitivity of mechanical parameters variations of the BLDCM system. Here, the resistance, inductance, flux linkage, and inertia of the BLDCM system are adjusted for the corresponding increases or decreases, and the corresponding curves under the conditions of the relevant mechanical parameters variations are given in Fig. 15. As can be seen from the figures, even if the relevant mechanical parameters increase or decrease in amplitude, DFPID-HSA can still achieve speed tracking well, without overshoot/undershoot and oscillation. It only changes in the delay time and stability time, but this does not affect the final stability of the system. Hence, it can be certified that DFPID-HSA has excellent robustness.

Experimental analysis

To further verify the feasibility of DFPID-HSA, the experimental platform for the BLDCM control system is set up, as shown in Fig. 16. The BLDCM used in the testing platform is 80BL110S50-445TKA, and its driver adopts the IR2235 drive chip of the International Rectification Company. IR2235 is a high-voltage, high-speed MOSFET and IGBT drive circuit, with its current amplification and protection functions while suppressing noise at the output. In the experiment, an incremental encoder E6C2-CWZ5B with a resolution of 600 is used for speed detection. The control board model is DE2-115, and the FPGA chip model is EP4CE115F29C7. The oscilloscope is MDO4000C of TEKTRONIX Company. In the experiment, this paper uses the logical resources of FPGA to build a NIOS II soft-core processor, and the DFPID-HSA is programmed in the constructed NIOS II soft-core by C language to realize real-time control.

Corresponding to the working conditions in the previous section, the algorithm is tested experimentally, and the experimental results are shown in Fig. 17. In the experiment, the target speed is still set at 2000 r/min, and the experiment time was mapped to 10 times. The external resistance is increased at 1 s to achieve a sudden load change, and the sudden change in speed is achieved at 1 s/2 s. The relevant parameters of each algorithm are appropriately scaled, and the optimization objective constraints in DFPI-HSA are adjusted to: \( k_{P1}, k_{I1}, k_{D1} = [0, 100], k_P, k_I, k_D = [0, 30] \). As can be seen from Fig. 17, the five algorithms can well realize
speed tracking under no-load, fixed load, variable load, or speed changes conditions. However, compared with the simulation test, the algorithms in the experiment all have fluctuations phenomenon. It can be seen from (a) in Fig. 17 and Table 11, the overshoot phenomenon of PID is still apparent, and its fluctuation frequency is fast. The ranges of FuzzyPID, PSO-FuzzyPID, GA-PID-FLC, and DPNN-FuzzyPID are more significant, but the frequency of the fluctuations is slower. Compared with the above four algorithms, DFPI-HSA has the weakest fluctuation phenomenon, showing its good robustness. In the cases of the fixed load, variable load, and speed changes, the control effect of DFPI-HSA is relatively best. Overall, in the experiment, DFPI-HSA still maintains its superiority and can realize the excellent control of BLDCM.

Conclusion
In this paper, a novel PID controller using the dual fuzzy logic system with HSA optimization called DFPI-HSA is presented to enhance the speed control performance of BLDCM. The stability of the proposed controller is analyzed by the pole determination method, the Lyapunov determination method, and the Nyquist determination method. Then the system has been demonstrated to be closed-loop stable. To test and verify the superiority of DFPI-HSA, its performance is analyzed and compared with DPNN-FuzzyPID, GA-PID-FLC, PSO-FuzzyPID, FuzzyPID, and PID under the conditions of no-load, fixed load, variable load, and speed changes. The results
show that DFPID-HSA is superior to other algorithms in the field of steady-state performance indicators, transient performance indicators, and integral performance indicators. In addition, the sensitivity analysis of DFPID-HSA is performed to evaluate its robustness under the condition of variable mechanical parameters. Finally, an experimental platform for the BLDCM drive system is built to further demonstrate the superiority and feasibility of DFPID-HSA in practical applications.

Figure 17. Experimental test results of DFPID-HSA: (a) No-load (b) Fixed Load (c) variable load (d) Speed changes.

| Controllers/ performance indicators | Oscillation range under no load (r/min) | Undershoot under fixed load (− r/min) | Oscillation range under variable load (r/min) | Settling time under speed changes (s) |
|-------------------------------------|----------------------------------------|---------------------------------------|---------------------------------------------|-------------------------------------|
| PID                                 | [1957.93, 2031.74]                      | 90.04                                 | [1930.95, 2046.15]                           | 0.65                                |
| Percentage                          | 3.69%                                   | 4.50%                                 | 5.76%                                       | 65%                                 |
| FuzzyPID                            | [1949.95, 2025.35]                      | 15.43                                 | [1922.57, 2020.00]                           | 0.30                                |
| Percentage                          | 3.77%                                   | 0.77%                                 | 4.87%                                       | 30%                                 |
| PSO-FuzzyPID                        | [1952.59, 2032.41]                      | 30.68                                 | [1932.77, 2032.05]                           | 0.28                                |
| Percentage                          | 3.99%                                   | 1.53%                                 | 4.96%                                       | 28%                                 |
| GA-PID-FLC                          | [1956.17, 2029.20]                      | 20.86                                 | [1939.37, 2030.31]                           | 0.25                                |
| Percentage                          | 3.65%                                   | 1.04%                                 | 4.55%                                       | 25%                                 |
| DPNN-FuzzyPID                       | [1969.79, 2016.94]                      | 24.14                                 | [1954.35, 2019.70]                           | 0.20                                |
| Percentage                          | 2.36%                                   | 1.21%                                 | 3.27%                                       | 20%                                 |
| DFPID-HSA                           | [1986.79, 2005.78]                      | 8.06                                  | [1982.92, 2009.18]                           | 0.16                                |
| Percentage                          | 0.95%                                   | 0.40%                                 | 1.31%                                       | 16%                                 |

Table 11. The comparison of performance indicators under different conditions.
References

1. Cabuk, A. S. Simulation of the effect of segmented axial direction magnets on the efficiency of in-wheel permanent magnet brushless DC motors used in light electric vehicles based on finite element method. Electr. Eng. 103(6), 3111–3117. https://doi.org/10.1007/s00020-021-01301-w (2021).

2. Godfrey, A. J. & Sankaranarayanan, V. A new electric braking system with energy regeneration for a BLDC motor driven electric vehicle. Eng. Sci. Technol. 21(4), 704–713. https://doi.org/10.1016/j.jestech.2018.05.003 (2018).

3. Carev, V., Rohal, J., Ipò, M. & Schmider, M. A multilayer brushless DC motor for heavy lift drones. Energies 14(9), 2504. https://doi.org/10.3390/en14092504 (2021).

4. Feng, J., Liu, K. & Wang, Q. Scheme based on buck-converter with three-phase H-bridge combinations for high-speed BLDC motors in aerospace applications. IET Electr. Power App. 12(5), 405–414. https://doi.org/10.1049/iet-epa.2017.0615 (2017).

5. Sen, A. & Singh, B. Peak current detection starting based position sensorless control of BLDC motor drive for PV array fed irrigation pump. IEEE T. Ind. Appl. 57(3), 2569–2577. https://doi.org/10.1109/TIA.2021.3066831 (2021).

6. SangWook, L. & Soo-Whang, B. A study on the improvement of the cam phase control performance of an electric continuous variable valve timing system using a cylcoid reducer and BLDC motor. Microsyst. Technol. 28(1), 59–70. https://doi.org/10.1007/s00542-019-04411-5 (2020).

7. Guerra, R. H. et al. Digital twin-based optimization for ultraprecision motion systems with backlash and friction. IEEE Access. 7(2019), 93462–93472. https://doi.org/10.1109/ACCESS.2019.2928141 (2019).

8. Elkholy, M. M. & El-Hay, E. A. Efficient dynamic performance of brushless DC motor using soft computing approaches. Neural Comput. Appl. 32(2), 1–14. https://doi.org/10.1007/s00521-019-04990-3 (2020).

9. Premkumar, K. & Manikandan, B. V. Bat algorithm optimized fuzzy PD based speed controller for brushless direct current motor. Eng. Sci. Technol. 19(2), 818–840. https://doi.org/10.1016/j.jestech.2015.11.004 (2016).

10. Gobinath, S. & Madheswaran, M. Deep perceptual neural network with fuzzy PID controller for speed control and stability analysis of BLDC motor. Soft Comput. 24(11), 10161–10180. https://doi.org/10.1007/s00500-019-04532-2 (2020).

11. Mu, S., Shibata, S., Yamamoto, T., Nakashima, S., Tanaka, K. Speed control of ultrasonic motor using a variable gain type PID control based on neural networks. in The 7th International Conference on Intelligent Systems and Image Processing 2019. 2019(1), 103–108 (2019). https://doi.org/10.12792/iissip2019.020

12. Dat, N. T., Cao, V. K. & Anh, H. Optimal FOC-PID parameters of BLDC motor system control using parallel PM–PSO optimization technique. Int. J. Comput. Intell. Syst. 14(1), 1142–1154 (2021).

13. Xie, W., Wang, J. S. & Wang, H. B. PI controller of speed regulation of brushless DC motor using DSP. Energ. Convers. Manage. 52(1), 264–273. https://doi.org/10.1016/j.enconman.2010.06.067 (2011).

14. Haber, R. E., Alqué, J. R., Alqué, A., Hernández, J. & Uribe-Exebarría, R. Embedded fuzzy-control system for machining processes. Results of a case study. Comput. Ind. 50(3), 353–366. https://doi.org/10.1016/j.compind.2003.05.002 (2004).

15. He, M., Zhang, T., Huang, J. & Luo, C. Speed control study of brushless DC motor based on fuzzy optimization PID. IOP Conf. Series Mater. Sci. Eng. 768(4), 042013 (2020).

16. Yan, H., Yi, W., Wang, K., Guan, J. & Wu, J. A research on brushless DC motor control system based on fuzzy parameter adaptive PI algorithm. AIP Adv. 10(10), 105208. https://doi.org/10.1063/5.0025000 (2020).

17. Premkumar, K. & Manikandan, B. V. Fuzzy PID supervised online ANFIS based speed controller for brushless dc motor. Neurocomputing 157(2015), 76–90. https://doi.org/10.1016/j.neucom.2015.01.032 (2015).

18. Valdez, F., Melin, P. & Castillo, O. A survey on nature-inspired optimization algorithms with fuzzy logic for dynamic parameter adaptation. Expert Syst. Appl. 41(14), 6459–6466. https://doi.org/10.1016/j.eswa.2014.04.015 (2014).

19. Rubaai, A. & Young, P. Hardware/software implementation of fuzzy-neural-network self-learning control methods for brushless DC motor drives. IEEE T. Ind. Appl. 52(1), 414–424. https://doi.org/10.1109/TIA.2015.2468191 (2016).

20. Rubaai, A., Castro-Sitriche, M. J., Ofili, A. R.: DSP-Based Laboratory Implementation of Hybrid Fuzzy–PID Controller Using Genetic Optimization for High-Performance Motor Drives. in Industry Applications Conference, 2007. 42nd IAS Annual Meeting Conference Record of the 2007 IEEE, IEEE, 44 (6), 1977–1986 (2008). https://doi.org/10.1109/TIA.2008.2066347

21. Hu, H., Wang, T., Zhao, S. & Wang, C. Speed control of brushless direct current motor using a genetic algorithm-optimized fuzzy proportional integral differential controller. Adv. Mech. Eng. 11(11), 168781401989019. https://doi.org/10.1177/168781401989019 (2019).

22. Li, H. C., Zhou, K. Q., Mo, L. P., Zain, A. M. & Qin, F. Weighted fuzzy production rule extraction using modified harmony search algorithm and BP neural network framework. IEEE Access 8(2020), 188620–188637. https://doi.org/10.1109/ACCESS.2020.302996 (2020).

23. Fu, L., Zhu, H., Zhang, C., Ouyang, H. & Li, S. Hybrid harmony search differential evolution algorithm. IEEE Access. 9(2021), 21532–21555. https://doi.org/10.1109/ACCESS.2021.3055530 (2021).

24. Pan, Q. K., Suganthan, P. N., Tasgetiren, M. F. & Liang, J. J. A self-adaptive global best harmony search algorithm for continuous optimization problems. Appl. Math. Comput. 216(3), 830–848. https://doi.org/10.1016/j.amc.2010.01.088 (2010).

25. Zou, D., Gao, L., Wu, J. & Li, S. Novel global harmony search algorithm for unconstrained problems. Neurocomputing 73(16–18), 3308–3318. https://doi.org/10.1016/j.neucom.2010.07.010 (2010).

26. Rahideh, A., Korakianitis, T. Brushless DC motor design using harmony search optimization. in 2011 2nd International Conference on Control, Instrumentation and Automation (ICCAI), 2011, 44–50 (2011). https://doi.org/10.1109/ICCAI.2011.61356628

27. Godl, N. C. PI controller tuning based on stochastic charging technique for performance enhancement of DTC induction motor drives. J. Inst. Eng. (India) Series B 101(6), 1–8. https://doi.org/10.4031/s40031-020-00496-2 (2020).

28. Valdez, F., Castillo, O. & Peraza, C. Fuzzy logic in dynamic parameter adaptation of harmony search optimization for benchmark functions and fuzzy controllers. Int. J. Fuzzy Syst. 22(1), 1–14. https://doi.org/10.1007/s40815-020-00860-7 (2020).

29. Precup, R. & David, R. C. Nature-inspired optimization algorithms for fuzzy controlled servo systems. Butterworth-Heinemann Elsevier Oxford UK Chapter 2, 55–22. https://doi.org/10.1016/B978-0-08-101795-9.00030-3 (2019).

30. Vanchinathan, K. & Selvaganesan, N. Adaptive fractional order pid controller tuning for brushless dc motor using artificial bee colony algorithm. Results Control Optim. 4(2021), 100032. https://doi.org/10.1016/j.rco.2021.100032 (2021).

31. Bava-Toosi, Y. Stability analysis—ScienceDirect. Introduction Linear Control Syst. 2019, 201–256. https://doi.org/10.1016/B978-0-12-812748-3.00003-3 (2019).
34. Xie, D., Zhu, J. Q. & Wang, F. Fuzzy PID control to feed servo system of CNC machine tool—ScienceDirect. *Procedia Eng.* **29**(1), 2853–2858. https://doi.org/10.1016/j.proeng.2012.01.403 (2012).

35. Hazari, M. R. et al. Fuzzy logic based virtual inertia control of DFIG based wind generator for stability improvement of hybrid power system. *IEEE Trans. Power Energy* **138**(8), 733–744. https://doi.org/10.1541/ijeepes.138.733 (2018).

36. Mirzaeinejad, H., Mirzaei, M. & Kazemi, R. Enhancement of vehicle braking performance on split-roads using optimal integrated control of steering and braking systems. *P. I. Mech. Eng. K.-J. Mul.* **230**(4), 401–415. https://doi.org/10.1177/146441931617332 (2016).

37. Zong, W. G., Kim, J. H. & Loganathan, G. V. A new heuristic optimization algorithm: Harmony search. *SIMULATION* **76**(2), 60–68. https://doi.org/10.1177/003754970107600201 (2001).

38. Zhao, F. Q., Liu, Y., Zhang, C. & Wang, J. B. A self-adaptive harmony PSO search algorithm and its performance analysis. *Expert Syst. Appl.* **42**(21), 7436–7455. https://doi.org/10.1016/j.eswa.2015.05.035 (2015).

39. Yan, H. C., Hong, W. C., Shen, W. & Ning, N. H. Electric load forecasting based on a least squares support vector machine with fuzzy time series and global harmony search algorithm. *Energies* **9**(2), 70. https://doi.org/10.3390/en9020070 (2016).

40. Chang, M. S. & Ku, T. C. A slicing tree representation and QCP-model-based heuristic algorithm for the unequal-area block facility layout problem. *Math. Probl. Eng.* **2013**(853586), 1–19. https://doi.org/10.1155/2013/853586 (2013).

41. Cheng, M. Y., Prayogo, D., Wu, Y. W. & Lukito, M. M. A Hybrid Harmony Search algorithm for discrete sizing optimization of truss structure. *Automat. Constr.* **69**(2016), 21–33. https://doi.org/10.1016/j.autcon.2016.05.023 (2016).

42. Premkumar, K. & Manikandan, B. V. Stability and performance analysis of ANFIS tuned PID based speed controller for brushless DC motor. *Carr. Signal Transduct. Ther.* **13**(1), 19–30. https://doi.org/10.2174/1574362413666180226105809 (2018).

43. Dutta, P. & Nayak, S. K. Grey wolf optimizer based PID controller for speed control of BLDC motor. *J. Electr. Eng. Technol.* **16**(2), 955–961. https://doi.org/10.1007/s42835-021-00660-5 (2021).

44. Khubalkar, S. W., Junghare, A. S., Aware, M. V., Chopade, A. S. & Da, S. S. Demonstrative fractional order—PID controller based DC motor drive on digital platform. *ISA T* **82**(SI), 79–93. https://doi.org/10.1016/j.isatra.2017.08.019 (2017).

45. Alkrwy, A., Hussein, A. A., Atyia, T. H. & Khamees, M. Adaptive tuning of PID controller using crow search algorithm for DC motor. *IOP Conf. Series: Mater. Sci. Eng.* **1076**(1), 012001. https://doi.org/10.1088/1757-899X/1076/1/012001 (2021).

**Author contributions**

T.W.: conceptualization, methodology, writing- original draf preparation, validation. H.W.: funding acquisition, review and editing. C.W.: project administration. H.H.: formal analysis, resources, supervision, writing—review and editing.

**Funding**

This work supported by the Science and Technology Development Project of Jilin Province [Grant numbers 20200201009J, 20210201051GX and 20210203161SF], and the Education Department Project of Jilin Province [Grant number JJKH20220686KJ].

**Competing interests**

The authors declare no competing interests.

**Additional information**

**Correspondence** and requests for materials should be addressed to C.W.

**Reprints and permissions information** is available at www.nature.com/reprints.

**Publisher’s note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

**Open Access** This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by/4.0/.

© The Author(s) 2022