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Active-Passive Combined Control System in Crane Type for Heave Compensation

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ABSTRACT For the purpose of researching the displacement control system of heave compensation for offshore drilling platform, a set of crane type active and passive combined heave compensation device are designed on the basis of the similarity principle. As it known that platform heaving will be caused by the wind, sea wave and ocean current when conducting the drilling operations on the offshore drilling platform, which then will disturb the drilling operation. Therefore, the compensation device must be adopted to keep the vertical relative motion between the drill string system and the drilling platform to zero during the operation. Meanwhile, to improve the real-time performance of the heave compensation, the control system is optimized by establishing the simulation model of the active-passive combined crane, and LS-SVM(Least Squares Support Vector Machine) is improved by the artificial immune algorithm to predict the motion trend of offshore platforms. Eventually, in order to acquire the best control scheme, the Proportion Integration Differentiation (PID), fuzzy PID, BP neural network PID control method are utilized to carry out the simulation analysis, and the BP neural network PID control is found to be the optimum. Experiments showed that after using the BP neural network PID control algorithm, the displacement compensation rate of hook for active-passive combined crane device is more than 90%, the performance of the heave compensation is better, and the control is in time.

INDEX TERMS Heave compensation, least squares support vector machine, BP neural network, PID control.

I. INTRODUCTION

In recent years, marine oil and gas has been developed rapidly, and the research of deep-sea drilling equipment has been attracted more attention. The floating drilling platforms in offshore drilling operations have complicated movements such as heave and rocking under the influence of natural factors, such as wind, wave and current, in particularly, heave movement has the greatest impact on drilling operations [1]. The up and down reciprocating movement of drilling system hung on the hook will be caused by the heave movement, and then cause the drilling pressure variation, affect the drilling efficiency, reduce the life of drill bit and drill pipe, increase the drilling cost, and eventually may cause serious accidents. As a result, the heave compensation device is developed to eliminate the influence of the heave movement of the offshore drilling platform on the drilling operation [2]–[3].

In accordance with the installation position of the heave compensation device on the platform, the device can be divided into many forms, which includes tour type, winch type and crane type. Among all these three types, the crane type heave compensation has been widely used in floating drilling platforms and has better application prospects [4]–[5].

The traditional PID control method and fuzzy PID control method are mainly used in the research of heave compensation control system. The traditional PID control method has the advantages of simpler algorithm, better stability and reliability, but it is not suitable for the complicated systems where the control effect is unsatisfactory and difficult to meet the requirements of control accuracy and effectiveness [6]. The fuzzy PID control method has stronger stability and anti-interference, and does not require precise mathematical

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models. For the complicated time-varying, lagging, nonlinear systems, it can achieve the incomparable effect of conventional control. However, the formulation of the rule table of the fuzzy control depends on the expertise, and the control errors vary with each individual [7]. Compared with the PID control which is commonly used on offshore drilling platforms, BP-PID has strong self-learning ability. Therefore, in the face of complicated and changeable marine conditions, it has better predictability, stability and robustness, and will also show better compensation for platform heave compensation. BP neural network is a multi-layer feedforward artificial neural network. It has good prediction performance on the research object with non-linear characteristics. Beyond that, it has a strong self-learning ability. Therefore, the BP neural network algorithm is introduced into the PID control to create a new type of controller - BP neural network PID controller [8].

According to the principle of similitude, a set of crane type active and passive combined control system for heave compensation is designed in this paper. The active and passive compensation is combined, and the compensation cylinder is installed upright and hinged with the crane. The heave compensation of platform is controlled by the movement of the crane. For the purpose of optimizing the control system, it is simulated on the basis of Simulink. Meanwhile, due to the displacement detection of displacement sensor has time lag, and the actuator of the heave compensation system has dynamic response delay, the movement trend of the offshore platform is forecasted through the predictive control method [9]. Finally, the simulation comparative analysis is carried out by using the PID, fuzzy PID and BP neural network PID methods, so as to obtain the best control scheme to optimize the compensation device.

II. SYSTEM STRUCTURE DESIGN

According to the ratio of 1: 7 and the principle of similitude, the proportional reduction model of crane type active-passive combined control system for heave compensation is designed and manufactured. As shown in Figure 1, the black parts are crane, rocker and other mechanical parts, and the blue part is the component part of hydraulic control system.

The working principle is as follows: The variable frequency controlled constant tension is adopted by the tension motor to produce the backward tension by the wire rope on the winch, so as to support the crane. The accumulator undertakes parts of the load of the crane through passive compensation cylinder. The liquid gas springs inside periodically store and release the gravitational potential energy of the crane. When the crane rises, the accumulator releases energy, while the energy is stored as the crane descends, thus to reduce the energy consumption of the heave compensation device. The Proportional directional valve is controlled by the Programmable Logic Controller (PLC) to raise or drop the compensation cylinder to achieve the heave compensation of the system. The PLC collects the heave signal of working platform through the displacement sensor. According to the signal, the proportional directional valve is controlled to change the direction [10]. When the platform moves upward, the proportional directional valve is controlled to move by the PLC, the piston of the active compensation cylinder is moved downward and the crane is driven to move downward to compensate the heave motion of the platform. When the platform moves downwards it works reverse.

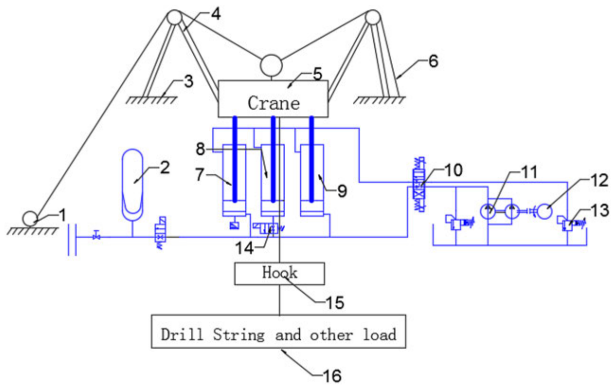


FIGURE 1. Schematic diagram of crane type active-passive combined heave compensation device. 1 Tension Motor, 2 Accumulator, 3 Ocean Work Platform, 4 Rocker Arm Mechanism, 5 Crane with Fixed Capstan, 6 Wire Rope, 7 Active Compensation Cylinder, 8 Passive Compensation, 9 Cylinder Active Compensation Cylinder, 10 Proportional solenoid valve, 11 Hydraulic Pump, 12 Motor, 13 Safety Relief Valve, 14 2/ 2-Way Commutation Valve, 15 Hook, 16 Drill String and Other Loads.

The main design parameters of the crane type active-passive combined heave compensation device are the maximum static load is 9kN, the compensation stroke is 450 mm, the maximum heave compensation speed is 0.1 m/s, the compensation accuracy error is within 7% $\sim$ 9%, and the wave simulation platform travel is 400 mm.

III. SYSTEM MODELING

The crane type active-passive combined heave compensation device is mainly consists of four subsystems: PLC control system, signal detection system, electro-hydraulic combined drive system and crane lifting system. As shown in Figure 2, the control system is able to manipulate the heave motion of the offshore platform, manage the balance of the crane to overcome the weight, and command the crane motion for heave compensation.

The yellow block diagram in the Figure 2 is the electrical control part of the system. When the offshore platform is stationary, the tension motor is controlled by the PLC cabinet, so that the crane overcomes its own weight and maintains its balance position. When the offshore platform has the heaving motion under the action of the wave loading cylinder, the displacement of the compensating cylinder obtained by the displacement sensor and the displacement of the wave loading cylinder will be compared by the PLC cabinet. Then the corresponding electrical signal is outputted from the PLC cabinet, the displacement of the proportional directional valve and the cylinder are controlled to compensate the heave movement of the platform and keep the balance of the crane.

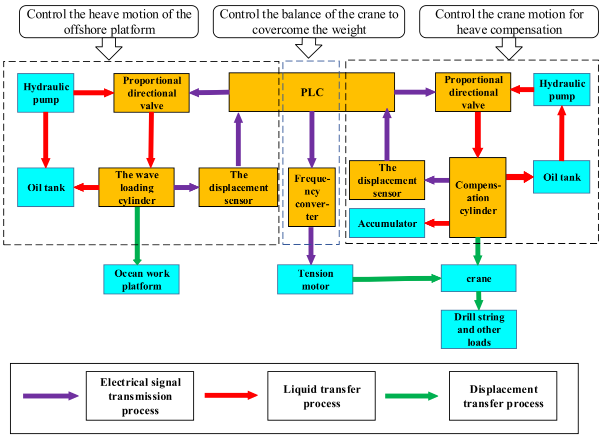


FIGURE 2. Control block diagram of crane type active and passive combined heave compensation device.

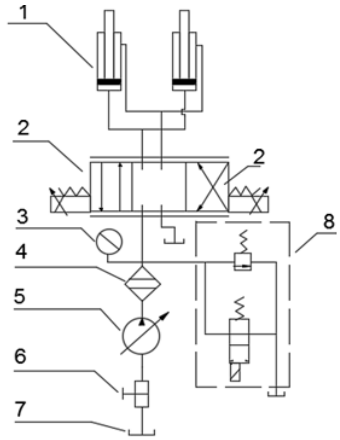


FIGURE 3. Schematic diagram of active heave compensation device. 1 Compensating Hydraulic Cylinder, 2 Solenoid proportional directional valve, 3 Pressure Gauge, 4 Filter, 5 Hydraulic pump, 6 Cut-Off Valve, 7 Oil Tank, 8 Overflow Valve.

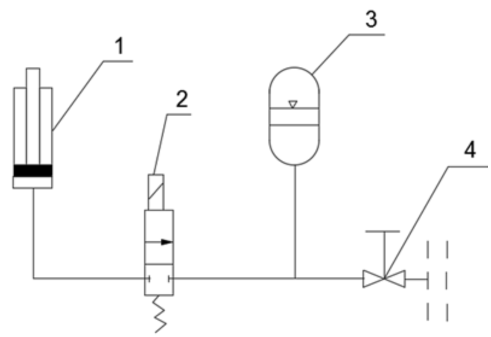


FIGURE 4. chematic diagram of passive heave compensation device. 1 Compensation Hydraulic Cylinder, 2 Isolation Valve (Normally Open), 3 Accumulator, 4 Cut-Off Valve.

A. HYDRAULIC CYLINDER MODELING

The electro-hydraulic control part is mainly composed of hydraulic cylinder and electromagnetic proportional valve. The two models are developed separately and then combined to form the model of the electro-hydraulic control system of the device according to the actual working conditions. The crane type active-passive combined heave compensation device are consists of two active compensation cylinders and one passive compensation cylinder which are to realize the heave compensation and the active-passive compensation combination. The active compensation has a fast responsiveness and can improve the accuracy. The passive compensation can reduce the energy consumption of the system by using the accumulator. The working principle of the active compensation cylinder and the passive compensation cylinder are shown in Figure 3 and Figure 4 respectively.

The power of the hydraulic cylinder in the active heave compensation device is provided by the hydraulic pump, as shown in Figure 3. The hydraulic cylinder are connected with the electromagnetic proportional reversing valve, and the flow rate of liquid in the pipeline is managed by controlling the rotation angle of the hydraulic pump or the displacement of the valve core of the electromagnetic proportional reversing valve. The pressure variation in the rod cavity and rodless cavity of the hydraulic cylinder will be caused by the flow rate of pipeline, so as to achieve the displacement movement manipulation of the piston rod of the hydraulic cylinder, and make it rise or fall. Although the active compensation method has high precision and fast response, the energy consumption is more.

The working principle of the passive heave compensation device is similar to the active one, as shown in Figure 4, the power of the hydraulic cylinder in the passive device is provided by the accumulator. In the process of heave compensation, the gas in the downward accumulator of the piston rod is compressed by giving a downward pressure to the hydraulic cylinder when the crane needs to move downward. While, the compressed gas in the accumulator will release energy and make the piston rod go up when the crane needs to move up. When the isolation valve closes, the piston rod will stop moving to deal with the emergency stop. The passive compensation method has low precision and slow response, and it does not need to provide additional energy.

The flow equations of hydraulic cylinder are [11]:

$$Q_y = \mathrm{C}_i(P_y - P_w) + \mathrm{C}_e P_y + \frac{v_y d_{p_y}}{k d_t} + \frac{d_{v_y}}{d_t} \tag{1}$$

$$Q_w = \mathrm{C}_i(P_y - P_w) + \mathrm{C}_e P_w - \frac{v_w d_{p_w}}{k d_t} + \frac{d_{v_w}}{d_t} \tag{2}$$

where, Q_y, Q_w are the flow of rod cavity and rodless cavity of hydraulic cylinder; C_i, C_ε are the hydraulic cylinder internal and external leakage coefficient respectively; k is the effective bulk modulus of the system; P_y, P_w are the pressure of rod cavity and rodless cavity of hydraulic cylinder; v_y, v_W are the effective volume of rod cavity and rodless cavity of hydraulic cylinder (including the solenoid proportional directional valve, the connecting pipe and the effective volume of the working chamber).

Let

$$v_y = v_{yp} + A_y X \tag{3}$$

$$v_w = v_{wp} + A_w X \tag{4}$$

where: v_{yp}, v_{wp} are the volume of the rod cavity and the rodless cavity at the equilibrium position; A_y, A_w are the effective area of the rod cavity and the rodless cavity; X is the displacement of the piston rod of the hydraulic cylinder.

Obtain the derivative of formula (3) and (4):

$$\frac{d_{v_y}}{d_t} = A_y \frac{d_x}{d_t} \tag{5}$$

$$\frac{d_{v_w}}{d_t} = A_w \frac{d_x}{d_t} \tag{6}$$

The flow equation of the hydraulic cylinder is:

$$Q_L = \mathrm{C}_L P_L + \frac{v_L d_{pL}}{4k d_t} + A_y \frac{d_x}{d_t} \tag{7}$$

where: C_L is the equivalent leakage coefficient of the hydraulic cylinder; P_L is the actual pressure of the hydraulic system; v_L is the equivalent volume of the hydraulic cylinder.

The balance equation of the active hydraulic cylinder is:

$$P_L A_y = P_w A_w - P_y A_y = m\frac{d^2X}{dt^2} + J\frac{dX}{dt} + nX + \frac{1}{2}(F - F_B) \tag{8}$$

The balance equation of the passive hydraulic cylinder is:

$$F_B = P_B A_B = m_B \frac{d^2X}{dt^2} + J_B \frac{dX}{dt} + n_B X \tag{9}$$

Substitute formula (9) into formula (8) is:

$$P_L A_y = P_w A_w - P_y A_y = (m - \frac{1}{2}m_B)\frac{d^2X}{dt^2} + (J - \frac{1}{2}J_B)\frac{dX}{dt} + (n - \frac{1}{2}n_B)X + \frac{1}{2}F \tag{10}$$

where: the equivalent mass of the active cylinder and the passive cylinder are represented by m, m_B; the viscous friction coefficient of the active cylinder and the passive cylinder are expressed by J, J_B; the load spring stiffness of the active cylinder and the passive cylinder are denoted by n, n_B; t is time; F is the external load acting on the hydraulic rod, that is, the force of the crane and the drill string system on all the hydraulic cylinders (there are two active cylinders and one passive cylinder in the compensation system); F_B is the external load acting on the passive compensation cylinder hydraulic rod.

Transform the formula (7) and the formula (10) by Lagrangian transformation:

$$Q_L(\mathrm{S}) = \mathrm{C}_L P_L(\mathrm{S}) + \frac{v_L}{4k} s p_L(\mathrm{S}) + A_y s X(\mathrm{S}) \tag{11}$$

$$A_y P_L(\mathrm{s}) = (m - \frac{1}{2}m_B)s^2 X(\mathrm{s}) + (J - \frac{1}{2}J_B)sX(\mathrm{s}) + (n - \frac{1}{2}n_B)X(\mathrm{s}) + \frac{1}{2}F(\mathrm{s}) \tag{12}$$

where: S is the Lagrangian operator.

According to the load pressure-flow characteristics of the solenoid proportional directional valve [10]:

$$Q_L = \mathrm{r}_q h - \mathrm{r}_{ce} P_L \tag{13}$$

Combine formula (11) and formula (12), formula (13) (14), as shown at the bottom of the next page:

TABLE 1. Partial parameter selection of model.

Symbol	Value	Symbol	Value
C_e	$3\times10^{-10}\ \mathrm{m^3\cdot(s\cdot pa)^{-1}}$	J	$2088\ \mathrm{N\cdot m^{-2}}$
k	$7\times10^{-8}\ \mathrm{N\cdot m^{-2}}$	J_B	$1639\ \mathrm{N\cdot m^{-2}}$
A_y	$550\ \mathrm{mm^2}$	n、n_B	$0\ \mathrm{N\cdot m^{-1}}$
A_w	$804\ \mathrm{mm^2}$	v_L	$4.5\times10^5\ \mathrm{m^2\cdot s^{-1}}$
L	400 mm	r_{ce}	$2.4\times10^{-10}\ \mathrm{m^3\cdot(s\cdot pa)^{-1}}$
C_L	$2.3\times10^{-10}\ \mathrm{m^3\cdot(s\cdot pa)^{-1}}$	r_q	$0.009\ \mathrm{m^2\cdot s^{-1}}$

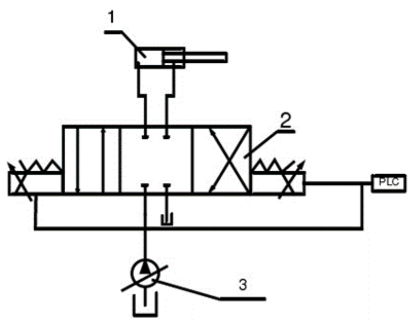


FIGURE 5. Schematic diagram of the solenoid proportional directional valve. 1 Hydraulic Cylinde, 2 solenoid proportional directional valv, 3 Hydraulic Pump.

where: r_q is the flow gain of the valve core; r_{ce} is the coefficient of total flow and pressure; h is the displacement of the directional valve core.

As for the general valve control cylinder system, the load spring stiffness is zero (that is n, n_b is equal to 0). Then the transfer function is shown as formula 15, where the solenoid proportional directional valve displacement h is the input and the displacement of the piston rod h is the output. The specific transfer function is obtained according to the parameters of Table 1 (15), as shown at the bottom of the next page.

B. MATHEMATICAL MODEL OF SOLENOID PROPORTIONAL DIRECTIONAL VALVE

As shown in Figure 5, the three-potential four-way solenoid proportional directional valve is adopted by the electric hydraulic combined drive system of the crane type active-passive combined heave compensation device. The PLC alters the displacement of the proportional directional valve core to control the flow rate and implement the left movement, right movement and keep still of hydraulic cylinder piston rod. In the hydraulic system, the output displacement of the proportional directional valve is proportional to the input signal [12]–[14].

The function between the valve core displacement and the voltage control signal is:

$$h(\mathrm{s}) = \frac{\bar{\omega}}{1 + T_{hv}s} u(\mathrm{s}) \tag{16}$$

The transfer function is:

$$G_h(s) = \frac{\bar{\omega}}{1 + T_{hv}s} \tag{17}$$

Select the HYDAC three-position four-way solenoid proportional directional valve. The maximum value rated flow of valve is 40l/min, and the nominal current of HYDAC is 188A at 12VDC, and 86 A at 24 VDC. T_{hv} is the time constant of the valve core movement; ω is the gain of displacement-voltage of valve core.

C. SYSTEM TRANSFER FUNCTION

The displacement of the proportional directional valve is controlled by the electrical signal of the crane heave compensation system, by which also drives the displacement of the hydraulic cylinder piston, and move the crane up and down, so as to realize the heave compensation of the offshore platform. The system transfer function is composed of solenoid proportional directional valve transfer function and hydraulic cylinder transfer function. The closed-loop transfer function of the system is (18), as shown at the bottom of the next page:

IV. CONTROL STRATEGY SIMULATION

Offshore platforms are affected by a variety of random waves, sea breeze and ocean currents, so the working environment of the heave compensation device is complicated and changeable. Because the control system is affected by many factors, the system control strategy should be optimized to have a better control effect. Firstly, the LS-SVM (Least Squares Support Vector Machine) method is used to forecast the heave displacement of the offshore platform, and then the predicted displacement is input into the controller of the control system. Finally, the performance of PID control, fuzzy PID control and BP neural network PID control in the heave compensation are compared and analyzed, and the optimal control method is acquired.

A. PREDICTION OF HEAVE DISPLACEMENT OF OFFSHORE WORK PLATFORM

The crane type active-passive combined heave compensation system is a valve control system. The controlled object has the characteristics of nonlinear, lag, etc. Meanwhile, the process of heave compensation is also affected by the factors such as mechanical friction, wire rope vibration, hydraulic cylinder leakage, and the proportional directional valve lag. Therefore, in order to improve the robustness, adaptability and quick response ability of the compensation control system, a valid prediction method should be proposed to predict the heave movement of the platform. Support vector machine is a novel machine learning algorithm based on the principle of structural risk minimization. It maps the input sample data into a high-dimensional feature space and transforms the actual problem into a quadratic programming problem. The LS-SVM improves the standard support vector machine (SVM), adopts the optimization objective function which is different from the support vector, optimizes the support vector machine by replacing the inequality constraints with the equality constraint problem, simplifies the computational complexity of the algorithm, and improves the prediction efficiency [15] Consequently, the LS-SVM is adopted to predict the heave movement displacements of platform.

1) LEAST SQUARES SUPPORT VECTOR MACHINE

Set a data set $\{(x_i, y_i)\}$, $(i = 1, 2, 3\ldots, m)$ as a training sample, $x_i \epsilon R^m$ is the input of training samples, $y_i \epsilon R^m$ is the output of training samples, m is the sample size, the optimization function of the LS-SVM algorithm is:

$$\min J(\mathrm{w}, \mathrm{e}) = \frac{1}{2}(\mathrm{w} \cdot \mathrm{w}^T) + \frac{1}{2}\alpha \sum_{m=1}^{m} e_i^2,$$
$$st\ y_i = \mathrm{w}^T\theta(\mathrm{X}_i) + \mathrm{b} + e_i,\ i = 1, \ldots m. \tag{19}$$

where: w is the weight vector of the hyper plane; b is a constant; e_i is an error variable; α is an adjustable parameter; $\theta(x_i)$ is a kernel space mapping function.

Construct Lagrange function

$$L = J(\mathrm{w}, \mathrm{e}) - \sum_{m=1}^{m} \delta_i\{\mathrm{w}^T\theta(\mathrm{X}_i) + \mathrm{b} + e_i - y_i\} \tag{20}$$

where: δ_i is Lagrange multiplier.

According to the Kuhn-Tucker condition (Karush- Kuhn-Tucker condition, KKT condition for short), take the partial

$$X = \frac{\frac{\mathrm{r}_q}{A_y}h - \frac{\mathrm{r}_{ce}}{A_y^2}(\frac{v_L}{4k\mathrm{r}_{ce}}\mathrm{s} + 1)\frac{1}{2}F}{\frac{(m-\frac{1}{2}m_B)v_L}{4k\mathrm{r}_{ce}}\mathrm{s}^3 + \left[\frac{(m-\frac{1}{2}m_B)\mathrm{r}_{ce}}{A_y^2} + \frac{(J-\frac{1}{2}J_B)v_L}{4kA_y^2}\right]\mathrm{s}^2 + \left[\frac{(J-\frac{1}{2}J_B)\mathrm{r}_{ce}}{A_y^2} + \frac{(n-\frac{1}{2}n_B)v_L}{4kA_y^2}\right]\mathrm{s} + \frac{(n-\frac{1}{2}n_B)\mathrm{r}_{ce}}{A_y^2}} \tag{14}$$

$$G_x(\mathrm{s}) = \frac{\frac{\mathrm{r}_q}{A_y}}{\frac{(m-\frac{1}{2}m_B)v_L}{4kA_y^2}\mathrm{s}^3 + \left[\frac{(m-\frac{1}{2}m_B)\mathrm{r}_{ce}}{A_y^2} + \frac{(J-\frac{1}{2}J_B)v_L}{4kA_y^2}\right]\mathrm{s}^2 + \left[\frac{(J-\frac{1}{2}J_B)\mathrm{r}_{ce}}{A_y^2} + 1\right]\mathrm{s}} \tag{15}$$

derivative of the formula (20):

$$\begin{cases} \dfrac{\partial L}{\partial \delta_i} = 0 \\ \dfrac{\partial L}{\partial \mathrm{b}} = 0 \\ \dfrac{\partial L}{\partial e_i} = 0 \\ \dfrac{\partial L}{\partial W} = 0 \end{cases} \rightarrow \begin{cases} \mathrm{w}^T\theta(\mathrm{x}_i) + \mathrm{b} + e_i - y_i = 0 \\ \sum_{m-1}^{m} \delta_i = 0 \\ \delta_i - \alpha e_i = 0 \\ \sum_{m-1}^{m} \delta_i\theta(\mathrm{x}_i) - \mathrm{w} = 0 \end{cases}$$

$$\rightarrow \begin{cases} \mathrm{w}^T\theta(\mathrm{x}_i) + \mathrm{b} + e_i - y_i = 0 \\ \sum_{m-1}^{m} \delta_i = 0 \\ \qquad\qquad\qquad \mathrm{i} = 1, \ldots, \mathrm{m} \\ \delta_i = \alpha e_i, . \\ \mathrm{w} = \sum_{m-1}^{m} \delta_i\theta(\mathrm{x}_i) \end{cases} \tag{21}$$

Eliminate w and e, get:

$$\begin{bmatrix} 0 & \beta_i^T \\ \beta_i & \Omega + \alpha^{-1} I \end{bmatrix} \begin{bmatrix} \mathrm{b} \\ A \end{bmatrix} = \begin{bmatrix} 0 \\ Y \end{bmatrix} \tag{22}$$

where $\Omega = \theta(x_i).\theta(x_i)^T$; $Y = [y_1, y_2, \ldots, y_m]^T$; $\beta i = [1, 1, \ldots, 1]^T$; $A = [\delta_1, \delta_2, \ldots \delta_m]^T$; I is a unit matrix. Then the function estimation of LSSVM is:

$$f(\mathrm{x}) = \sum_{m=1}^{m} \delta_i K(\mathrm{x}, \mathrm{x}_i) + \mathrm{b} \tag{23}$$

Because the ocean wave data is nonlinear, the radial basis function (RBF) is used as the kernel function of the model.

$$K(\mathrm{x}, \mathrm{x}_i) = \exp(-\|x - x_i\|^2/\sigma^2) = \Omega = \theta(\mathrm{x}_i)\theta(\mathrm{x}_i)^T \tag{24}$$

In the LS-SVM model, the penalty factor α and the parameters of the kernel function σ are selected, both of which has a major impact on the learning and generalization ability of LS-SVM.

The least squares support vector machine (LS-SVM) algorithm is simulated by choosing different penalty factors α and kernel function parameters σ as the inputs and the simulation results are shown in Figure 6 and 7 respectively.

It can be learned from the simulation that penalty factor and kernel function parameter have a greater impact on the least squares support vector machine prediction method. When the penalty factor is 0.38 and the kernel function parameter is 0.38, the root mean square error of the prediction results is 2.1613 mm. While increase the penalty factor to 5.8 and keep the kernel function parameter to 0.38, the root mean square error of the prediction results is 0.3921 mm. Therefore, it can be concluded that there is no obvious rules for the optimal combination of penalty factor and kernel function parameter in LS-SVM prediction model.

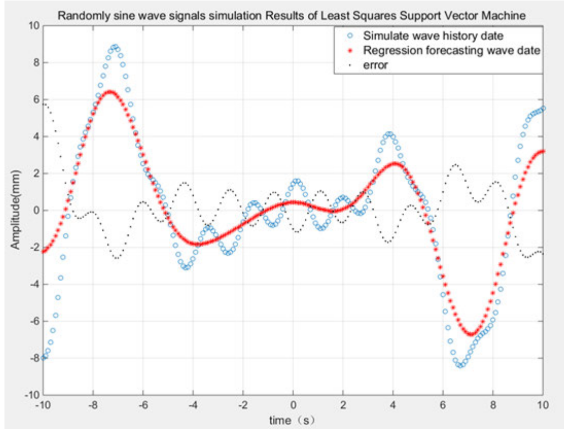


FIGURE 6. LSSVM prediction simulation result when penalty factor is 0.38 and kernel function parameter is 0.38.

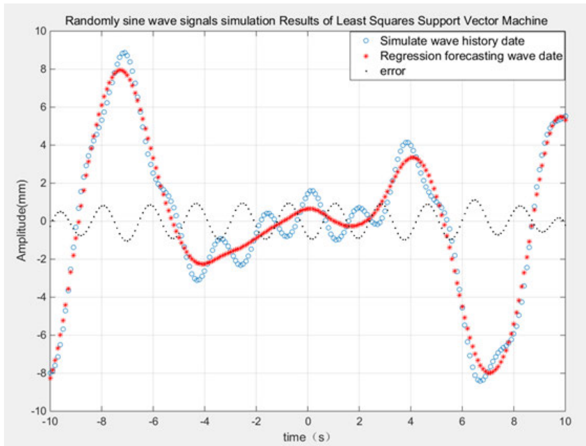


FIGURE 7. LSSVM prediction simulation result when penalty factor is 5.8 and kernel function parameter is 0.38.

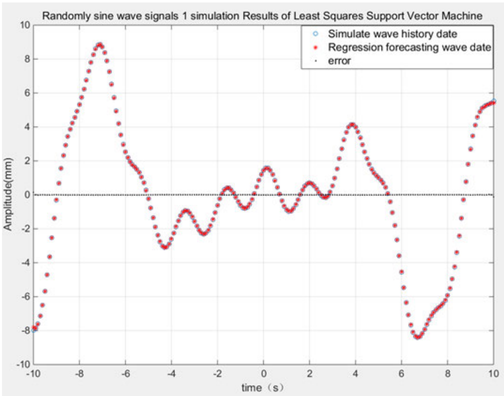
2) IMPROVE LEAST SQUARES SUPPORT VECTOR MACHINE

To overcome the selection blindness of subjective experience, the artificial immune algorithm is used to optimize the selection of these two parameters (penalty factors α and kernel function parameters σ).

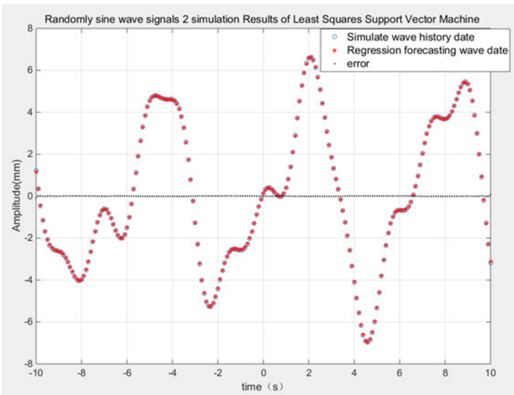
In the artificial immune improved LS-SVM parameters algorithm, the antigen corresponds to the objective function of the optimization problem, and the antibody corresponds to the solution of the optimization problem. The optimal root mean square error of the prediction model is selected as the objective function device, and the calculation formula is

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left\|\frac{y_i - f(\mathrm{x}_i)}{y_i}\right\|} \tag{25}$$

$$G(\mathrm{s}) = G_h(\mathrm{s}) \cdot G_x(\mathrm{s}) = \frac{\bar{\omega}}{1 + T_{hv}s} \cdot \frac{\frac{\mathrm{r}_q}{A_y}}{\frac{(m-\frac{1}{2}m_B)v_L}{4kA_y^2}\mathrm{s}^3 + \left[\frac{(m-\frac{1}{2}m_B)\mathrm{r}_{ce}}{A_y^2} + \frac{(J-\frac{1}{2}J_B)v_L}{4kA_y^2}\right]\mathrm{s}^2 + \left[\frac{(J-\frac{1}{2}J_B)\mathrm{r}_{ce}}{A_y^2} + 1\right]\mathrm{s}} \tag{18}$$



(a) Randomly sine wave signals 1



(b) Randomly sine wave signals 2

FIGURE 8. Simulation results of least squares support vector machine.

where: yi is the actual amplitude of the wave in the i moment, $f(xi)$ is the predicted amplitude of wave in the i moment, m is the number of data samples.

The artificial immune algorithm calculates the affinity between the antibody and the antigen by initializing the antibody group. The affinity size is sorted and N antibodies are selected with the highest affinity. The selected antibodies are cloned and multiplied, then the cloned antibodies are mutated with a certain percentage, and the antibodies whose affinity is higher than the inhibition threshold are deleted. Within the specified iteration steps, the above processes are continued to be circulated to calculate the affinity and so on. The artificial immune algorithm is used to find the optimal penalty factor α and kernel function parameters σ. The offshore operation platform is in a complicated working environment. Under different sea conditions, the effect of ocean waves on the working platform is similar to that of a sine wave signal with many different amplitudes and frequencies [16]. A variety of sine wave signals with different amplitude and frequency are randomly selected and superimposed to simulate the waves. The least square support vector machine is used to predict the randomly generated wave, as shown in Figure 8.

It can be seen from the simulation results that least squares support vector machine can provide a good prediction to the displacement of wave, and supply an accurate forecast to the heave displacement of platform for heave compensation

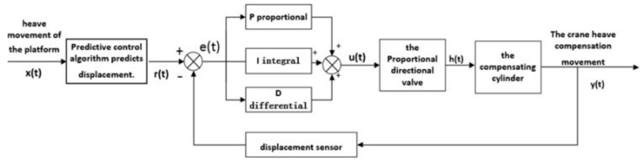


FIGURE 9. PID control schematic diagram.

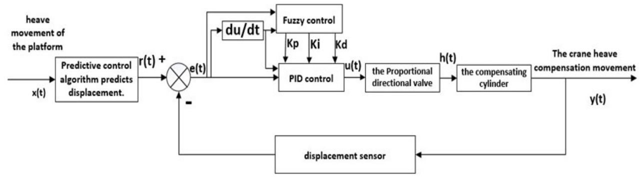


FIGURE 10. Structure of fuzzy PID control system.

system, so as to reduce the lag caused by displacement sensor and system actuator.

B. PID CONTROL

PID control has the advantages of simple principle, convenience of use, good stability and robustness. The adjustment of various parameters of the PID controller depends on the quality of the adjustment process. PID control schematic is shown in Figure 9. The PID control law is:

$$
\begin{aligned}
r(t)r(\mathrm{t}) &= k_p(\mathrm{e(t)} + \frac{\int_0^t e(\mathrm{t})dt}{T_i} + \mathrm{T}_d\frac{de(\mathrm{t})}{dt}) \\
\Rightarrow r(\mathrm{t}) &= k_p\mathrm{e(k)} + k_i\sum_{j=0}^{k} e(\mathrm{j})\mathrm{T} + k_d(e(k) - e(k-1))
\end{aligned} \tag{26}
$$

where: r is the output signal of controller; e is the deviation signal; T_i is the integral time constant; T_d is the differential integral constant; k_p is the proportional gain; k_i is the integral gain; k_d is the differential gain; T is the sampling period; k is the sampling number.

C. FUZZY -PID CONTROL

Fuzzy control has good robustness, strong anti-interference ability, and low steady-state accuracy [17]. The traditional PID control has high accuracy but common robustness and lack of adaptability. Therefore, the usage of fuzzy control to realize the on-line automatic adjustment of PID parameters can combine the following advantages: short adjustment time, small amount of adjustment and high precision of steady state. The fuzzy PID control system structure is shown in Figure 10, the fast response ability and stability of the control system are improved by using the fuzzy control to adjust the PID parameters.

D. BP NEURAL NETWORK AND PID CONTROL

BP neural network (back propagation neural network) is a multi-layer feedforward artificial neural network algorithm which is trained by error inverse propagation. It is suitable

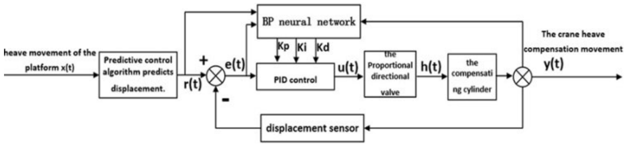


FIGURE 11. **Schematic diagram of control scheme.**

for analysis and prediction the objects with nonlinear characteristic and has strong self-learning ability. The BP neural network and PID combined control scheme is used in this paper, as shown in Figure 11. The approximation ability of nonlinear function of BP neural network is used to optimize the conventional PID controller. The PID control parameters that are suitable for the current environment can be obtained quickly through the repeated learning and training to the network [18].

The 3-5-3 type BP neural network model is established according to the crane type active-passive combined heave compensation system, which means the input layer has 3 and 5 values while the output layers has 3 values. Insert the PID control algorithm into the BP network model. The ideal control parameters can be obtained through the repeated learning and training of the network. Let the heave displacement $y(t)$ of platform at a certain moment, hydraulic cylinder compensation displacement $r(t)$, deviation $e(t)$ between platform displacement and compensation displacement are the inputs of the platform, and the control parameters *kp, ki, kd* of PID are the outputs. As shown in Figure 12.

The input of BP neural network middle layer is:

$$I_{i,2}(\mathrm{k}) = \sum_{j=0}^{M} W_{ij}X_j \quad (\mathrm{i} = 1, 2, \ldots, 5;\ j = 1, 2, \ldots 5) \tag{27}$$

The output of the middle layer is:

$$O_{i,2}(\mathrm{k}) = f(I_{i,2}(\mathrm{k})) \quad (\mathrm{i} = 1, 2, \ldots, 5) \tag{28}$$

where, $I_{i,2}$ is the input of the middle layer neurons; W_{ij} is the connection weight of the input layer and the middle layer; X_j is the output of the input layer; $O_{i,2}$ is the output of the middle layer neurons. The symmetric sigmoid function is selected as the excitation function of the middle layer.

$$f(\mathrm{X}) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{29}$$

The input of the output layer of the BP neural network is:

$$I_{l,3}(\mathrm{k}) = \sum_{i=1}^{5} W_{li}O_{i,2} \quad (l = 1, 2, 3) \tag{30}$$

The output of the output layer is:

$$O_{l,3}(\mathrm{k}) = g(I_{l,3}(\mathrm{k})) \quad (l = 1, 2, 3) \tag{31}$$

When l=*1,2,3*, the output of $O_{l,3}(k)$ is K_p,K_i,K_d respectively. Where, $I_{i,3}$ is the input of the output layer neurons; W_{li} is the connection weight for the intermediate layer and the output layer; $O_{i,3}$ is the output of the middle layer neurons; the output of the output layer is K_p,K_i,K_d, and the nonnegative sigmoid function is chosen as the activation function of the output layer.

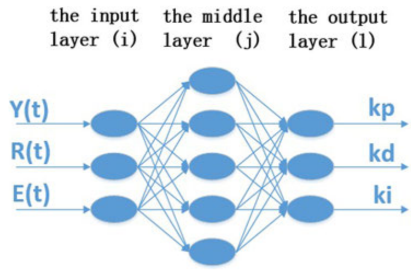


FIGURE 12. **PID structure of BP network.**

$$g(\mathrm{X}) = \frac{1}{2}(1 + \tanh x) = \frac{e^x}{e^x + e^{-x}} \tag{32}$$

Performance Index Function

$$\mathrm{E(k)} = \frac{1}{2}[r(\mathrm{k}) - y(\mathrm{k})]^2 \tag{33}$$

where: $r(k)$ is the input signal of sampling at K times; $y(k)$ is the output signal of sampling at K times.

The gradient descent method is adopted to be the weighted learning algorithm which can effectively solve the problem of slow convergence.

The correction algorithm of the weight value of the network output layer is

$$\Delta W_{li,3}(\mathrm{k}) = \zeta \Delta W_{li,3}(\mathrm{k}-1) + \eta\lambda_{l,3}O_{i,2}(\mathrm{k}) \tag{34}$$

Where: The correction algorithm of the weight value of the network middle layer is

$$\lambda_{l,3} = e(\mathrm{k}) \cdot \mathrm{sgn}(\frac{\beta y(\mathrm{k})}{\beta \Delta u(\mathrm{k})}) \cdot \frac{\beta \Delta u(\mathrm{k})}{\beta O_{l,3}(\mathrm{k})} \cdot g'(\mathrm{I}_{l,3}(\mathrm{k})) \tag{35}$$

$$g' = g(\mathrm{x})[1 - g(\mathrm{x})] \tag{36}$$

where: ζ is the coefficient of inertia; λ is the learning rate.

According to the fluctuation displacement of the offshore platform at each moment, the crane compensates for the lifting and descending, and the system is learned and trained to get the best PID control parameters. 20 different displacement compensations at different times are taken to adjust the parameters *kp, ki, kd* and to get the step response of system. The training samples of BP neural network are formed, and the BP neural network model is established for the crane type active-passive combined heave compensation system.

E. COMPARISON AND SIMULATION RESULTS OF THE CONTROLLER

Under the action of the input step signal, the performance of each controller is compared and analysed. The experimental results are shown in Figure 13.

The simulation experiment results show that under the action of the conventional PID controller, the system overshoots and the oscillation is obvious. However, under the

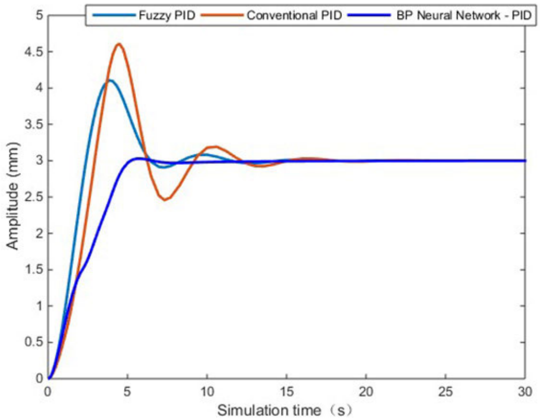


FIGURE 13. Simulation step responses of PID, fuzzy PID and BP neural network - PID controller.

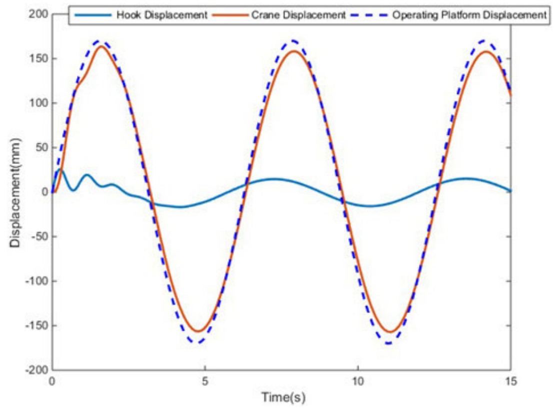


FIGURE 14. PID control simulation chart of crane type heave compensation system.

action of fuzzy PID controller, the system responds quickly but the overshoot phenomenon is still obvious. Only when the system is under the action of BP neural network PID controller, the response speed as well as the convergence is improved and the robustness of the system is strengthened. As a result, the BP neural network PID control has a better performance.

In order to verify the compensation effect of the crane type active-passive combined heave compensation system, the simulation system model is established by considering various nonlinear factors and transmission efficiency. As for the compensation of offshore drilling, the maximum compensation displacement is 450mm. The conventional PID controller, fuzzy PID controller and BP neural network PID controller are adopted respectively to simulate the wave acting on the working platform. The input value is sine wave where the amplitude is 170mm. The simulation results are shown in Figure 14, 15 and 16.

Then the predicted wave is input into the system, and the simulation results are shown in Figure 17, 18 and 19.

It can be seen from the simulation results of the three controllers, the amplitude of the hook vibration under the compensation of PID control system is comparatively larger,

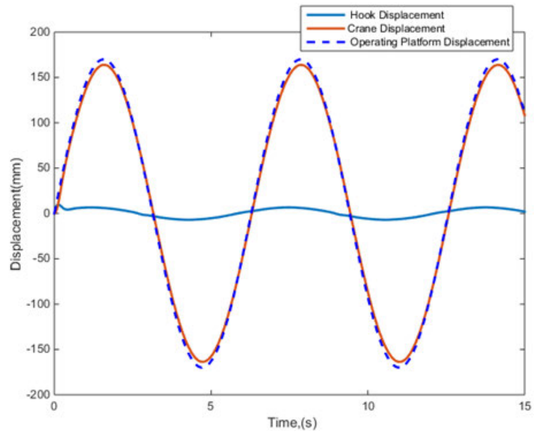


FIGURE 15. Fuzzy PID control simulation chart of crane type heave compensation system.

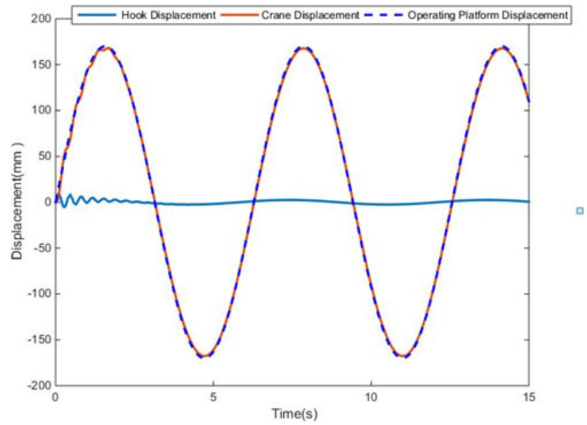


FIGURE 16. BP neural network PID control simulation chart of crane type heave compensation system.

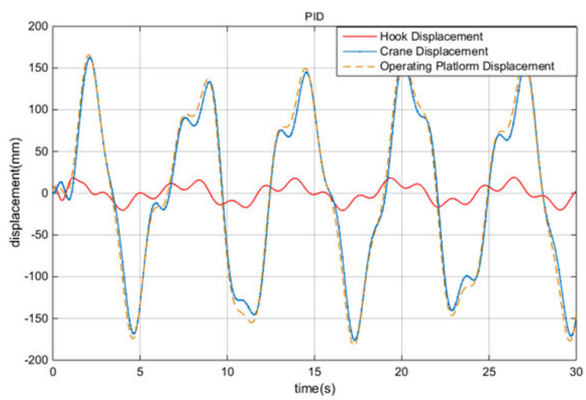


FIGURE 17. PID control simulation chart of predicted wave.

the relative error of the crane compensation displacement compensated by the fuzzy PID control system is larger than the other controllers; when the crane heave compensation system is controlled by the BP neural network PID controller, the hook displacement is stable between 5mm and -5mm, and the compensation rate(compensation displacement/operating platform displacement) reaches up to 98.1%,thus this system has a better compensation effect.

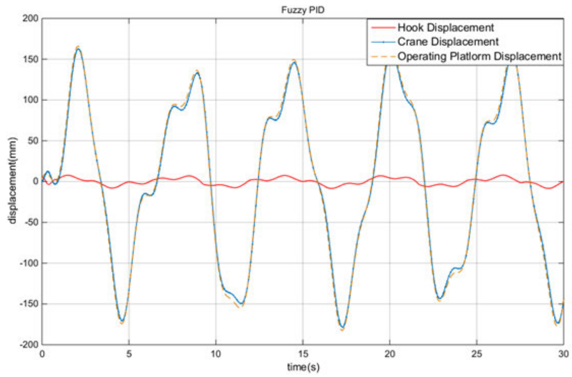


FIGURE 18. Fuzzy PID control simulation chart of predicted wave.

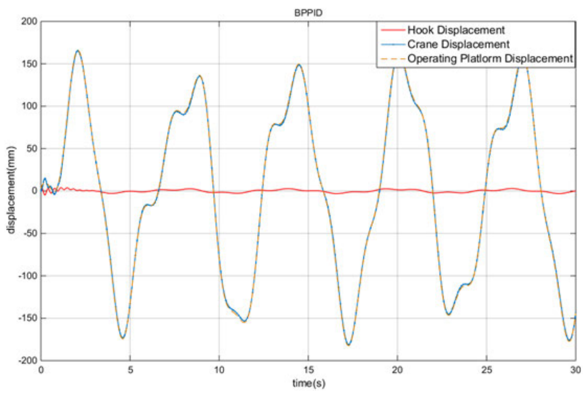


FIGURE 19. BP neural network PID control simulation chart of predicted wave.

FIGURE 20. The equal proportional reduction model of the crane type active and passive combined heave compensation system. 1 Stroke Column of, Operating Platform, 2 Traveling Block, 3 Compensation Cylinder, 4 Circulating Filter Cooling Refueling Device,5 Oil Tank, 6 Crane, 7 Offshore Operating Platform, 8 PLC Control Cabinet, 9 Active Cylinder of Rocker Mechanism, 10 Guide Rail of Crane.

V. SYSTEM EXPERIMENTAL VERIFICATION

The experiment platform of equal proportional reduction model of the crane type active-passive combined heave compensation system is shown in Figure 20. The system here consists of mechanical structure, control system, signal detection and oil source circuit. This experiment platform is used to carry out the experiment under the condition that the static load is 9kN, and the compensation stroke is 450mm.

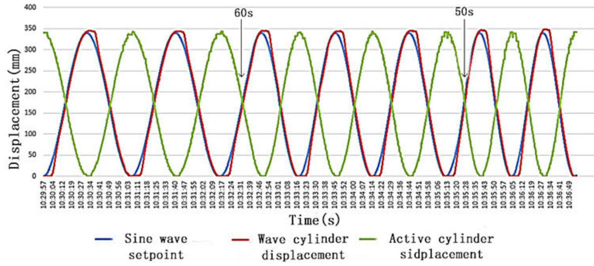


FIGURE 21. Experimental curve of the crane type active and passive combined heave compensation system when amplitude is changed.

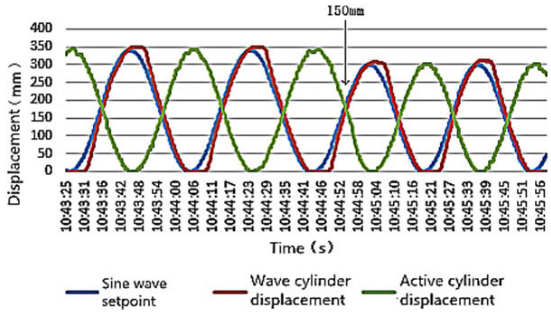


FIGURE 22. Experimental curve of the crane type active and passive combined heave compensation system when waveform is changed.

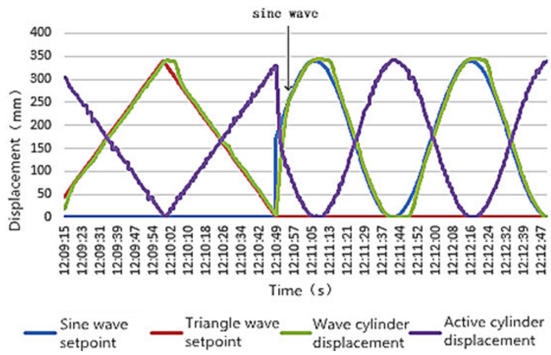


FIGURE 23. Experimental curve of the crane type active and passive combined heave compensation system when the period of waveform is changed.

In order to verify the compensation function of the control system, the amplitude, the waveform, and the period of the movement of the working platform are altered to conduct the experiment. The experimental results are shown in Figure 21, 22 and 23.

It can be seen from Figure 21 that when the motion amplitude of the working platform is varies from 170 mm to 150 mm, the crane can be manipulated by the control system to carry out the corresponding motion to compensate the displacement of the working platform.

As seen in Figure 22, when the motion wave of the working platform changes from a triangular wave to a sine wave, the crane also can be handled to implement the corresponding compensation motion to the displacement of the working platform.

As shown in Figure 23, the crane could be commanded by the control system to compensate the displacement of the platform when the motion period of the platform changes from 70s to 60s and then to 50s.

In conclusion, the crane is able to be manipulated by the control system to compensate the heave motion of the platform when the platform under different cases of motion amplitude, waveform and period. Meanwhile, it can be seen from the experimental diagram that the heave compensation of the system has a better implementation while the crane-type heave compensation device is manipulated by the BP neural network PID controller.

VI. CONCLUSION

(1) According to the principle of similitude, a crane type active-passive combined heave compensation system was designed in the proportion of 1:7. The compensation for the heave movement of the platform can be implemented by the system through the rise and fall of the crane. Two active hydraulic cylinders and one passive cylinder were combined together. Meanwhile the PLC control system was adopted to control the action of compensating cylinder to compensate the heave movement of offshore platform. From this, the compensation accuracy of the system is improved, and the system is intelligent and controllable.

(2) During the modeling process, the system was simplified according to the principle of mass concentration and energy conservation, and obtained the relational equations between voltage and displacement of the proportional directional valve, the relation equation between the displacement of the piston rod of the hydraulic cylinder and the displacement of the proportional directional valve, and the closed-loop transmission function of the system. From the simulation experiment, it can be concluded that the artificial immune improved LS-SVM algorithm is capable of predicting the displacement of the offshore platform accurately when the platform is affected by the random waveform, and improving the control accuracy of the heave compensation control system.

(3) From the simulation comparison experiment of conventional PID controller, fuzzy PID controller and BP neural network PID controller, the results show that BP neural network PID controller has a better control effect, which can change PID parameters in real time, improve the control system Stability and compensation accuracy, and has good robustness.

(4) It is verified from the field test that the compensation rate of BP neural network PID control system is over 90%. Moreover, the compensation effect is proved to be better, and the crane type active-passive combined heave compensation system is feasible for the operation of the offshore platform.

Furthermore, there are some related works can be done for the following research. For example, the viewpoint of drilling platform compensation is only at the heave motion in this paper. In reality, the operating platform generates six degrees of freedom because of the waves of the ocean. Compensations for other degrees of freedom could be considered in the future study. In addition, the development of the algorithms in the control field is growing rapidly, thus a further improvement of the algorithm should be conducted to increase the compensation rate of the heave compensation system, and to optimize the control system in the case of short wave motion cycle.

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