Research Article

Speed Control of PMSM Based on an Optimized ADRC Controller

YiBo Meng, BingYou Liu, and LiChao Wang

1 Anhui Polytechnic University, College of Electrical Engineering, Wuhu 241000, China
2 Key Laboratory of Advanced Perception and Intelligent Control of High-End Equipment, Ministry of Education, Wuhu 241000, China
3 S. M. Wu Manufacturing Research Center, University of Michigan, Ann Arbor, MI 48105, USA

Correspondence should be addressed to BingYou Liu; lby009@mail.ustc.edu.cn

Received 5 January 2019; Revised 23 April 2019; Accepted 6 May 2019; Published 22 May 2019

1. Introduction

Permanent-magnet synchronous motors are widely used in various applications due to their simple control, high efficiency, good torque characteristics, and low loss [1]. Current control methods for PMSM include proportional–integral–derivative (PID), sliding mode, adaptive, predictive, and active disturbance rejection control [2–5]. However, the application environment is generally complex and often has various disturbances because PMSM is a nonlinear, multivariable, and strongly coupled system. Hence, these control methods cannot easily perform fast and high-precision control. For example, PID control is sensitive to changes in the parameters of the controlled object model, and only the deviations of the given feedback are adjusted. PID is a single-degree-of-freedom control, and balancing the tracking performance and immunity of the system is difficult. Sliding mode control belongs to the bang-bang control, and the control volume is a noncontinuous quantity. Therefore, the problem of “flicker” inevitably arises. Adaptive control is a time-varying nonlinear system with low control accuracy, and satisfying the control requirements is difficult. Although adjusting the controller parameters in predictive control is unnecessary, accurate object model parameters, which are sensitive to changes in model parameters, are required. Moreover, the evaluation function value needs to be calculated multiple times in a control cycle, which requires a high level of computing power for the microprocessor. This will increase the cost of the control system and reduce the efficiency of industrial production. ADRC does not depend on the parameters of the object model and can estimate and compensate for internal and external disturbances in real time. ADRC also has a strong anti-interference capability and can be used in PMSM to achieve satisfactory results [6, 7].

ADRC technology has been utilized for more than 20 years because of its high precision, simple structure, strong anti-interference capability, fast response, and easy parameter setting. These characteristics have elicited the attention of scholars at home and abroad. The application of ADRC in motor, flight, robot, and other industrial types of control has
produced fruitful results. ADRC technology also plays an important role in various fields. For example, ADRC technology was applied to an idle controller, and the extended state observer (ESO) was used to compensate for the interference load and frictional torque of the engine. Meanwhile, a feed-forward compensator was designed to improve interference suppression performance [8]. ADRC was transformed into an indirect direct perturbed Lurie system and then applied to a single-input single-output system. Global and local stabilities were verified with the Lyapunov theorem, and the manner in which linear dynamics was integrated into ADRC technology was described. ADRC was introduced into the rail control of a solar sail to maintain its place on the solar–lunar orbit [9, 10]. ADRC technology was also applied to a time-delay system, which is difficult to control; the parameter tuning method of ADRC technology under different time-delay systems was also summarized [11]. A linear system was used to compensate for the actual system as the nominal system to solve the aircraft attitude tracking problem accurately and efficiently under uncertain model and external disturbances [12]. Wang Ronglin applies ADRC to a position servo system of a rocket launcher driven by a PMSM, which improves the movement accuracy and robustness of the servo system [13]. A nonaffine nonlinear system with unknown external perturbation was used to estimate the unknown parts of a system using ESO, thereby solving the difficult problem of virtual control derivative acquisition [14, 15]. Zhang xinhua applied self-disturbance rejection control technology to a three-degree-of-freedom magnetic levitation permanent magnet planar motor to solve the problem of reduced electromagnetic force due to the deflection of the mover or the sharply decreased magnetic flux density with height [16]. ESO was utilized to linearize dynamically the information of a class of objects with unknown nonlinear properties and perturbations; the optimal control law was designed with LQR theory [17]. Jin Qibing used ADRC to solve the problem of model reduction error in the design process of a two-input/two-output time-delay system controller. The proposed method reduces the influence of the reduced-order error and improves the anti-interference capability and robustness of the control system [18].

However, the applications of these ADRC technologies are based on the traditional ADRC. The traditional nonlinear function of ADRC has many issues in conductivity and smoothness near the origin and segment points, and these issues reduce the performance of ADRC. Many scholars have attempted to improve ADRC to achieve higher precision and stronger anti-interference capability and reduce the limitations of the traditional ADRC. For example, the nonlinear function in ADRC was replaced by a linear function, which reduces the number of tuning parameters required in ADRC to a certain extent, and was then applied to the pressurized water reactor power. However, the linear ADRC reduced the working efficiency of the system and was prone to "peaking" in the initial state [19]. Zhao Zhiliang designed a piecewise smoothing function consisting of linear and fractional power functions and applying the new function to nonlinear ESO. The new and traditional ESO were compared through a numerical simulation. The new ESO achieved smaller peaks and stronger noise immunity than traditional ESO. However, the addition of a power function increased the complexity of the linear function and the response time of the system [20]. In another study, nonlinear ESO was modified into a linear ESO and combined with the least-squares method. The linear function was applied to the nonlinear state error feedback rate to improve the capability of the system to resist interference [21]. Liu Bingyou designed a new nonlinear function that was constructed by interpolation. The new function was applied to ESO, and excellent performance was obtained. However, only the analysis of the new ADRC at the theoretical stage was performed. No actual motor verification was conducted, and the validity of the method was not confirmed. Moreover, the gain and filter performance of the new function were not analyzed [22].

Parameters are added to improve the structure of ADRC, but this addition complicates the tuning and control of the entire system. If a linear ADRC is used, then the control efficiency of the entire system will not be as high as that of nonlinear ADRC, and the "peaking" phenomenon in the initial state could lead to system instability. Therefore, this study designs an optimized ADRC that acts on the PMSM based on the nonlinear function of nonlinear ADRC. First, a mathematical model of the dynamic equation of the PMSM motion equation is established. Second, a new type of nonlinear function is designed to verify the performance of the new function. Then, the design and parameter settings of the ADRC are established. Lastly, a simulation and experimental study of the entire ADRC are performed, and system simulation is conducted by combining ADRC with PMSM. The optimized ADRC exhibits better performance than the traditional ADRC in terms of tracking accuracy and anti-interference capability. The improvement of ADRC by nonlinear function is an effective way, providing a new method for the optimization of ADRC in the future. It also provides a new idea for the combination of linear and nonlinear ADRC and promotes the development of ADRC.

2. Mathematical Model of PMSM

A structural diagram of vector control in PMSM is shown in Figure 1. The speed loop is controlled by ADRC, and the current loop is controlled by PI.

A mathematical model of the PMSM used in this study is established under the following conditions: (1) the distribution of the permanent magnetic rotor field in the air gap space is a sine wave; (2) the magnetic circuit is linear, and the inductance parameters are constant, in which the core saturation of the stator is ignored; (3) core eddy current and hysteresis loss are neglected; and (4) the damping of the rotor winding is ignored. Given that the d-q mathematical model of PMSM is versatile, under these conditions, the voltage equation of PMSM is

\[ U_d = Ri_d - \omega_r L_d i_q + L_d \frac{di_d}{dt} \quad (1) \]

\[ U_q = Ri_q + \omega_r L_d i_d + \omega_r \psi + L_q \frac{di_q}{dt} \quad (2) \]
3. Optimized ADRC

ADRC comprises three parts. The first part, the tracking differentiator (TD), is used to track signals, including differential ones. The second part, ESO, is utilized to observe the internal state and estimate the unpredictable state of the system. The third part, the nonlinear state error feedback (NLSEF), is used to provide a stable and effective output signal.

3.1. Design of Nonlinear Function. A nonlinear function is used in ESO and NLSEF. Therefore, the nonlinear function is the core of the entire design of the ADRC in the present study. The function expression of \( f_{\text{a}}(e, \alpha, \delta) \), which is generally used in this study, is as follows:

\[
f_{\text{a}}(e, \alpha, \delta) = \begin{cases} 
|e| & |e| > \delta \\
\frac{\alpha}{\delta^\alpha} e & 0 < e \leq \delta, \quad \delta > 0 
\end{cases}
\]

The two segment points in the \( f_{\text{a}} \) function are \( \delta \) and \( -\delta \). The function is derived at the segment point to verify its derivative. We take the derivative of the \( f_{\text{a}} \) function at point \( \delta \) to verify its derivative.

\[
f_{\text{a}}'(e, \alpha, \delta) = \begin{cases} 
\alpha \delta^{-\alpha} & \delta > 0 \\
\frac{1}{\delta^\alpha} - \frac{\alpha}{\delta^{\alpha+1}} & e = \delta 
\end{cases}
\]

The derivative values are not the same at different segment points. Consequently, the primitive function is not derivable at the segment point. Although the \( f_{\text{a}} \) function is continuous at the origin and segment points, it is not derivable and lacks continuity and smoothness. Therefore, this study improves the \( f_{\text{a}} \) function as a new nonlinear function with well-continuity and smoothness at the origin and segment points.

When \( |e| > \delta \) the expression of \( n_f_{\text{a}}(e, \alpha, \delta) \) is \( n_f_{\text{a}}(e, \alpha, \delta) = |e|^\alpha \text{sign}(e) \);

When \( |e| \leq \delta \) the expression of \( n_f_{\text{a}}(e, \alpha, \delta) \) is \( n_f_{\text{a}}(e, \alpha, \delta) = p \sin e + q e^r + r \tan e \).
The interpolation fitting method combined with polynomial and trigonometric function is selected because the δ in the \( nfal(e,\alpha,\delta) \) function is usually less than 1. In this interval, \( \sin e \) has better stationarity than \( e \), and \( \tan e \) has better convergence than \( e^3 \). It is also continuous and derivable at the origin point.

If the fitting process is derivable and continuous, then

\[
\begin{align*}
\text{nfal} (e, \alpha, \delta) &= \delta^\alpha, \quad e = \delta \\
\text{nfal} (e, \alpha, \delta) &= -\delta^\alpha, \quad e = -\delta \\
\text{nfal}' (e, \alpha, \delta) &= a\delta^{a-1}, \quad e = \delta, -\delta
\end{align*}
\]

The solution is as follows:

\[
\begin{align*}
p &= \frac{\delta^\alpha - \alpha \cdot \delta^{a-1} \cdot \cos^2 \delta \cdot \tan \delta}{\sin^2 \delta} \\
q &= 0 \\
r &= -\frac{\delta^\alpha \cdot \cos \delta - \alpha \cdot \delta^{a-1} \cdot \sin \delta}{\sin \delta \cdot \tan^2 \delta}
\end{align*}
\]

The expression of can be obtained as

\[
\text{nfal} (e, \alpha, \delta) = \begin{cases} 
|e|^{\alpha} \cdot \text{sign} (e), & |e| > \delta \\
\delta^\alpha - \alpha \cdot \delta^{a-1} \cdot \cos^2 \delta \cdot \tan \delta \cdot \sin e - \delta^\alpha \cdot \cos \delta - \alpha \cdot \delta^{a-1} \cdot \sin \delta \cdot \tan e, & |e| \leq \delta
\end{cases}
\]

By analyzing the \( nfal(e,\alpha,\delta) \) function, the coefficient of \( e^2 \) is set as 0 when employing the interpolation fitting method, \( p \sin e \) and \( r \tan e \) are two items in the equation. Thus, the new function has improved convergence after interpolation fitting.

To simulate and compare the \( nfal(e,\alpha,\delta) \) and \( fal(e,\alpha,\delta) \) function, we set \( \delta=0.01 \) and \( \alpha=0.25 \). The function curve is shown in Figure 3, which indicates that the new function has improved continuity and smoothness at the origin and segment points.

The nonlinear function is regarded as a link; therefore, the input of the link is \( e \), the output is the dynamic value of the nonlinear function, and the ratio of the output dynamic value and input \( e \) is defined as the equivalent gain of the link.

\[
\begin{align*}
\lambda_1 (e, \alpha, \delta) &= \frac{\text{fal} (e, \alpha, \delta)}{e} \\
\lambda_2 (e, \alpha, \delta) &= \frac{\text{nfal} (e, \alpha, \delta)}{e}
\end{align*}
\]

We take \( \delta = 0.1, \alpha = 0.25 \) as an example. The equivalent gain curve of the two nonlinear functions is shown in Figure 4.

The figure indicates that when \( e \leq \delta = 0.1 \) is the input. The gain of the original nonlinear function is constant, and the gain of the new nonlinear function is a smooth curve. The original nonlinear function has an inflection point at 0.1, and the new nonlinear function image is a smooth curve, which fully meets the characteristics of “small error, large gain, large error, and small gain,” and provides considerable convenience to system parameter adjustment.

The filtering and anti-interference performance of the \( nfal(e,\alpha,\delta) \) function are also important. The function filter shown in Figure 5 is used to verify the filtering and antialiasing performance of the \( nfal(e,\alpha,\delta) \) function.

As shown in Figure 5, \( V \) is selected as the sinusoidal signal with the addition of Gaussian white noise. \( K \) is the proportional coefficient and \( y \) is the filtered output. The parameters of the selected filter are as follows: \( K=20, \alpha=0.5, \delta=0.1 \). As shown in Figures 6 and 7.

Figures 6 and 7 show that the filtered image only has a small part of irregular fluctuations and basically restores the sine function of the original input perfectly, which is sufficient to demonstrate that the \( nfal(e,\alpha,\delta) \) function filter
has an excellent filtering effect. This result can prove that the $nfal(e, \alpha, \delta)$ function has good filtering effect and antijamming performance.

3.2. Design of the TD. TD achieves a smooth approximation of the generalized derivative of the input signal through a nonlinear function in ADRC. The effect is to arrange the transition process according to the reference input and the control object to obtain a smooth input signal. TD's algorithm is expressed as follows:

$$
V_1(t + h) = V_1(t) + hV_2(t)
$$
$$
V_2(t + h) = V_2(t) + hf\text{han}(V_2(t) - V(t), V_2(t), r, h)
$$

where $V(t)$, $h$, $r$, and $f\text{han}$ are the input signal, integration step, factor of the tracking rate, and the nonlinear function, respectively.

The expression is as follows:

$$
f\text{han}\begin{cases}
-ra/d, & |a| \leq d \\
r \text{sgn}(a), & |a| > d
\end{cases}
$$

$$
a = \begin{cases}
V_2 + \frac{y}{h_0}, & |y| \leq d_0 \\
V_2 + \frac{\text{sgn}(y)(a_0 - d)}{2}, & |y| > d_0
\end{cases}
$$

$$
a_0 = \sqrt{d^2 + 8r|y|}
$$

$$
d = rh_0
$$

$$
d_0 = h_0d
$$

$$
y = v_1 - v + hv_2
$$

TD uses the tracking and filtering characteristics of the input signal and can arrange transitional processes for the controller. By arranging appropriate transition processes, TD can effectively alleviate the drastic changes in the control volume and overshoot of the output caused by abrupt set value changes, thereby eliminating the conflict between rapidity and overshoot. The signal-to-noise ratio is considerably improved by integrating the method to quickly trace the generalized derivative of the input signal. Moreover, the tracking signal of the input signal, which has a filtering effect, can be obtained. The transition process is arranged in the input signal step jump, which can effectively reduce the overshoot. The tracking differentiator can break through the noise mask of the differential controller and has a significant effect on the response speed and stability of the system. The parameters for TD are set to $r = 10$ and $h = h_0 = 0.01$. The unit step input signal is selected for the simulation. Figures 8 and 9 show the response curve of TD.

Figure 8 shows that when the input signal is a unit step signal, the overshoot is 0% with an adjustment time of 0.628 s and the differential signal has a settling time of 0.778 s. Figure 9 shows that when the input signal is a unit square wave signal with a period of 3 s, the overshoot is 0% with an adjustment time of 0.635 s, and the differential signal has a settling time of 0.735 s. These results indicate that TD can quickly and accurately track input signals without overshoot providing high-quality differential signals.

3.3. Design of the ESO. ESO is the core of the ADRC. Utilizing ESO could help estimate varying quantities of unknown disturbances and unmodeled dynamics via compensation in the feedback. An estimation of each state variable can be obtained through ESO, which helps achieve the purpose of object reconstruction. ESO is based only on the input and output information of the control object and does not depend on the specific mathematical model that generates...
the disturbance. Therefore, ESO has strong robustness and versatility. The algorithm is expressed as follows:

\[ \varepsilon_1 = Z_1 - \omega \]
\[ Z_1 = Z_2 - \beta_{11} nfal(\varepsilon_1, \alpha_1, \delta) \]
\[ Z_2 = Z_3 - \beta_{12} nfal(\varepsilon_1, \alpha_2, \delta) + b_0 u \]
\[ Z_3 = -\beta_{13} nfal(\varepsilon_1, \alpha_3, \delta) \]

where \( \varepsilon_1 \) is the observational error; \( Z_1 \) is the tracking signal of the input signal; \( Z_2 \) is the differential signal of the input signal; \( Z_3 \) is the observed signal of \( f(t) \); \( u \) is the control output; \( b_0 \) is the estimated value of the compensation factor; \( \delta \) is the filter factor; \( \beta_{11}, \beta_{12}, \) and \( \beta_{13} \) are the gains of the optimized ESO; and \( \alpha_1, \alpha_2, \) and \( \alpha_3 \) are nonlinear factors. In the optimized ESO, the perturbations of the model perturbation parameters and measurement noises are processed in a unified manner. The expanded nonlinear links are used to estimate and compensate for the real-time action, thereby simplifying the objects with nonlinear uncertainties into integral series structures. Linearization and determinism of the system are then realized. The deterministic and linearized system can be controlled using existing classical control theory. The parameters for the optimized ESO are set to \( \alpha_1 = 0.5, \alpha_2 = 0.25, \alpha_3 = 0.125, b_0 = 2.485, \delta = 0.01, \) and \( \beta_{11} = 60, \beta_{12} = 240, \beta_{13} = 890. \) The unit step input and square wave signal are selected for the simulation. Figures 10 and 11 show the response curve of the optimized ESO.

Figure 10 shows that when the input signal is a unit step signal, \( Z_1, Z_2, \) and \( Z_3 \) steadily track the unit step signal, the differential signal of the input signal, and the total perturbation signal of the system at 0.098, 0.312, and 0.825 s, respectively. Figure 11 shows that when the input signal is a unit square wave signal with a period of 3 s, \( Z_1, Z_2, \) and \( Z_3 \) tracing the unit square wave signal, the differential signal of the square wave signal, and the total system disturbance at the rising and falling edges of 0.095, 0.616, and 1.212 s, respectively. These findings fully demonstrate that the optimized ESO can quickly and accurately estimate the amount of unknown disturbances and unmodeled dynamic changes and can compensate for them in the feedback.

3.4. Design of the NLSEF. NLSEF is an error in the nonlinear algorithm controller between the estimations of state variables generated from TD and ESO and forms the controlled variable with the compensation of the total disturbance. Traditional NLSEF only uses the ratio and the differential of the error signal to calculate nonlinearity. The optimized NLSEF adds the integral part of the signal, improves the control
precision of the system, and enhances system immunity. The algorithm of NLSEF is expressed as follows:

\[ e_1 = v_1 - z_1 \]

\[ e_0 = \int e_1 dt \]

\[ e_2 = v_2 - z_2 \]

\[ u_0 = \beta_{21} n_{fal} (e_0, \alpha_1, \delta_1) + \beta_{22} n_{fal} (e_1, \alpha_2, \delta_1) + \beta_{23} n_{fal} (e_2, \alpha_3, \delta_1) \]

(16)
where $e_1$, $e_2$, $e_3$ denote the integration, error signal, and differential, of the error signal, respectively; $\alpha_1$, $\alpha_2$, and $\alpha_3$ are nonlinear factor; and $\beta_{21}$, $\beta_{22}$, and $\beta_{23}$ are the gains of the optimized NLSEF. The parameters for the optimized NLSEF are set as $\alpha_1=0.5$, $\alpha_2=0.25$, $\alpha_3=0.125$, $\delta_1=1$ and $\beta_{11}=5$, $\beta_{12}=25$, $\beta_{13}=75$. The unit step input and sinusoidal signal are selected for the simulation. Figures 12 and 13 show the response curve of the optimized NLSEF.

Figure 12 shows that when the input signal is a unit step signal, the output curve stably tends to approach the input curve at 0.512 s. In Figure 13, when the input signal is a sinusoidal signal with a period of 4s, the output curve tends to be stable and does not jump in 2.012 s. These findings fully demonstrate that the control signal after the optimization of NLSEF is filtered and has better stability than that before processing. The adaptability and robustness of the system are thus improved.

3.5. Overall Design. Various modules of ADRC are designed in the aforementioned steps. We now combine the new modules of ADRC and use the speed loop model as the controlled object. The combination of the optimized ADRC and the speed loop is shown in Figure 14.
4. Simulation Results

The optimized ADRC model is simulated by Simulink in MATLAB, and the simulation waveform of ADRC is obtained to verify and optimize ADRC performance. The same parameters are selected for simulation in the traditional and optimized ADRC as follows. The bandwidth method of ADRC is combined, and the principle of the parameters selected is proposed as follows:

4.1. Parameters of TD. We do not consider the filtering, so we can choose $h = h_0$. The parameters in the tracking differentiator that need to be set are simulation step $h$ and tracking factor $r$ because they affect the tracking accuracy of the output signal. $r$ affects the tracking accuracy of the output signal and the time of the transition process. A large $r$ results in short transition time. Therefore, the general parameters of TD are as follows: $r = 10$, $h = h_0 = 0.02$.

4.2. Parameters of ESO. The selected bandwidth of $\delta$ cannot be chosen too large because it will lose the advantage of the nonlinear equation. By contrast, an extremely small bandwidth will lead to instability of the integrated system. Therefore, choosing $0.01$ is appropriate. The factor of nonlinear generally meets the empirical value of $0.5, 0.25, \text{and } 0.125$. The gain generally satisfies the following formula:

$$\beta_{11} = 3\omega_0,$$
$$\beta_{12} = 3\frac{\omega_0^2}{5},$$
$$\beta_{13} = \frac{\omega_0^3}{9} \tag{17}$$

When $\omega_0$ is large, the ESO can track a small amplitude of error disturbance. Increasing $\beta_{13}$ properly improves the optimized performance but easily causes an overshoot of the total disturbance estimate, leading to the shock of the control value. Therefore, we take $60, 240, \text{and } 889$.

4.3. Parameters of NLSEF. Although the gain is small, the error attenuation speed is high, and the anti-jamming capability is strong, an extremely small gain will cause high-frequency oscillation of the output, which will adversely affect the actual object. Therefore, we take $5, 25, \text{and } 75$. The speed of error decay and the output are also appropriate.

The same parameters are selected for simulation in the traditional and optimized ADRC. The specific parameter selection is shown in Table 1.

According to the PMSM vector control system and the ADRC structure diagram, we construct the optimized ADRC MATLAB Model and PMSM vector control system MATLAB model as shown in Figures 15 and 16.

(1) The two response curves of ADRC when the step input is 1 rad are shown in Figure 17. The diagram shows that the traditional ADRC overshoot is 9.76% with an adjustment time of 0.39 s and the optimized ADRC overshoot is 0% with an adjustment time of 0.24 s. Hence, the optimized ADRC has a faster adjustment speed and smaller overshoot than the traditional ADRC.

(2) The two response curves of ADRC when the input is $\sin(\pi t)$ are shown in Figure 18. The diagram shows that the time at which the traditional ADRC reaches the first peak is 0.71 s and that of the optimized ADRC is 0.54 s. This finding reveals that the optimized ADRC has a higher response speed and can form a stable sinusoidal output faster than traditional ADRC.

(3) First, 1-rad step is inputted and a step disturbance is added in 2 s. Figure 19 shows the response curve of the small disturbance at 1 rad, and Figure 20 shows the other response curve of the large disturbance at 20 rad. Figure 19 shows that the overshoot of the traditional ADRC affected by a small disturbance is 17.91%, and the time needed to restore the stable output is 1.89 s. Meanwhile, the overshoot of the optimized ADRC affected by a small disturbance and the time needed to restore the stable output are essentially 0 s. Figure 20 shows that the overshoot of traditional ADRC affected by a larger disturbance is 259.34%, and the time necessary to restore the stable output is 2.01 s. By contrast, the overshoot of optimized ADRC affected by the large disturbance is 9.54%, and the time necessary to restore the stable output is 0.92 s. These results indicate that the optimized ADRC has a smaller overshoot and higher restoration speed than the traditional ADRC whether the disturbance is small or large. Therefore, the optimized ADRC has better capacity of resisting disturbance than the traditional ADRC.
### Table 1: Parameters of the ADRC.

<table>
<thead>
<tr>
<th>Component of ADRC</th>
<th>Parameter name</th>
<th>Symbol</th>
<th>Numerical value</th>
</tr>
</thead>
<tbody>
<tr>
<td>TD</td>
<td>Velocity factor</td>
<td>$r_0$</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>Simulation step</td>
<td>$h_0$</td>
<td>0.02</td>
</tr>
<tr>
<td>ESO</td>
<td>Nonlinear factors</td>
<td>$\alpha_1$</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>Nonlinear factors</td>
<td>$\alpha_2$</td>
<td>0.25</td>
</tr>
<tr>
<td></td>
<td>Nonlinear factors</td>
<td>$\alpha_3$</td>
<td>0.125</td>
</tr>
<tr>
<td></td>
<td>Liner interval width</td>
<td>$\delta$</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>Gain</td>
<td>$\beta_{11}$</td>
<td>60</td>
</tr>
<tr>
<td></td>
<td>Gain</td>
<td>$\beta_{12}$</td>
<td>240</td>
</tr>
<tr>
<td></td>
<td>Gain</td>
<td>$\beta_{13}$</td>
<td>889</td>
</tr>
<tr>
<td></td>
<td>Compensation factor</td>
<td>$b_0$</td>
<td>2.485</td>
</tr>
<tr>
<td>NLSEF</td>
<td>Gain</td>
<td>$\beta_{21}$</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>Gain</td>
<td>$\beta_{22}$</td>
<td>25</td>
</tr>
<tr>
<td></td>
<td>Gain</td>
<td>$\beta_{23}$</td>
<td>75</td>
</tr>
<tr>
<td></td>
<td>Filter factor</td>
<td>$\delta_1$</td>
<td>1</td>
</tr>
</tbody>
</table>

![Figure 15: Optimized ADRC MATLAB model.](image1)

![Figure 16: PMSM vector control system MATLAB model.](image2)
Figure 17: Response curves of unit step input.

Figure 18: Response curves of sinusoidal input.

Figure 19: Response curves of small disturbance input.
5. Experimental Results

The experimental platform is a 400W Yaskawa servomotor. The experimental apparatus are shown in Figure 23. The motor parameters are shown in Table 3. The system measures the motor speed through a 1024 photoelectric encoder and uses the same parameters as those in the simulation for traditional ADRC and optimized ADRC.

Figure 24 shows the traditional ADRC (a) and the optimized ADRC (b). When the input is 1000 cts/sec, the optimized ADRC tracking curve has less fluctuation and distortion than the traditional ADRC tracking curve, which is suitable for the input signal curve.

Figure 25 shows the traditional ADRC (a) and the optimized ADRC (b). When the input is 1000 cts/sec, the optimized ADRC has less adjustment time and overshoot than the traditional ADRC while also having smaller fluctuations in speed.

Figures 24 and 25 fully explain that the optimized ADRC has higher tracking accuracy and smaller steady-state fluctuation error than the traditional ADRC at low and high speeds.

Figures 26(a), 26(b), and 26(c) show the traditional ADRC when the input is sinusoidal, and Figures 26(d), 26(e), and 26(f) show the optimized ADRC. Figures (a)
and (d), (b) and (e), and (c), and (f) show an amplitude of 3000, 6000, and 12,000 cts/sec, respectively, and the frequency is 1 Hz. Figures (a), (b), and (c) show that the traditional ADRC speed amplitude is larger than the fixed amplitude and phase lag, and the tracking error is large. Figures (d), (e), and (f) show that the optimized ADRC speed amplitude is consistent with the given value, phase advance or hysteresis is absent, and the tracking error is evident.

Therefore, the ADRC control effect is better than that of the conventional ADRC whether in low, medium, or high speed. The experimental and simulation results fully prove that the optimization of ADRC tracking accuracy and anti-jamming performance is better than that of the traditional ADRC.

6. Conclusion

As a continuously developing and improving new nonlinear controller, ADRC has been increasingly applied in numerous fields. This study introduces a method to optimize ADRC, constructs a new nonlinear function using the interpolation fitting method to optimize the control effect of ADRC, and elaborates the construction process of the new nonlinear function. The new nonlinear function is then applied to the various components of ADRC. A simulation is conducted to verify the feasibility of the proposed optimization method compared with the traditional ADRC under the same conditions. The simulation verifies the good performance of the optimized ADRC. The two control methods are also compared by using an actual motor. The experimental results show that the optimized ADRC has smaller overshoot, faster adjustment time, and smaller speed fluctuation than the conventional ADRC at constant low and high speeds. At low and high speeds, the optimized ADRC also has faster tuning times, smaller phase shifts, and faster speed fluctuations than conventional ADRC. The experimental and simulation results fully prove that the optimized ADRC is more robust and adaptive and has better anti-interference capability than the traditional ADRC. It also provides a new idea for the combination of linear and nonlinear ADRC and promotes the development of ADRC. Our future work will be carried out.
Figure 24: Response curves of 1000cts/sec.

<table>
<thead>
<tr>
<th>ADRC</th>
<th>Input signal</th>
<th>Overshoot(%)</th>
<th>Adjustment time(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Traditional ADRC</td>
<td>Unit step</td>
<td>9.76</td>
<td>0.39</td>
</tr>
<tr>
<td></td>
<td>Sinusoidal</td>
<td>/</td>
<td>0.71</td>
</tr>
<tr>
<td></td>
<td>Small disturbance</td>
<td>17.91</td>
<td>1.89</td>
</tr>
<tr>
<td></td>
<td>Big disturbance</td>
<td>259.34</td>
<td>2.01</td>
</tr>
<tr>
<td></td>
<td>Square wave pulse</td>
<td>/</td>
<td>1.98</td>
</tr>
<tr>
<td>Optimized ADRC</td>
<td>Unit step</td>
<td>0</td>
<td>0.24</td>
</tr>
<tr>
<td></td>
<td>Sinusoidal</td>
<td>/</td>
<td>0.54</td>
</tr>
<tr>
<td></td>
<td>Small disturbance</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Big disturbance</td>
<td>9.54</td>
<td>0.92</td>
</tr>
<tr>
<td></td>
<td>Square wave pulse</td>
<td>/</td>
<td>0.43</td>
</tr>
</tbody>
</table>
in the following aspects: (1) the optimized ADRC is applied to the position loop and current loop in the motor; (2) the ADRC parameter setting of the speed loop is analyzed to find the optimal ADRC parameters; (3) change the inherent structure of the ADRC and improve the ADRC from the structural aspect.

**Data Availability**

The data used to support the findings of this study are available from the corresponding author upon request.

**Conflicts of Interest**

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

**Table 3: Motor parameters.**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input voltage</td>
<td>200V</td>
</tr>
<tr>
<td>Rated current</td>
<td>2.5A</td>
</tr>
<tr>
<td>Working frequency</td>
<td>250Hz</td>
</tr>
<tr>
<td>Rated power</td>
<td>400W</td>
</tr>
<tr>
<td>Torque</td>
<td>1.27N·m</td>
</tr>
<tr>
<td>Rated speed</td>
<td>3000r/min</td>
</tr>
<tr>
<td>Maximum speed</td>
<td>6000r/min</td>
</tr>
<tr>
<td>Motor resolution</td>
<td>1024cts</td>
</tr>
</tbody>
</table>

**Acknowledgments**

This research is supported by The AnHui Natural Science Foundation (no. 1808085MF182). This research is supported
Figure 26: Continued.
Figure 26: Response curves of sinusoidal input.
References


