J. Marine Sci. Appl. (2015) 14: 202-207
DOI: 10.1007/s11804-015-1292-z

Energy Optimization of the Fin/Rudder Roll Stabilization System Based on the Multi-objective Genetic Algorithm (MOGA)

Lijun Yu*, **Shaoying Liu, Fanming Liu and Hui Wang**

College of Automation, Harbin Engineering University, Harbin 150001, China

Abstract: Energy optimization is one of the key problems for ship roll reduction systems in the last decade. According to the nonlinear characteristics of ship motion, the four degrees of freedom nonlinear model of Fin/Rudder roll stabilization can be established. This paper analyzes energy consumption caused by overcoming the resistance and the yaw, which is added to the fin/rudder roll stabilization system as new performance index. In order to achieve the purpose of the roll reduction, ship course keeping and energy optimization, the self-tuning PID controller based on the multi-objective genetic algorithm (MOGA) method is used to optimize performance index. In addition, random weight coefficient is adopted to build a multi-objective genetic algorithm optimization model. The objective function is improved so that the objective function can be normalized to a constant level. Simulation results showed that the control method based on MOGA, compared with the traditional control method, not only improves the efficiency of roll stabilization and yaw control precision, but also optimizes the energy of the system. The proposed methodology can get a better performance at different sea states.
Keywords: ship motion; energy optimization; ship roll reduction; performance index; self-tuning PID; multi-objective genetic algorithm (MOGA); roll stabilization; fin/rudder roll stabilization; yaw control precision

Article ID: 1671-9433(2015)02-0202-06

1 Introduction

How to reduce energy consumption is a key problem of the fin/rudder roll reduction system. It is a new tendency for the ship roll reduction system. Various roll reduction devices have been well employed to accomplish the ship roll reduction. For example, fin stabilizer is the most fundamental and effective roll reduction device for ships in waves (Treakle *et al*., 2000; Huang *et al*., 2014). The rudder is mainly applied to control the ship course, in addition it improves roll reduction (Fang and Luo, 2007). Tanks are also an important roll reduction device (Fang and Luo, 2007). In this paper, the fin/rudder roll stabilization system (Perez and Goodwin, 2008) is adopted. It is a new kind of ship roll reduction device, that uses the rudder to assist the fin stabilizer to further improve roll reduction and ship course precision.

A wide variety of control algorithms have been proposed to reduce the ship roll motion, such as classical PID (Minorsky, 1947) optimal control (Fang and Luo, 2007) and H_2/H_∞ (Oda *et al*., 1996). Various control algorithms of the fin/rudder roll reduction system highlight the roll reduction efficiency and the ship course control precision (Koshkouei *et al*., 2007). However, they seldom consider the problems of energy optimization. Liu and Jin (2013) have proposed a method to optimize additional resistance. In this paper, the energy consumption of overcoming the resistance and the yaw caused by the additional energy consumption is regarded as performance index.

While the ship sails in the seaway, different ship speed, encounter angle and sea states lead to different roll moment and yaw moment of ship. But the classical PID controller (Crossland, 2003) is designed in the specific sea state. To optimize the PID controller, the self-tuning PID controller based on the MOGA (Lee *et al*., 2007; McGookin *et al*., 2000) is proposed to tune three parameters. During the past decade, due to its generality and several advantages over conventional optimization methods, multi-objective genetic algorithm does not require user to prioritize, scale, or weight objectives. Therefore, genetic algorithm had been successfully applied to solve multi-objective optimization problems (Suksonghong *et al*., 2014; Malik *et al*., 2014; Long, 2014). Besides, MOGA is very suitable for solving multi-objective optimization problems because they deal simultaneously with a set of solutions and find a number of Pareto optimal solutions in a single run of algorithm (Vicente *et al*., 2012). This paper presents the self-tuning PID controller based on the MOGA, which adapts to different sea states (Pan and Das, 2013). Using this algorithm, the system has better roll reduction efficiency and ship course precision, at the same time it can dramatically reduce the energy consumption and the cost of navigation.

The rest of this paper is organized as follows. In Section 2, the ship model is presented. The establishment of performance index of roll reduction system is addressed in Section 3. The optimization of performance index is described in Section 4. The experimental results and analysis are presented in Section 5. The conclusion is given in Section 6.

Received date: 2014-06-30.
Accepted date: 2014-10-08.
Foundation item: Supported by the National Natural Science Foundation of China (Grant No. 61174047) and the Fundamental Research Funds for the Central Universities (HEUCF041406).
***Corresponding author Email:** yulijun@hrbeu.edu.cn

2 Mathematical models

According to the Newton law and the ship motion characteristics, nonlinear four degrees of freedom (4-DOF) model is established based on rudder roll reduction model, the nonlinear 4-DOF mathematical model includes the surge, sway, roll and yaw. Motions in pitch and heave can often be neglected in comparison with the other motions (Holden *et al.,* 2007). The control forces and moments of fin/rudder roll reduction system are given. The ship model is described as

$$\begin{cases}(m-X_{\dot u})\dot u = X_{\text{hyd}}+X_{\text{rudder}}+X_{\text{fin}}+X_{\text{prop}}+ \\ \qquad m\left(vr+x_G r^2 - z_G pr\right) \\ (m-Y_{\dot v})\dot v-(mz_G+Y_{\dot p})\dot p+(mx_G-Y_{\dot r})\dot v = \\ \qquad Y_{\text{hyd}}+Y_{\text{rudder}}+Y_{\text{fin}}+Y_{\text{prop}}-mur \\ -(mz_G+K_{\dot v})\dot v+(I_{xx}-K_{\dot p})\dot p-K_{\dot r}\dot p = \\ \qquad K_{\text{hyd}}+K_{\text{rudder}}+K_{\text{fin}}+K_{\text{prop}}+mz_G ur \\ (mx_G-N_{\dot v})\dot v-N_{\dot p}\dot p+(I_{zz}-N_{\dot r})\dot r = \\ \qquad N_{\text{hyd}}+N_{\text{rudder}}+N_{\text{fin}}+N_{\text{prop}}-mx_G ur \\ \qquad \dot\phi = p \\ \qquad \dot\psi = r\cos(\phi)\end{cases} \tag{1}$$

where m is the ship mass, ϕ is roll angle, ψ is yaw angle, u is surge, v is sway, r is yaw rate, p is roll rate, I_{xx} and I_{zz} are the inertia about the x_0 and z_0 axes, respectively. x_G and z_G are the coordinate of the center of gravity CG with respect to the body-fixed frame, i.e., $\overline{CG}=[x_G,0,z_G]$.

The following are explained in this paper: hydrodynamic forces and moments, rudder forces and moments, fin forces and moments, and propeller propulsion forces and moments.

Holden *et al.* (2007) have given the hydrodynamic forces and moments, the nonlinear hydrodynamic models as:

$$\begin{cases}X_{\text{hyd}} = X_{\dot u}\dot u + X_{u|u|}u\,|u| + X_{vr}vr \\ Y_{\text{hyd}} = Y_{\dot v}\dot v + Y_{\dot r}\dot r + Y_{\dot p}\dot p + Y_{|u|v}|u|v + Y_{ur}ur + Y_{v|v|}v|v| + \\ \qquad Y_{v|r|}v|r| + Y_{r|v|}r|v| + Y_{\phi|uv|}\phi|uv| + Y_{\phi|ur|}\phi|ur| \\ K_{\text{hyd}} = K_{\dot v}\dot v + K_{\dot p}\dot p + K_{|u|v}|u|v + K_{ur}ur + K_{v|v|}v|v| + \\ \qquad K_{v|r|}v|r| + K_{r|v|}r|v| + K_{\phi|uv|}\phi|uv| + K_{\phi|ur|}\phi|ur| + \\ \qquad K_{|u|p}|u|p + K_{|p|p}|p|p + K_p p - \rho g\nabla GZ(\phi) \\ N_{\text{hyd}} = N_{\dot v}\dot v + N_{\dot r}\dot r + N_{|u|v}|u|v + N_{|u|r}|u|r + N_{r|r|}r|r| + \\ \qquad N_{r|v|}r|v| + N_{\phi|uv|}\phi|uv| + N_{\phi u|r|}\phi u|r| + N_{|p|p}|p|p + \\ \qquad N_p p + N_{|u|p}|u|p\end{cases} \tag{2}$$

Liang *et al.* (2012) have given the rudder forces and moments, the equation is written as:

$$\begin{cases}X_{\text{rudder}} = -D\cdot\delta_r \\ Y_{\text{rudder}} = L\cdot\delta_r \\ K_{\text{rudder}} = -r_r\cdot L\cdot\delta_r \\ N_{\text{rudder}} = -\text{LCG}\cdot L\cdot\delta_r\end{cases} \tag{3}$$

where L represent the rudder-induced lift force, D is the rudder-induced resistance, they are expressed as the Eq. (4). r_r is the roll arm of rudder force, LCG is the yaw moment arm of rudder force, δ_r is effective rudder angle when a ship sails in the seaway. The related equations of the lift force and the drag force can be presented as:

$$\begin{cases}L = 0.5\rho U^2 A C_L(\alpha_e) \\ D = 0.5\rho U^2 A\left[C_{D0} + C_L^2(\alpha_e)/(0.9\pi\Lambda)\right]\end{cases} \tag{4}$$

where U is the flow velocity upstream from the foil, A is the area of the hydrofoil, ρ is the fluid density, Λ is the effective aspect ratio of hydrofoils, $C_L(\alpha_e)$ is the lift coefficient, C_{D0} is the drag coefficient.

The stabilizer fin-induced forces and moments (Perez and Goodwin, 2008) can be expressed as:

$$\begin{cases}X_{\text{fin}} = -(D\cos(\alpha) - L\sin(\alpha))\cdot\alpha_e \\ Y_{\text{fin}} = (L\cos(\alpha) + D\sin(\alpha))\cdot\sin(\beta)\cdot\alpha_e \\ K_{\text{fin}} = -2r_f\cdot(L\cos(\alpha) + D\sin(\alpha))\cdot\alpha_e \\ N_{\text{fin}} = -\text{FCG}\cdot(L\cos(\alpha) + D\sin(\alpha))\cdot\sin(\beta)\cdot\alpha_e\end{cases} \tag{5}$$

where r_f is the roll arm of fin force, FCG is the longitudinal distance from fin pressure center to the ship gravity center, β is fin mechanical angle, α_e is the effective fin angle when a ship sails in the seaway.

X_{prop}, Y_{prop}, K_{prop}, and N_{prop} are the propeller propulsion forces and moments. Assuming that thrust force and resistance are equal, the resistance can be approximately equal to $X_{u|u|}U_0^2$ when a ship sails in the seaway. The propeller thrust forces and moments are described as

$$\begin{cases}X_{\text{prop}} = -X_{u|u|}U_0^2 \\ Y_{\text{prop}} = 0 \\ K_{\text{prop}} = 0 \\ N_{\text{prop}} = 0\end{cases} \tag{6}$$

where U_0 is the initial ship speed.

3 Establishment of performance index

In order to meet roll reduction efficiency and ship course precision when optimizing the energy, the performance index is extended from the following two aspects.

3.1 Energy consumption of overcoming the resistance

When the ship course is a straight line with little sway and yaw motion amplitude, by using the linear approximation theory, force analysis is shown in Fig. 1.

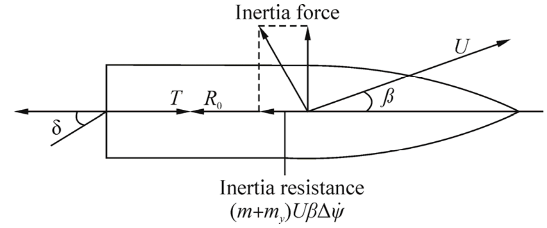

Fig. 1 Force analysis of ship navigation

3.2 Yaw caused by the additional energy consumption

When there is the yaw, on the one hand, it will increase the navigation time with the increasing navigation course, which leads to additional energy consumption. On the other hand, turning rudders more frequently can reduce course deviation, but it will increase the yawing angular velocity, which increases the resistance of ship navigation and attrition of steering gear. In Fig. 2, the illustration shows the deviation between the actual ship position and the desired path.

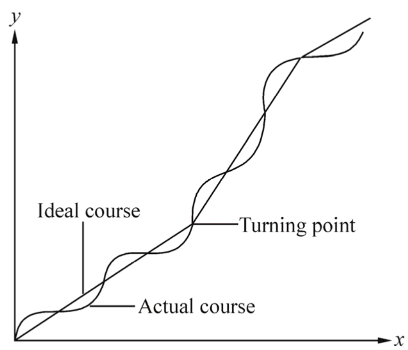

Fig. 2 Ship course

$$\Delta t = \int_0^{t_0} \frac{(\Delta\psi - \beta)^2}{2} \mathrm{d}t + 0\left(\Delta t^2\right) \tag{7}$$

Therefore, when the ship sails in the seaway, the actual navigation time is $t_0 + \Delta t$, here t_0 is the smallest navigation time in the ideal navigation conditions, Δt is the navigation time with the increasing navigation course. The propulsion resistance and navigation time determine the total energy consumption. Navigation time is increased, the total energy consumption is:

$$E = \int_0^{t_0+\Delta t} (m + \Delta m_y) u^2 \beta \Delta\dot{\psi} \, \mathrm{d}t + \int_0^{t_0+\Delta t} R_\delta u \, \mathrm{d}t + \int_0^{t_0+\Delta t} R_0 u \, \mathrm{d}t \tag{8}$$

The total energy consumption is E_0 in the ideal navigation condition:

$$E_0 = \int_0^{t_0} R_0 u \mathrm{d}t \tag{9}$$

$E - E_0$ is the energy loss in the actual sailing. When the ship course is a straight line, the measure of energy saving index can be described as:

$$J_1 = \frac{E - E_0}{E_0} \tag{10}$$

When the ship course is a straight line, R_0 and u are constant. Therefore, energy savings are the sum of an increased rate of average navigation resistance and an increased rate of navigation time.

$$J_1 = \frac{1}{t_0} \int_0^{t_0} \left[\frac{(\Delta\psi - \beta)^2}{2} + \frac{(m + \Delta m_y) u \beta \Delta\dot{\psi} + R_\delta}{R_0} \right] \mathrm{d}t \tag{11}$$

where R_0 is the ship resistance, which mainly include wave resistance and friction resistance, it can be represented as

$$R_0 = [C_w + (1+K)C_f] \cdot \frac{\rho}{2} u^2 V^{2/3} \tag{12}$$

where C_w, C_f and K are wave resistance coefficient, friction resistance coefficient and ship shape coefficient; ρ is the fluid density; V is the ship displaces.

The empirical formula of rudder resistance is adopted.

$$R_\delta = \frac{1}{2} \rho U^2 A_r (1 - W_f{}^2)(1 + 3.6 S^{1.5}) \frac{6.13 \Lambda_r}{\Lambda_r + 2.25} \sin^2 \delta_r \tag{13}$$

where U is the ship speed (m/s), A_r is the area of the rudder, W_f is wake fraction, S is the ship ratio, L_r is the aspect ratio of the rudder, δ_r is the rudder angle.

The ship resistance and rudder resistance expressions are substituted in Eq. (11), considering the impact of steering angle, equation (11) can be represented as

$$J_1 = \frac{1}{t_0} \int_0^{t_0} [\lambda_1 \Delta\psi^2 + \lambda_2 \Delta\psi \Delta\dot{\psi} + \lambda_3 \Delta\dot{\psi}^2 + \lambda_4 \Delta\psi \delta_r + \lambda_5 \Delta\dot{\psi} \delta_r + \lambda_6 \delta_r^2] \mathrm{d}t \tag{14}$$

where $\lambda_i, i = 1, 2, \cdots, 6$ are the weight coefficients, $\Delta\psi$ is the heading error, $\Delta\dot{\psi}$ is the yaw rate, δ_r the rudder angle.

3.3 Establishment of performance index

This section aims to establish a new performance index based on the original performance index (Jin and Wang, 2009; Jin *et al*., 2011). Generally, the weight coefficients of $\Delta\psi\Delta\dot{\psi}$, $\Delta\psi\delta_r$ and $\Delta\dot{\psi}\delta_r$ are smaller and ignored. When the ship is in severe roll motion, which will reduce the power of the host, at the same time, it reduces the speed. Thus, energy optimization and roll reduction efficiency must consider roll angle. Practical application shows that the roll angle is within a certain range, which can reduce the viscous resistance and wave-making resistance. It can be beneficial to improving the power of the host and reduce fuel consumption, which also increases speed and cost savings. Therefore, roll angle should be taken into account. From the control effect and stability, the roll angle should be as small as possible. The roll angle and steering frequency can be added to performance index. After that it is considered to be discrete. In order to reduce costs and decreaseattrition of steering gear, so steering frequency is added into the performance index. Thus overall performance index can be expressed as:

$$J_1 = \frac{1}{N} \sum_{i=1}^{N} \left(\lambda_1 \Delta\psi_i^2 + \lambda_2 \Delta\dot{\psi}_i^2 + \lambda_3 \phi_i^2 + \lambda_4 \delta_i^2 + \lambda_5 f_i^2 \right) \tag{15}$$

where N is the total number of the time interval in the control system simulations, $\Delta\psi_i$ is the ith heading error,

$\Delta\dot{\psi}_i$ the ith yaw rate, ϕ_i the ith roll angle with roll reduction control, δ_i the ith rudder angle, f_i the ith steering frequency, λ_i the weight coefficient, J_1 the performance index. The smaller the J_1, the better the performance.

4 Optimization of performance index

In order to optimize performance index, the self-tuning PID controller based on the MOGA optimization method (Suksonghong *et al*., 2014) is applied. Each objective function is not independent and should proceed in parallel to get the optimal solutions. There are five methods to solve multi-objective optimization problems in genetic algorithm. In this paper, weight coefficient transformation method is adopted. Thus, the multi-objective optimization problem can be transformed into single objective optimization problem.

Selecting the appropriate weight coefficient is often difficult in actual problems. There are three kinds of weight coefficient setting methods: fixed weight coefficient method (Fang *et al*., 2012), random weight coefficient method (Hoko and Wang, 2011) and adaptive weight coefficient method. The random weight coefficient method overcomes local optimal solution and slow search speed and other shortcomings in the original genetic algorithm. In this paper, random weight coefficient is adopted to build multi-objective genetic algorithm optimization model.

The flowchart of the self-tuning PID controller based on the MOGA used in this work is shown in Fig. 3.

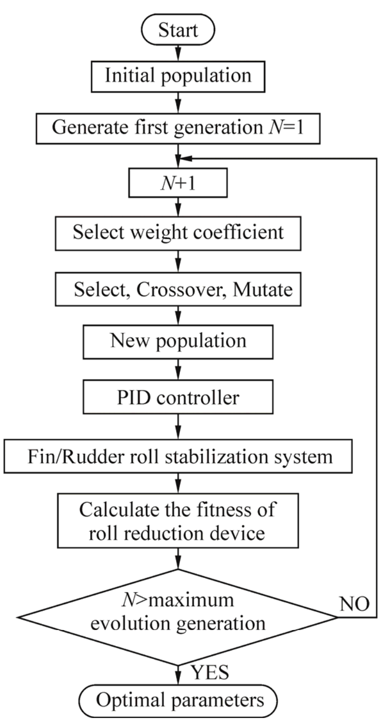

Fig. 3 Flowchart of self-tuning PID controller based on the MOGA

The PID transfer function is usually expressed in the following form:

$$G(s) = K_P + \frac{K_I}{s} + K_D s \tag{16}$$

where K_P is the proportional, K_I is the integral gain and K_D is the derivative gain.

However, based on experience and actual work conditions, Eq. (16) can be rewritten as below:

$$G(s) = K_P + K_I \frac{K_1}{T_1 s + 1} + K_D \frac{K_2 s}{(T_2 s + 1)(T_3 s + 1)} \tag{17}$$

For optimization, the PID controller with three parameters in Eq. (17) must be well tuned. Therefore, the self-tuning PID controller based on the MOGA is proposed. The main steps of MOGA are explained below:

First, the method to calculate weight coefficient and improve fitness function is presented.

The random weight coefficient is used. The Eq. (15) has given weight coefficient $\lambda_1 - \lambda_5$ of each objective function, they are described as

$$\lambda_i = \frac{r_i}{\sum_{j=1}^{5} r_j} \ (i = 1, 2, \ldots 5) \tag{18}$$

where r_i and r_j are random positive integers.

In the Eq. (15), because the target unit is not uniform, both values are very different. It will lead to some objective function does not work. So Eq. (15) is modified to Eq. (19). The objective function can be normalized to a constant level.

$$J_1 = \frac{1}{N}\left(\lambda_1 \frac{\Delta\psi_i^2}{\Delta\psi_{i\max}^2} + \lambda_2 \frac{r_i^2}{r_{i\max}^2} + \lambda_3 \frac{\phi_i^2}{\phi_{i\max}^2} + \lambda_4 \frac{\delta_i^2}{\delta_{i\max}^2} + \lambda_5 \frac{f_i^2}{f_{i\max}^2}\right) \tag{19}$$

where $\Delta\psi_{i\max}$, $r_{i\max}$, $\phi_{i\max}$, $\delta_{i\max}$, $f_{i\max}$ are the most suitable value of each objective function in each generation population, respectively.

Because each value of the objective function is the square root, the fitness function should be non-negative. In addition, the fitness function value increases with the increasing problem solution. Thus the fitness function is defined as

$$J = 1 / J_1 \tag{20}$$

In this paper, two different types of control modes are applied to the fin/rudder roll stabilization system, a type of classical PID controller is selected to optimize ship performances in certain conditions. In order to obtain the optimal PID controller, the self-tuning PID controller based on the MOGA is presented.

In this paper, population size is 50, crossover probability is 0.8, mutation probability is 0.05, the parameters K_P in the range of [0, 100], K_I in range of [0, 50], K_D in the range of [0, 100], the optimization time is 200 s, the step size is 0.1 s, termination condition is 40 iterations.

5 Simulation results and discussion

To facilitate the study, the ship model is adopted. The main dimensions of the ship and the fin and the rudder can be found in Holden *et al.* (2007).

When the ship speed and sea states are set, classical PID controller has good control effect. However, when the ship sails in various speed and sea states, the classical PID controller is ineffective. In order to obtain the optimal PID controller, the self-tuning PID controller based on the MOGA is chosen in correspondence to these conditions. Simulations are carried out with two different speeds and three different encounter angles. The ship speed is set to be 18 knots and 30 kn, respectively. Encounter angle γ is set to be 0°, 90° and 180°.

In classical PID controller, the sea state 5 corresponds to 4 m significant wave height $H_{1/3}$. The ship speed is set to be 18 kn, the encounter angle is set to be 90°. In this case, a set of optimal PID controller parameters K_P, K_I and K_D are obtained in termination populations using the self-tuning PID controller based on the MOGA that are 10.591, 0.432 and 0.026 1, respectively.

The cost function values of the roll angle, yaw angle and rudder angle for two types of controller with respect to different contrast curves are shown in Figs. 4–6, respectively. The curve of performance index is shown in Fig. 7. The simulation data comparison results are summarized in Table 1, which can be used to judge the effect of two types of controller. From Fig. 4, it can be seen that compared with the classical PID, the roll reduction is improved greatly. From Fig. 5, the yaw angle is smaller compared with the classical PID, thus the ship course precision is improved. In Fig. 6, the rudder angle is smaller compared with the classical PID. Furthermore, from Fig. 6, it can be seen that the steering frequency decreases, which means energy consumption caused by the yaw and attrition of steering gear can be decreased. Fig. 7 shows that the performance index is the best in the self-tuning PID controller based on the MOGA. From the overall investigation on the total fitness function with different dynamic ocean conditions, Table 1 can be applied to judge the performance index of each type of controller. It can be concluded that the average value of the roll angle, yaw angle and steering frequency can be significantly decreased by using the self-tuning PID controller based on the MOGA. Therefore, the system is able to meet the roll reduction efficiency and ship course precision and reduce energy consumption.

According to the simulations, the performance index can be improved so that the ship has better performance.

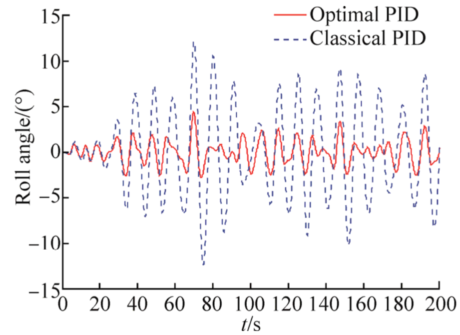

Fig. 4 Roll angle simulation

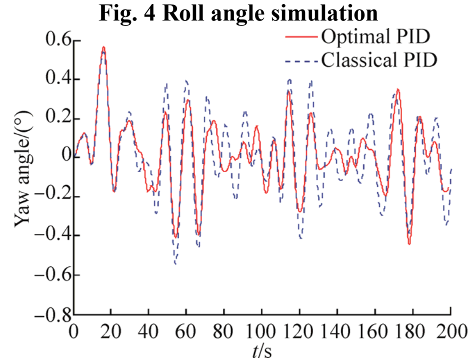

Fig. 5 Yaw angle simulation

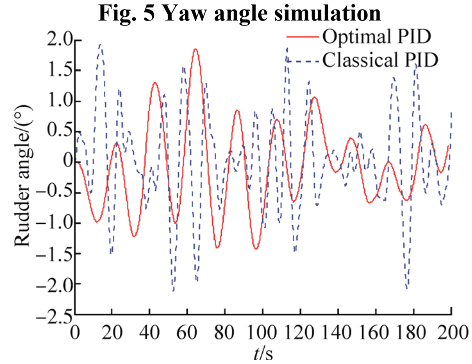

Fig. 6 Rudder angle simulation

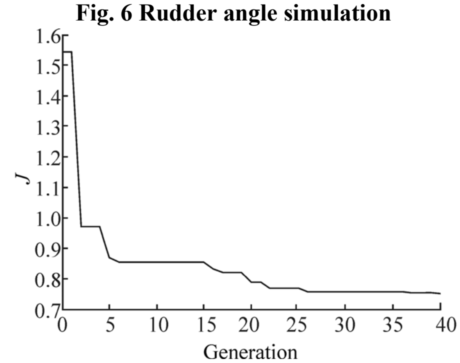

Fig. 7 Performance index *J* for best controller

Table 1 Comparison of roll angle

Speed (kn)/ encounter angle(°)	Roll angle/(°)		Yaw angle/(°)		Rudder angle/(°)	
	Classical PID	Optimal PID	Classical PID	Optimal PID	Classical PID	Optimal PID
18/0	3.312 4	2.245 5	0.124 5	0.097 8	0.126 8	0.105 3
18/90	6.178 1	1.657 1	0.316 1	0.273 4	0.981 5	0.712 7
18/180	0.832 8	0.561 2	0.024 1	0.019 6	0.008 9	0.007 1
30/0	3.701 6	1.413 4	0.112 7	0.041 2	0.243 6	0.213 7
30/90	5.182 7	0.763 7	0.278 1	0.201 5	1.463 1	1.125 9
30/180	0.391 3	0.214 0	0.009 8	0.006 7	0.126 8	0.104 2

6 Conclusions

This paper presents a proposal on how to reduce energy consumption of roll reduction devices. Firstly, the nonlinear 4-DOF mathematical model is established. According to the model characteristics, the energy consumption caused by overcoming the resistance and the yaw is analyzed. Considering the actual needs, steering frequency is added into the fitness function. A new performance index is established. In order to obtain the optimal PID controller, the self-tuning PID controller based on the MOGA presented in this paper improves the fitness function. According to a series of simulation comparisons, the self-tuning PID controller based on the MOGA is generally superior to the classical one. The system has better roll reduction efficiency and ship course precision. At the same time the system energy is optimized using the self-tuning PID controller based on the MOGA. This paper provides a reference method for the performance of the ship roll reduction system.

References

Crossland P (2003). The effect of roll stabilization controllers on warship operational performance. *Control Engineering Practice,* **11**(4), 423-431.
DOI: 10.1016/S0967-0661(01)00156-3

Fang MC, Lin YH, Wang BJ (2012). Applying the PD controller on the roll reduction and track keeping for the ship advancing in waves. *Ocean Engineering*, **54**, 13-25.
DOI: 10.1016/j.oceaneng.2012.07.006

Fang MC, Luo JH (2007). On the track keeping and roll reduction of the ship in random waves using different sliding mode controllers. *Ocean Engineering*, **34**(3), 479-488.
DOI: 10.1016/j.oceaneng.2006.03.004

HoKo C, Wang SF (2011). Precast production scheduling using multi-objective genetic algorithms. *Expert Systems with Applications*, **38**(7), 8293-8302.
DOI: 10.1016/j.eswa.2011.01.013

Holden C, Galeazzi R, Rodriguez C, Perez T, Fossen TI, Blanke M, de Almeida Santos Neves M (2007). Nonlinear container ship model for the study of parametric roll resonance. *Modeling, Identification and Control,* **28**(4), 87-103.
DOI: 10.4173/mic.2007.4.1

Huang S, Duan WY, You YG, Jiang JH, Wang WS (2014). Nonlinear time domain simulation of sloshing and coupled ship motion. *Journal of Harbin Engineering Univers*ity, **35**(9), 1045-1052. (in Chinese)
DOI: 10.3969/j.issn.1006-7043.201307076

Jin HZ, Wang F (2009). Rudder/Fin roll stabilization with energy optimization using a lower-speed steering gear. *Acta Armamentarii*, **30**(7), 945-950. (in Chinese)

Jin HZ, Gao YN, Zhou SB (2011). Adaptive terminal-sliding- mode combination control for heading and rolling of marine robot based on energy optimization. *Journal of Mechanical Engineering*, **47**(15), 37-43. (in Chinese)

Koshkouei AJ, Burnham K, Law Y (2007). A comparative study between sliding Mode and PID controllers for ship roll stabilization. *IET (IEE) Control Theory Appl*., **1**(5), 1266-1275.
DOI: 10.1049/iet-cta:20060277

Lee LH, Lee CU, Tan YP (2007). A multi-objective genetic algorithm for robust fight scheduling using simulation. *European Journal of Operational Research*, **177**(3), 1948-1968.
DOI: 10.1016/j.ejor.2005.12.014

Liang LH, Sheng XL, Zhang ST, Liu HW (2012). Optimize rudder's parameters based on genetic algorithm. *Techniques of Automation and Applications*, **31**(12), 11-15. (in Chinese)

Liu ZQ, Jin HZ (2013). Extended radiated energy method and its application to a ship roll stabilisation control system. *Ocean Engineering*, **72**(1), 25-30.
DOI: 10.1016/j.oceaneng.2013.06.009

Long Q (2014). A constraint handling technique for constrained multi-objective genetic algorithm. *Swarm and Evolutionary Computation*, **15**, 66-79.
DOI: 10.1016/j.swevo.2013.12.002

Malik A, Zhang ZM, Agarwal RK (2014). Extraction of battery parameters using a multi-objective genetic algorithm with a non-linear circuit model. *Journal of Power Sources*, **259**, 76-86.
DOI: 10.1016/j.jpowsour.2014.02.062

McGookin EW, Murray-Smith DJ, Li Y, Fossen TI (2000). Ship steering control system optimization using genetic algorithms. *Control Engineering Practice,* **8**(4), 429-443.
DOI: 10.1016/S0967-0661(99)00159-8

Minorsky N (1947). Experiment with activated tanks. *Trans ASME*, **96**, 735-747.

Oda H, Ohtsu K, Hotta T (1996). Statistical analysis and design of a rudder roll stabilization system. *Control Engineering Practice*, **4**(3), 351-358.
DOI: 10.1016/0967-0661(96)00012-3

Pan I, Das S (2013). Frequency domain design of fractional order PID controller for AVR system using chaotic multi-objective optimization. *International Journal of Electrical Power & Energy Systems*, **51**, 106-118.
DOI: 10.1016/j.ijepes.2013.02.021

Perez T, Goodwin GC (2008). Constrained predictive control of ship fin stabilizers to prevent dynamic stall. *Control Engineering Practice,* **16**(4), 482-494.
DOI: 10.1016/j.conengprac.2006.02.016

Suksonghong K, Boonlong K, Goh KL (2014). Multi-objective genetic algorithms for solving portfolio optimization problems in the electricity market. *International Journal of Electrical Power and Energy Systems*, **58**, 150-159.
DOI: 10.1016/j.ijepes.2014.01.014

Treakle TW, Mook DT, Liapis SI, Nayfeh AH (2000). A time-domain method to evaluate the use of moving weight to reduce the roll motion of a ship. *Ocean Engineering*, **27**(12), 1321-1343.
DOI: 10.1016/S0029-8018(99)00051-7

Vicente H, Ayala H, Coelho LS (2012). Tuning of PID controller based on a multi-objective genetic algorithm applied to a robotic manipulator. *Expert Systems with Applications*, **39**(10), 8968-8974.
DOI: 10.1016/j.eswa.2012.02.027