PERFORMANCE OPTIMIZATION OF SHIP COURSE VIA ARTIFICIAL NEURAL NETWORK AND COMMAND FILTERED CDM-BACKSTEPPING CONTROLLER

Abstract
This paper proposes a robust nonlinear ship course controller, under the control of which the system is globally asymptotically stabilized with high control quality. The proposed controller is synthesized by combining coefficient diagram method and command filtered backstepping based on first order filter to avoid the complex analytic derivation of the virtual control, the controller parameter are tuned using radial basis function neural network. It can not only obtain a higher accuracy in ship course controlling, but also infinitely approach the nonlinear system with quicker and more stable convergence. The simulation results illustrate that the projected controller shortens the settling time evidently with good system stability. It has a better performance than the traditional controllers.

Keywords
Ship course, Command filtered backstepping, Radial basis function neural network

1 INTRODUCTION

Ship motion control is an essential research field in traffic engineering. Its objective is to get better the level of intelligence and automation, and guarantee the safety comfort and economy of the navigation. Ship system is uncertain nonlinear system with large inertia [1-4].

More than a few control approach were proposed to ship systems such as the PID controller, it is commonly adopted at nominal operating points. On the contrary, due to the poor robustness of PID, it cannot show its advantages. The sliding mode control shows its advantages in robustness. However, its drawback appears in the well known “chattering” phenomenon. The backstepping control was employed in these systems that steer the ship on its course. However, many problems which needed solutions, one of them is the increasing orders of control systems, the repeated derivatives of control laws in the design cause the problem of “computational increase” due to the successive derivative of the virtual control for system with order greater then three, which need introducing the first order filter into traditional backstepping method [5-10], to simplifies the complexity of the controller. Another problem is the identification the controller parameters which are heuristically determined by trial and errors. In order to obtain optimal quality of control for the considered nonlinear course controller, its parameters need tuning by using optimization algorithms.

To reply to the presented problem, a robust nonlinear controller based command filtered backstepping method [11-13] and coefficient diagram method [14-17] is developed were its parameters are optimised using basis radial neural network optimization (RBFNN) [18-21]. This approach is also suitable for parameters estimation and system identification works, one of the most significant functions, called the ‘Gaussian function’, is used in the hidden layer. The principle advantages of employing RBF include computational ease; robust generalization and aptitude to handle real-time tasks are sustained by advanced mathematical theory.

This paper is organized as follows. Section 2, an overview of the dynamic model of ship system is presented. Section 3 is dedicated to a brief description of linear CDM control. Section 4 is devoted to establish the stability analysis of the command filtered cdm-backstepping. The proposed auto-tuning method is presented in section 5. Section 6 evaluates the performance of the proposed approach using computer simulations. The paper concludes with a discussion on the obtained results.

2 DYNAMIC MODEL OF THE SHIP

The mathematical model of a ship system is described as

\[
\begin{align*}
    x_1 &= x_2 \\
    \dot{x}_2 &= x_3 \\
    \dot{x}_3 &= a_1 x_2 + a_2 x_3 + x_4 + a_3 x_5 \\
    \dot{x}_4 &= a_4 x_4 + a_5 u \\
    a_1 &= -\alpha \frac{1}{\tau_{I_2}}, \quad a_2 = -\frac{1}{\tau_1}, \quad a_3 = \frac{\beta}{\tau_{I_2}}, \\
    a_4 &= -\frac{1}{\tau_R}, \quad a_5 = \frac{K_R}{\tau_R}.
\end{align*}
\]

Where \( x_1 \) is the ship course, \( x_2 \) the angular velocity, \( x_3 \) the angular acceleration, \( x_4 \) is the rudder angle and \( u \) is the controlling input. The constant \( \alpha, \beta, \tau_1, \tau_2, \tau_R, K_R \) are the system parameters.
3 LINEAR CDM CONTROL

CDM is an algebraic design useful for polynomial structure of the system on the parameter space. It is based on the use of the stability index and the equivalent time constant derived from the characteristic polynomial. The performance specification, stability index and equivalent time constant are defined in the transfer function of the closed-loop system and related to the controller parameters algebraically.

The system output as shown in Figure 1 is defined as

\[ y(s) = \frac{N(s)F(s)}{P(s)} - \text{ref}(s) + \frac{A(s)N(s)}{P(s)}d(s) \]

Where \( y \) is the system output, \( \text{ref} \) is the reference input, \( u_s \) is the control input and \( d \) is the external disturbance signal, \( N(s) \) and \( D(s) \) represents the numerator and the denominator of the transfer function of the system, respectively, \( A(s) \) and \( B(s) \) are the denominator polynomial and the feedback numerator of the controller transfer function, while \( F(s) \) is the pre-filter, \( P(s) \) is the characteristic polynomial.

The equivalent time constant \( T_s \), the stability index \( \gamma_1 \), and the stability limit \( \gamma^* \) [15-17] are calculated as

\[ T_o = t_s/(2.5 \sim 3) \]

\[ \gamma_1 = \mu_1^2/(\mu_1+1) \] for \( i = 1 \) to \( n-1 \)

\[ \gamma^* = 1/\gamma_{i+1} + 1/\gamma_{i-1} \]

\[ \gamma_1 = 2.5 \] for \( i = 2 \) to \( n-1 \)

\[ \gamma_0 = \gamma_n = \infty \] where \( t_s \) is the settling time. As a final point the pre-filter, \( F(s) = P(0)/N(s) \) is utilized for reducing the steady state error, where the characteristic polynomial is specified as follows [15].

\[ P(s) = \mu_1 \left[ \sum_{i=2}^{n} \prod_{j=1}^{i-1} \gamma_j X(T_0 s^j) + T_0 s + 1 \right] \]


![Figure 1. Structure of the CDM control system](image)

4 FILTERED COMMAND CDM-BACKSTEPPING AND STABILITY ANALYSIS

In this section, the design and analysis stability of the command filtered CDM-backstepping control for motion ship control is developed with reduce of the derivation burden by avoiding the analytic computation of the time-derivatives of the virtual input signal [7].

The controller design begin by defining the tracking error coordinates \( e_1 = x_1 - x_d \) with \( x_d \) is the reference signal, its time derivative can be written as \( \dot{e}_1 = x_2 - x_d \), by mean of adding and subtracting the terms \( \phi_i \) and \( \phi_{if} \) from \( x_2 \), the time derivative of \( e_1 \) become

\[ \dot{e}_1 = x_1 - \dot{x}_d = x_2 + \phi_1 - \phi_{if} - \dot{x}_d \]

after that

\[ \dot{e}_2 = (x_2 - \phi_{if}) + \phi_1 - \dot{x}_d \]

therefore, we can find \( e_1 = e_2 + \phi_1 + \phi_{if} - \dot{x}_d \), with \( \phi_{if} \) is a filtered version of the signal \( \phi_i \) obtained by means of the first order low pass filter with \( \phi_{if} = \sigma_i (\phi_i - \phi_{if}) \), such that \( \sigma_i \) is the filter’s cut-off frequency, and \( \phi_{if}(0) = \phi_i(x_{10}, x_{d0}, \dot{x}_{d0}) \) symbolize the initial value of the virtual control signal with \( x_{10} = 0 \), \( x_{d0} = x_{d0}(0) \) and \( \dot{x}_{d0} = x_{d0}(0) \).

The insertion of command filters requires the employ of compensated tracking error \( z_1 \) to compensate its influence on the closed loop system such that \( z_1 = e_1 - e_i \), its dynamics is given by \( z_1 = e_1 - e_i \).

Let us choose the first Lyapunov function associated with the compensated tracking error [7-9] such that

\[ V_1 = 0.5 z_1^2 \]

The time derivative of \( V_1 \) is given by

\[ \dot{V}_1 = z_1 (e_1 - e_i) \]

To guarantee its negativity the virtual control \( \phi_i \) and the dynamics of \( e_i \) must be selected as

\[ \phi_1 = -\lambda_1 e_1 + x_d \]

\[ e_i = -\lambda_1 e_i + \phi_{if} - \phi_i + e_2 \]

\[ e_{if}(0) = 0 \]

where \( e_i \) is a new variable, then we can find

\[ \dot{z}_1 = e_1 - e_i = e_2 + \phi_1 + \phi_{if} - \phi_i - \dot{x}_d - e_i \]

yields

\[ \dot{z}_1 = \dot{e}_1 - \dot{e}_i = e_2 + \phi_1 + \phi_{if} - \dot{x}_d - \dot{e}_i \]

For this reason, \( z_1 = z_2 - \lambda_1 z_1 \), as a consequence

\[ V_2 = -\lambda_1 z_1^2 + z_2 z \]

In the second step of the control construction, consider the subsystem specified by \( z_2 = x_1 \). The second compensated tracking error signal is designed as \( z_2 = e_2 - e \). Its time derivative is \( \dot{z}_2 = e_2 - e_2 \). The second error tracking is chosen \( e_2 = x_1 - \phi_{if} \), we then continue by compensating the second command filter using the new variable \( e_2 \) and describe \( z_2 = e_2 - e_2 \).

Considers the backstepping variable \( e_2 = x_2 - \phi_{if} \), its derivative is determined as

\[ \dot{e}_2 = x_2 - \phi_{if} = \phi_2 - \phi_{if} \]

\[ \dot{e}_2 = x_3 + \phi_2 - \phi_{if} + \phi_{if} - \phi_{if} \]

where the dynamic \( \phi_{if} \) is a filtered version acquired by passing the virtual control input \( \phi_i \) through the command-filtering first order low-pass filter, with

\[ \phi_{if}(0) = \phi_{if}(0) \]

\[ \phi_{if}(t) = \phi_{if}(0) \]

Denotes the initial value of the virtual control signal.

To prove the stability in the second step, the second Lyapunov function is defined to be

\[ V_2 = 0.5 z_1^2 + 0.5 z_2^2 \]

Differentiating it with respect to time provides

\[ \dot{V}_2 = z_1 \dot{z}_1 + z_2 \dot{z}_2 = -\lambda_1 z_1^2 + z_2 \dot{z}_2 + z_2 (e_2 - e_2) \]

\[ \dot{V}_2 = -\lambda_1 z_1^2 + z_2 \dot{z}_2 + z_2 (x_1 + \phi_2 - \phi_{if} + \phi_{if} - \dot{e}_2) \]

\[ \dot{V}_2 = -\lambda_1 z_1^2 + z_2 \dot{z}_2 + z_2 (x_1 + \phi_2 - \phi_{if} + \phi_{if} - \dot{e}_2) \]

\[ \dot{V}_2 = -\lambda_1 z_1^2 + z_2 \dot{z}_2 + z_2 (x_1 + \phi_2 - \phi_{if} + \phi_{if} - \dot{e}_2) \]
The compensated tracking error is considered as follows:
\[ \dot{e}_2 = -\lambda_2 e_2 + \phi_{3\gamma} - \phi_{\gamma} + e_3. \]

The derivative of the second Lyapunov function becomes:
\[ V_2 = -\lambda_1 z_1^2 + z_1 z_2 + z_2 (x_3 - z_1 - \lambda_2 e_2 + \phi_{\gamma} - \phi_2 + \phi_{3\gamma} - \phi_{\gamma} + \lambda_2 e_2 - \phi_{\gamma} + \phi_{3\gamma} + \phi_2 - e_3). \]

Then, \( V_2 = -\lambda_1 z_1^2 + z_1 z_2 + z_2 (e_3 - \lambda_2 z_2 - e_3) \) at that time.
\[ V_2 = -\lambda_1 z_1^2 - \lambda_2 z_2^2 + z_2 z_3, \]

Select the control Lyapunov function \( V_3 \) as \( V_3 = 0.5z_1^2 + 0.5z_2^2 + 0.5z_3^2 \), its derivative is:
\[ V_3 = -\lambda_1 z_1^2 - \lambda_2 z_2^2 + z_2 z_3 + z_2 z_3, \]

then describe the tracking error \( e_3 \) as \( e_3 = x_3 - \phi_{3\gamma} \), its derivation is as follows:
\[ \dot{e}_3 = -\lambda_3 e_3 - \phi_3 - \phi_{3\gamma}. \]

Define a compensated tracking error \( z_3 = e_3 - e_3 \), whose derivative is:
\[ \dot{z}_3 = a_1 x_3 + a_2 x_3 + x_3 + a_3 x_3^3 - \phi_{3\gamma} + \phi_3 - \phi_{3\gamma} - \phi_3 + \phi_{3\gamma} - \phi_{3\gamma} + \phi_3. \]

Where \( \phi_{3\gamma} = \phi_3 (\phi_{3\gamma} - \phi_{\gamma}) \), and \( \phi_{3\gamma} \) is a filtered version of the virtual control input \( \psi_{3\gamma} \). Observe by going through the command-filtering first order low-pass filter with \( \psi_{3\gamma} (\psi_{3\gamma}) = \psi_{3\gamma} \), and \( a_3 \) is the filter’s cut-off frequency, and \( \phi_{3\gamma} (\psi_{3\gamma}) = \psi_{3\gamma} (x_{10} x_{20} x_{30} \phi_{20}) \) denotes the initial value of the virtual control signal.

Thus the differential of the compensated tracking error is chosen as \( e_3 = e_3 - \lambda_3 e_3 - \phi_{3\gamma} - \phi_{3\gamma} \), and the virtual control is chosen as \( \phi_{3\gamma} = -z_2 - \lambda_3 e_3 + \phi_{3\gamma} - a_3 x_3 - a_3 x_3 - a_3 x_3 \)

The derivative of \( z_3 \) become \( \dot{z}_3 = e_3 - z_2 - \lambda_3 z_3 \) with \( e_3 = z_2 \), then \( \dot{z}_3 = z_4 - z_2 - \lambda_3 z_3 \).

The derivative of the third Lyapunov function is given as \( V_3 = -\lambda_4 z_1^2 - \lambda_2 z_2^2 + z_2 z_3 + z_2 z_3 + z_2 z_3 + z_2 z_3 + z_2 z_3 + z_2 z_3 \)

At that time, \( V_3 = -\lambda_4 z_1^2 - \lambda_2 z_2^2 + \lambda_3 z_3^2 + z_2 z_3 + z_2 z_3 + z_2 z_3 + z_2 z_3 + z_2 z_3 \).

The final Lyapunov function is chosen as \( V_4 = V_3 + 0.5z_4^2 \).

At that time, \( V_4 = -\lambda_4 z_1^2 - \lambda_2 z_2^2 + \lambda_3 z_3^2 + z_2 z_3 + z_2 z_3 + z_2 z_3 + z_2 z_3 + z_2 z_3 \).

This gives \( \dot{\zeta} = a_3 x_3 + a_3 x_3 \), we have, \( z_4 = e_3 = \zeta - \phi_{3\gamma} \).

The control signal is chosen as follows:
\[ a_{n1}(x) = -\psi_{3\gamma} + \psi_{3\gamma} + \zeta - \phi_{3\gamma}. \]

In addition:
\[ e_c(t) = c_{m1}(x) + b_{m1}(x) \phi_{3\gamma} - b_{m1}(x) \phi_{3\gamma} \]

Where \( a_{n1}(x) \), \( a_{n2}(x) \), \( c_{m1}(x) \), \( b_{m1}(x) \), and \( b_{m2}(x) \) are control gain constants, and are calculated as follows. Suppose that the gains \( \delta \) and \( \zeta \) are such that:
\[ \|e_c(t)\| = \|e_c(t)\| \]

The constants of gain \( a_{n1}(x) \) and \( a_{n2}(x) \) are specified by:

With \( \kappa \) is a constant.

Combining the expression of \( e_4 \) and (9), yields
\[ e_4 = [b_{m1}(x) - b_{m1}(x) - b_{m1}(x)] \psi_{3\gamma} \]

selecting the gain constants such that \( c_{m1}(x) = b_{m1}(x) \) and \( b_{m2}(x) = 0 \), then
\[ e_c = -c_4 \]

Its second derivative is given as:
\[ \ddot{e}_c(t) = \zeta^2(t) - \zeta^2(t) \]

Using (8), (9) and (11), \( \zeta^2(t) \) is found to be:
\[ \zeta^2(t) = a_3 x_3 - \rho_1 e_c \]

With \( \rho_1 = \rho_1 \), the insertion of \( 14 \) into \( 13 \) gives
\[ \dot{e}_c(t) = \zeta^2(t) - \zeta^2(t) \cdot c(a_3 x_3 - \rho_1 e_c) \]

and using (12):
\[ \dot{z}_3(t) = f(x) + \rho_1 z_4(t) \]

In addition, \( f(x) = a_4 x_4 - \phi_{3\gamma} \), and \( \rho_2 = \rho_2 \), then taking
\[ \rho_2 = \delta \text{sign}(z_5) \]

To confirm the stability in the fourth step, the Lyapunov function \( V_4 \) is considered to be \( V_4 = V_2 + 0.5z_4^2 \), its derivative is found to be
\[ V_4 = -\lambda_4 z_1^2 - \lambda_2 z_2^2 + \lambda_3 z_3^2 + z_2 z_3 + z_2 z_3 + z_2 z_3 + z_2 z_3 + z_2 z_3 \]

changing \( \dot{E} \) by (15) we reach
\[ \dot{E} = -\lambda_4 z_1^2 - \lambda_2 z_2^2 + \lambda_3 z_3^2 + z_2 z_3 + z_2 z_3 + z_2 z_3 + z_2 z_3 + z_2 z_3 \]

If \( \Omega(t) > 0, \dot{V}_4 < 0 \). The stability is ensured and the gains \( \delta \) and \( \zeta \) must be taken using inequality (10).

5 RBFNN BASED COMMAND FILTERED CDM-BACKSTEPING

A RBFNN is a three-layer feed-forward neural network, input layer, hidden layer, and output layer [19-21]. It has nonlinear mapping ability from input to output, however, it is linear from hidden layer to output layer. The learning rate is quickened greatly and the global optimal is ensured. A standard RBFNN form is shown in Figure 2.
The first layer \( O = [o_1, o_2, \ldots, o_n]^T \) is the input vector in the structure of the RBFNN. At the hidden layer the neurons are activated by radial-basis functions. Consider the radial vector of RBFNN given as follows \( H = [h_1, h_2, \ldots, h_j, \ldots, h_m]^T \), where \( h_j \) is Gaussian function known by
\[
 h_j = \exp\left(-\frac{\|O - C_j\|^2}{2b_j^2}\right) \quad /17/
\]
The neuron’s center of the network at node \( j \) is given by
\[
 C = [c_{j1}, c_{j2}, \ldots, c_{j1}, \ldots, c_{jm}]^T, \quad i = 1, 2, \ldots, n \quad /18/
\]
The radial width vector is \( B_j = [b_1, b_2, \ldots, b_m]^T \), where \( b_j \) is the radial parameter and \( b_j > 0 \).

The weight vector of the network is \( W \) and specified by
\[
 W = [w_1, w_2, \ldots, w_j, \ldots, w_m]^T \quad /19/
\]
The network output \( y_m \) is produced by a linearly weighted sum of the number of basis functions in the hidden layer.
\[
y_m(k) = w_1h_1 + w_2h_2 + \ldots + w_mh_m = \sum_{j=1}^{m} w_jh_j \quad /20/
\]
Where \( w_j \) represent the weight and \( h_j \) symbolize the output of the \( j^{th} \) node in the hidden layer.

The identification algorithm of Jacobian information of controlled system is assured below. Firstly considers the performance index function of identifier as follows
\[
 J_m = 0.5(y(k) - y_m(k))^2 \quad /21/
\]
On the way to minimize the error between the identification model output \( y_m(k) \) and the real output system \( y(k) \), gradient descent technique is used here to adapt weights of the output layer, node center and node radial parameters. The corresponding formulas are as follows.
\[
w_j(k) = w_j(k-1) + \eta(y(k) - y_m(k))h_j + \alpha(w_j(k-1) - w_j(k-2)) \quad /22/
\]
\[
 \Delta b_j = (y(k) - y_m(k))w_jh_j \left|\frac{O - C_j}{b_j^2}\right|^2 \quad /23/
\]
\[
b_j(k) = b_j(k-1) + \eta \Delta b_j + \alpha(b_j(k-1) - b_j(k-2)) \quad /24/
\]
\[
 \Delta c_j = (y(k) - y_m(k))w_j \left|\frac{O - C_j}{b_j^2}\right|^2 \quad /25/
\]
\[
c_j(k) = c_j(k-1) + \eta \Delta c_j + \alpha(c_j(k-1) - c_j(k-2)) \quad /26/
\]
Where \( \eta \) is the momentum factor, \( \alpha \) is learning rate. The Jacobian matrix is given as follows.

\[
\frac{\partial y(k)}{\partial u(k)} \approx \frac{\partial y_m(k)}{\partial \Delta u(k)} = \sum_{j=1}^{m} w_jh_j \frac{c_j - o_j}{b_j^2} \quad /27/
\]

Where \( o_j = \Delta u(k) \) and \( \Delta u(k) = u(k) - u(k-1) \)

The structure of the optimized control approach is shown in Figure 3. The controller parameters are modified online using the results of RBFNN identification.

![Figure 3. Schematic of command filtered CDM-backstepping control system based on RBFNN](image)

The incremental of the command filtered CDM-backstepping control algorithm can be found by means of (8), (12) and the dynamic of the errors \( e_1 \), \( e_2 \) and \( e_3 \) given in section 4.

\[
e(k) = e_1(k) \quad /28/
\]
The five inputs of the command filtered CDM-backstepping controller are as follows
\[
\begin{align*}
 o_{c1}(k) &= -\delta(k)c(k)\lambda_1(k)(e_1(k)/\alpha_2\lambda_1(k)) \\
 o_{c2}(k) &= -\delta(k)c(k)\lambda_2(k)(e_2(k)/\alpha_3) \\
 o_{c3}(k) &= \delta(k)c(k)\lambda_3(k)(e_3(k)/\alpha_4) \\
 o_{c4}(k) &= -\delta(k)c(k)e_4(k)/\alpha_5 \\
 o_{c5}(k) &= -\delta(k)c(k)e_5(k)/\alpha_6
\end{align*} \quad /29/
\]
So the controller output is defined as follows
\[
\Delta u(k) = w_1o_1(k) + w_2o_2(k) + w_3o_3(k) + w_4o_4(k) + w_5o_5(k) \quad /30/
\]
The task is to reduce to zero the system average square error \( E(k) \) by adjusting all the variable weights, \( E(k) \) is designed as
\[
E(k) = 0.5e^2(k) \quad /31/
\]
The adjustment of the controller parameters is attained by using the gradient descent method and given as

\[
\begin{align*}
 \Delta \lambda_1 &= -\eta \frac{\partial E}{\partial \lambda_1} = -\eta e_1(k) \frac{\partial y}{\partial \Delta u}o_1(k) \\
 \Delta \lambda_2 &= -\eta \frac{\partial E}{\partial \lambda_2} = -\eta e_1(k) \frac{\partial y}{\partial \Delta u}o_2(k) \\
 \Delta \lambda_3 &= -\eta \frac{\partial E}{\partial \lambda_3} = -\eta e_1(k) \frac{\partial y}{\partial \Delta u}o_3(k) \\
 \Delta \zeta &= -\eta \frac{\partial E}{\partial \zeta} = -\eta e_1(k) \frac{\partial y}{\partial \Delta u}o_4(k) \\
 \Delta \delta &= -\eta \frac{\partial E}{\partial \delta} = -\eta e_1(k) \frac{\partial y}{\partial \Delta u}o_5(k)
\end{align*} \quad /32/
\]
With \( \frac{\partial y}{\partial u} \) is the Jacobian information of controlled system. It is obtained by RBFNN identification results.

6 COMPUTER SIMULATIONS

In order to test the efficacy of the Radial Basis Function Neural Networks optimization approach, simulation testing have been carried out, it illustrates the comparison of the traditional and optimized controller, in two phases, ideal case and robustness analysis.

The following numerical parameters are utilized 
\[ T_R = 156 \, s, \quad K_R = 96 \, deg, \quad T_I = -1183.7, \quad T_2 = 31.5, \quad \alpha = 1, \quad \beta = 1. \]
Where the initial conditions are taken equal to zero. The control quality of the ship course was evaluated using a digitised version of the integral performance index, having the form
\[ J_E = \sum_{i=1}^{N} e^2(k) / 33/ \]

Where \( N \) is number of iterations in control simulations.

6.1 Ideal case

The comparison results between the performance of the conventional controller and the optimized controller is illustrated in Figure 4 and 5. From Figure 4, it is understandable that the system with conventional controller gives high values in settling time, steady state error and \( J_E \). The optimized controller improves the performance where the settling time and steady state error are extremely minimized; the results obtained are depicted in Table 1. Figure 5 shows the comparison of the actuators controls action where the amplitude of control input is very suitable for the optimized controller. Hence, tuning of filtered CDM-backstepping gains is useful in minimizing the settling time, steady state error and control effort.

Table 1. Performance comparison of controllers

|                | Conventional controller | Optimized controller |
|----------------|-------------------------|----------------------|
| Settling time  | \( t_s = 180 \, s \)    | \( t_s = 140 \, s \) |
| Performance criteria | \( J = 2.4452 \times 10^4 \) | \( J = 6.3231 \times 10^3 \) |

6.2 Test of robustness

To confirm the robustness of the optimized controller parameters, an external disturbance and varying system parameters from their nominal values in the range of -25% to 25% are applied at \( t = 0 \, s \). It can be concluded from the performance comparison of the controllers in Figures 6 and 7 that the settling time increases. Meanwhile the controller with optimized controller performs better than the conventional controller, which possesses less settling time, less steady state error; smaller value of performance criteria \( J_E \) and satisfactory control effort, Hence, the proposed control is the best in robustness under the external disturbance and parameters variation.

7 CONCLUSION

This paper has presented the radial basis function neural networks method for optimization of a ship course control. The efficacy of the suggested approach is illustrated in tuning the command filtered CDM-backstepping parameters subject to an optimal integral criterion. Comparing with conventional methods, the proposed method has the superiority such as strong robustness and satisfactory control performance in presence of uncertainties and disturbances.

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