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The fuzzy particle swarm optimization algorithm design for dynamic positioning system under unexpected impacts

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ABSTRACT

The unexpected factors which affect vessel motion, mainly come from environmental influences. To enhance the quality of dynamic positioning system control with environmental influences, this paper aim to develop a fuzzy particle swarm optimization algorithm that applies to dynamic positioning system for stabilizing a vessel motion under unexpected impacts. Optimized-tuning of the structure parameter for fuzzy scheme is realized by the particle swarm optimization method. The coverage domain width and the overlap degree influence of membership function are adjusted dynamically from system errors. Thereby optimizing the control signal and enhancing the dynamic positioning system quality. Simulation studies with comparisons on a supply vessel are carried out. The proposed in a better response compared to other method such as fuzzy that proved effective of the proposed controller.

Keywords: Dynamic positioning system; environment impacts; membership function; particle swarm optimization; nonlinear system; supply vessel.

INTRODUCTION

The offshore resources extraction is growing and expanding, especially deep water, so the dynamic positioning system (DPS) plays an important role. The purpose of DPS is able to hold on a vessels position exclusively with means of its own propulsion system [1]. The environment conditions are regularly changing which have an effect on a hull. So the vessel moves under various conditions that make the object highly nonlinear and the control aim more difficult to achieve. There were many modern theories which aimed at reducing the errors of controller were applied [2]. In the study of Gu et al (1993) present a neural application to measure the wave amplitude and the outer forces, which act on the vessel [3]. The developmental results express that solution is highly realizable. However, it is necessary to take a practical test such as current and wind condition for verifying the advantage solution. For enhancing the control quality in the real environment, Xia et al (2005) develop a cerebellar model articulation controller (CMAC) which combined the PID algorithm to measure the nonlinear components [4]. The response indicated that the controller can be adjusted itself to outer forces. But the vessel operates at the high frequency domain, it is not able to maintain position and heading. Tannuri et al (2010) apply a sliding control solution for making use of nonlinear multivariable mathematical models [5]. The strong point of the strategy is robust to variations in its displacement and the environmental conditions. By enhancing the efficiency of controller for nonlinear object, Benetazzo et al (2015) use the Luenberger observation to detect fault of actuators, based on fault isolation logical [6]. The simulation results effectuated for a supply vessel model show that, in the case of actuators faults, DPS is guaranteed by the proposed solution. This subject needs consider to the influence of unexpected factors on the vessel motion such as wave, wind and time-delay of the control signal. Hu et al (2015) present an adaptive fuzzy controller for the DPS with unexpected impacts from environmental operation [7]. The unexpected impacts are approximated by adaptive fuzzy structure. The proposed solution scheme does not require knowledge of vessel dynamic model parameters and time-varying environmental disturbances. Fang et al (2016) apply a Neural-Fuzzy algorithm into practice to find out the best of ship propulsion systems. In this case, environment disturbances were estimated and reduced by the neural structure [8]. However, the DPS is operated under real environment, the sensor signal treatment with a Kalman suggests and the thruster power lags are critical aspects that should be carefully considered. The unexpected impacts make DPS structure to be complicated and uncertain. Many studies which achieve good results deal with the DPS problems. But the control target should be confirmed under the operating condition of different seas to improve the quality structure of controller.

Hierarchical fuzzy structure fit out an effective method approach for DP nonlinear systems with unexpected impacts due to the fuzzy system ability to approximate a nonlinear composition. Simultaneously considering unexpected impacts from environment, this paper provides the fuzzy particle swarm optimization (FPSO) advantage control technical for DPS optimization. The unknown parameters caused by environmental factors that are approximated by the fuzzy function. Particle swarm optimization (PSO) suggestion is adopted to calibrate the fuzzy structure. Thereby enhancing the quality of system and optimizing the controller structure for vessel motion that help the DPS fast-forward to a stability domain.

PROBLEM FORMULATION AND PRELIMINARIES

Dynamic Positioning System

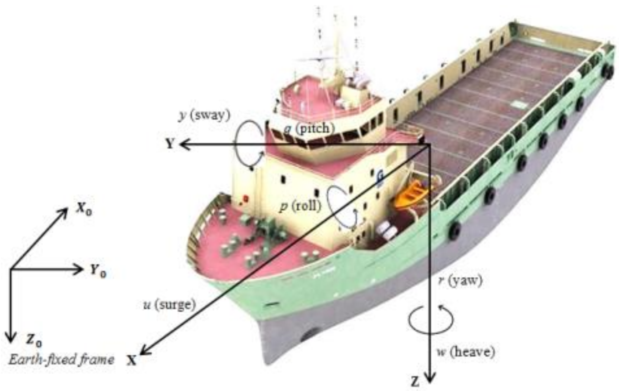

Figure 1. The earth-fixed $X_0Y_0Z_0$ and the vessel-fixed XYZ reference frames [9].

The nonlinear motion of vessel in DPS mode is described as follow three degrees of freedom [10]. Two separate coordinate systems presented by Figuge 1 include: one is a vessel-fixed non-inertial frame $O-XYZ$ and the other is the inertial system approximated to the earth $O_0-X_0Y_0Z_0$. Model representation of the DPS with three degrees of freedom, namely, surge, sway, yaw and external force acting is shown in Equation (1) and Equation (2) as below:

$$\dot{\eta} = J(\eta)v \tag{1}$$

$$M\dot{v} + Dv = \tau + \tau_{envi} + \tau_h \tag{2}$$

where position (x, y) and heading (ψ) of the absolute coordinate system $X_0Y_0Z_0$ are denoted as a vector from $\eta = (x, y, \psi)^T$. The vector $v = (u, v, r)^T$ describes velocities of the vessel motion in the relative frame of reference. The vertical centering of the relative coordinate system XYZ is placed at the roll axis of vessel, x_G denotes the longitudinal position of the gravity central of the vessel towards the relative frame of reference. The transformation matrix $J(\psi)$ and $M \in R^{3x3}$ and $D \in R^{3x3}$ are the inertia and damping matrix, respectively. Such matrixes are taken as

$$J(\psi) = \begin{bmatrix} \cos(\psi) & -\sin(\psi) & 0 \\ \sin(\psi) & \cos(\psi) & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{3}$$

$$M=\begin{bmatrix} m-X_{\dot{u}} & 0 & 0 \\ 0 & m-Y_{\dot{v}} & mx_G-Y_{\dot{r}} \\ 0 & mx_G-N_{\dot{v}} & I_z-N_{\dot{r}} \end{bmatrix};\quad D=\begin{bmatrix} -X_u & 0 & 0 \\ 0 & -Y_v & mu_0-Y_r \\ 0 & -N_v & mx_G u_0-N_r \end{bmatrix} \tag{4}$$

where m is the vessel mass, I_Z is the moment of inertia about the body-fixed Z -axis, x_G represents the lcation of G in x -axis direction, u_0 is velocity component at mid-vessel. The inertia quantities are increased by the acceleration of the surge, sway, and yaw direction of transformation as expressed in Eq. (5):

$$X_{\dot{u}} \square \frac{\partial X}{\partial \dot{u}}, Y_{\dot{v}} \square \frac{\partial Y}{\partial \dot{v}}, N_{\dot{r}} \square \frac{\partial N}{\partial \dot{r}}, Y_{\dot{r}} \square \frac{\partial Y}{\partial \dot{r}}, N_{\dot{v}} \square \frac{\partial N}{\partial \dot{v}} \tag{5}$$

As in most DPS applications, D is the damping matrix and M is the inertia matrix including added mass effects, which is symmetric and positive definite. However, for low speed applications where the damping matrix is reduce, it can be supposed that $N_v = Y_r$. The damping compositions in surge, sway, and yaw directions are defined by Equation (6):

$$X_u \square \frac{\partial X}{\partial u}, Y_v \square \frac{\partial Y}{\partial v}, N_r \square \frac{\partial N}{\partial r}, Y_r \square \frac{\partial Y}{\partial r}, N_v \square \frac{\partial N}{\partial v} \tag{6}$$

The control vector τ produced by propeller and thruster systems. Vector τ_{envi} represents the impact forces from environmental factors, including wave, wind and current. Vector τ_h is the high-frequency spectral compositions of wave which have an effect on the vessel in Equation (7) as follows:

$$\tau=\left[\tau_x,\tau_y,\tau_\psi\right]^T \;;\; \tau_{envi}=\tau_{wave}+\tau_{wind}+\tau_{current} \;;\; \tau_h=h(s) \tag{7}$$

Wave Impact

The ocean waves are physical phenomena that happen in the water layer near surface. The wave velocity depends on the change in drag, the decrease in performance as well as the increased maneuverability. The mathematical is introduced by Fossen at all (2011) for modeling the wave contruction and determining. The wave height [10] which affected to DPS as Equation (8):

$$\tau_{wave}=\zeta(x,y,t)=\sum_{q=1}^{N}\sum_{r=1}^{M}\sqrt{2S(\omega_q,\psi_r)\Delta\omega\Delta\psi}\,sin\left(\omega_q t+\phi_{qr}-k_q\left(xcos\psi_r+ysin\psi_r\right)\right) \tag{8}$$

where the wave amplitude ζ_{aqr} is given by Equation (9):

$$\zeta_{aqr}=\sqrt{2S(\omega_q,\psi_r)\Delta\omega\Delta\psi} \tag{9}$$

where $\Delta\omega$ and $\Delta\psi$ represents one the harmonic wave amplitude. ψ_r,ω_q, ϕ_{qr} and S represents the direction, frequency, phase angle and wave spectrum. The phase angle of wave components is between 0 and 2π. The inertial system approximated to the earth, the surface in the coordinate (x,y) is described by Equation (10):

$$\zeta_{qr}\left(x,y,t\right)=\zeta_{aqr}sin\left(\omega_q t+\phi_{qr}-k_q\left(xcos\psi_r+ysin\psi_r\right)\right) \quad (10)$$

$k_q = 2\pi / \lambda_q$ is the number of wave, where λ_q is the wave length, the dispersion relation $\omega_q = \sqrt{kg}$ with g is the gravity acceleration.

Low Frequency Wind

The speed, wind direction depends on the location and pressure difference of the atmosphere. However, each geographic region on earth, the wind has its own particularity rule. The wind speed which takes an effect on the vessel is defined as V_w and the wind direction β_w is modeled by the slow variable quantities. The wind forces having an effect on the vessel motions are performed by Equation (11) [11] as

$$\tau_{wind}=\left[X_{wind},Y_{wind},N_{wind}\right]^T \quad (11)$$

where X_{wind},Y_{wind} and N_{wind} are computed using a similar approach to be expressed as

$$\begin{aligned} X_{wind}&=0.5C_X g_R\rho_w V_R^2 A_T\\ Y_{wind}&=0.5C_Y g_R\rho_w V_R^2 A_T\\ N_{wind}&=0.5C_N g_R\rho_w V_R^2 A_L L \end{aligned} \quad (12)$$

where C_X and C_Y are the traction ,C_N is a moment coefficient, ρ_w is the air density, A_T and A_L are the areas of ichnography, L is the overall length of vessel, V_R is the wind speed and g_R is the wind direction that impact the vessel are defined as

$$\begin{aligned} V_R&=V_w\\ g_R&=\beta_w-\psi_L-\psi_H \end{aligned} \quad (13)$$

Current Impact

The current is continuous orientation movement of the ocean. Current generated by forces influencing like earth magnetic field, wind, temperature, salt salinity, and moon gravity. Assume that the current is invariable for both direction and amplitude, in such a way as to correct the current speed V_c and the direction β_c are modeled as the slow variable parameters in the earth axis. The current relative velocity of vessel coordinates [10] is presented by Equation (14):

$$\begin{aligned} u_c&=V_c cos\left(\beta_c-\psi_L-\psi_H\right)\\ v_c&=V_c sin\left(\beta_c-\psi_L-\psi_H\right)\\ \tau_{current}&=\left[u_c,v_c,0\right]^T \end{aligned} \quad (14)$$

where ψ_L and ψ_H are the angular compositions affected by high and low frequency quantities, u_c and v_c are compositions of the current velocity.

High Frequency Wave

A linear wave object response approximation is preferred by the vessel control systems engineers, owing to its simplicity and applicability [10]. The linear equation of high frequency spectrum can be redefined follows as:

$$\tau_h = h(s) = \frac{K_w s}{s^2 + 2\lambda\omega_0 s + \omega_0^2} \tag{15}$$

where K_w is related to the on sea conditions. So we have $K_w = 2zwS_w$, S_w is the coefficient describing the wave density, z is the relative damping factor, w is the wave frequency. The damping factor z is chosen randomly ($z < 10$), $\omega_0 = 0.88(g/V)$, is the interfering frequency with V is the wind speed acting on the hull and λ is the adjusting parameters of damping factor. The high frequency motivation of vessel is mainly maintained by the high frequency wave and does not change the vessel position.

Assumption 1: The vessel motion is a high nonlinear and complicated system under the unexpected impacts which are mainly come from operating environment (wave, wind, current and high frequency component). Thereby, the structure parameter of controllers that is chosen by programmer experiment are not able to provide an effective approach for nonlinear systems with unexpected impacts.

Remark 1: Many methods let the user takes the decisions based on experience. Besides, the structure parameters are set up with a fixed status. Thereby carrying out on a nonlinear DPS does not give a high precision and effective. As such, the Assumption 1 is reasonable and more practical.

In this paper, the FPSO controller is designed for the DPS of vessel (1) and (2) under the Assumption 1 to ensure that the vessel is maintained at the desired values of its position and heading with arbitrary accuracy. And while the parameters of fuzzy structure are optimized by PSO algorithm.

FUZZY PARTICLE SWARM OPTIMIZATION CONTROL

Fuzzy System

In a recent study, a strategy is presented to reduce nonlinear characteristics of the DPS which are caused by unexpected impacts. Do et al (2017) consider the fuzzy controller for the supply vessel [9] (with the structure shown in Figure 3) which has a double-input e_η, de_η/dt, and single-output τ. The inference process system combine membership functions (MFs) with if-then rules and the fuzzy logic operators. The MFs collections are set as below:

$$\begin{aligned} &e_\eta && :\{NE \quad NS \quad ZE \quad PS \quad PO\} \\ &de_\eta/dt && :\{NS \quad ZE \quad PS\} \\ &\tau && :\{NE \quad NSS \quad NS \quad ZE \quad PS \quad PSS \quad PO\} \end{aligned}$$

The fuzzy rules are using same as in Table 1. In order to design a Takagi-Sugeno fuzzy logic with a compact rule base, the rule notation form within B_k^i is a binary variable that determines the consequence of the rule given as follow:

R_i : If $\hat{e}_1$ is A_{k1}^i ……….and $\hat{e}_n$ is A_{kn}^i then u_{fk} is B_k^i,

where $A_{k1}^i, A_{k2}^i, \ldots A_{kn}^i$ and B_k^i are fuzzy sets. By using the Max-Prod inference rule, the singleton fuzzifier and the center averaged defuzzifier. The fuzzy output can be performed as bellows:

$$u_{fk} = \frac{\sum_{i=1}^{h} \theta_k^{-i} [\prod_{j=1}^{n} \mu_{A_{kj}^i}(\hat{e}_j)]}{\sum_{i=1}^{h} [\prod_{j=1}^{n} \mu_{A_{kj}^i}(\hat{e}_j)]} = \theta_k^T \varphi_k(\hat{e}) \tag{16}$$

For $\mu_{A_{kj}^i}(\hat{e}_j)$ is the MFs of fuzzy system, h is the if-then rules amount, θ_k^{-i} is the destination at which $\mu_{B_k^i}(\theta_k^{-i}) = 1$ and $\varphi_k(\hat{e}) = \left[\varphi_k^1, \varphi_k^2, \ldots, \varphi_k^h\right]^T \in R^h$ is the fuzzy basis vector with φ_k^i is defined as

$$\varphi_k^i(\hat{e}) = \frac{\prod_{j=1}^{n} \mu_{A_{kj}^i}(\hat{e}_j)]}{\sum_{i=1}^{h} [\prod_{j=1}^{n} \mu_{A_{kj}^i}(\hat{e}_j)]} \tag{17}$$

The fuzzy of automatic tuning concepts is deployed in corresponding to the input error. Thereby reducing the error as well as maintaining the control aim. The MFs describe these input/output characteristics of vessel motion as details in Figure 2.

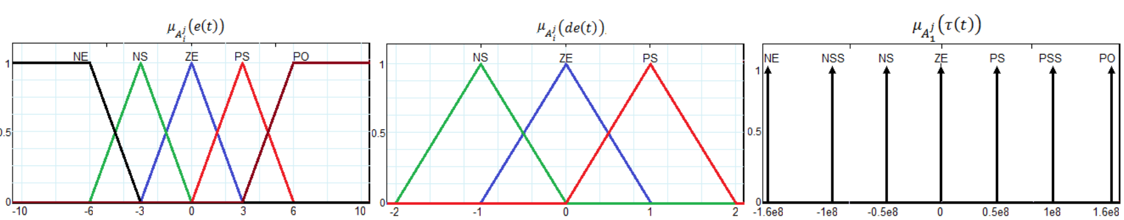

Figure 2. The MFs of error input $e(t)$, error velocity de/dt and impact force τ [9].

Since the fuzzy sets are set up by experience according to Remark 1. Thereby, the object membership function is fixed so the control signal for nonlinear DPS is not optimized with time-varying object. The fuzzy control rule is a context function that combines prefix state variables to the process control variables.

Table 1. The system rules of fuzzy inference [9].

$\tau_x / \tau_y / \tau_\psi$		*de* / *dt* NS	ZE	PS
$e(t)$	E	$NE_X / NE_Y / NE_\psi$	$NSS_X / NSS_Y / NSS_\psi$	$NS_X / NS_Y / NS_\psi$
	S	$NSS_X / NSS_Y / NSS_\psi$	$NS_X / NS_Y / NS_\psi$	$ZE_X / ZE_Y / ZE_\psi$
	E	$NS_X / NS_Y / NS_\psi$	$ZE_X / ZE_Y / ZE_\psi$	$PS_X / PS_Y / PS_\psi$
	S	$ZE_X / ZE_Y / ZE_\psi$	$PS_X / PS_Y / PS_\psi$	$PSS_X / PSS_Y / PSS_\psi$
	O	$PS_X / PS_Y / PS_\psi$	$PSS_X / PSS_Y / PSS_\psi$	$PO_X / PO_Y / PO_\psi$

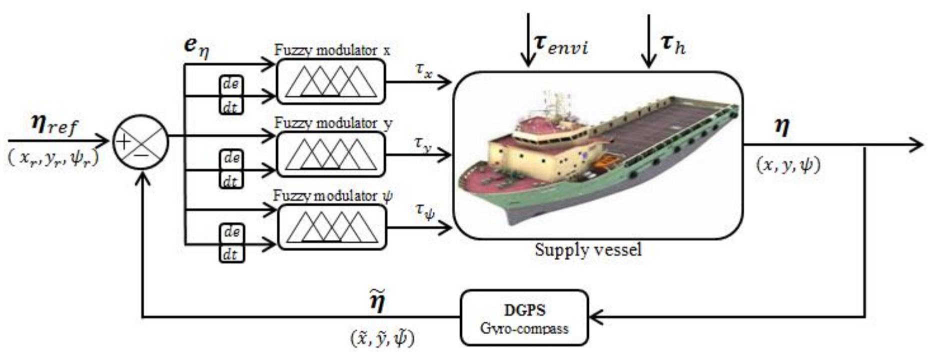

Figure 3. The fuzzy controller structure of dynamic positioning system [9].

Fuzzy Particle Swarm Optimization Design for Dynamic Positioning System

In this section, by combining the fuzzy system with the PSO algorithm, an FPSO controller for the DPS of vessel is designed to achieve the control objective stated in Introduction section. Thereby overcoming the problems mentioned by Remark 1. The building controller process includes of the following two steps.

Step 1: Define the fuzzy system with optimized parameter. As such, the parameters of control structure have been examined like Fuzzy system section. The fuzzy modulator which has a double-input, $e_x(t)$, $d_{e_x(t)} / d(t)$ and a single-output, $\tau(t)$. These fuzzy sets are defined as {*NE, NS, ZE, PS, PO*} correspond to negative big, negative small, zero, positive small and positive big which are adjusted flexibly by λ coefficient to optimize fuzzy structure. The MFs collections are similarly in Figure 4.

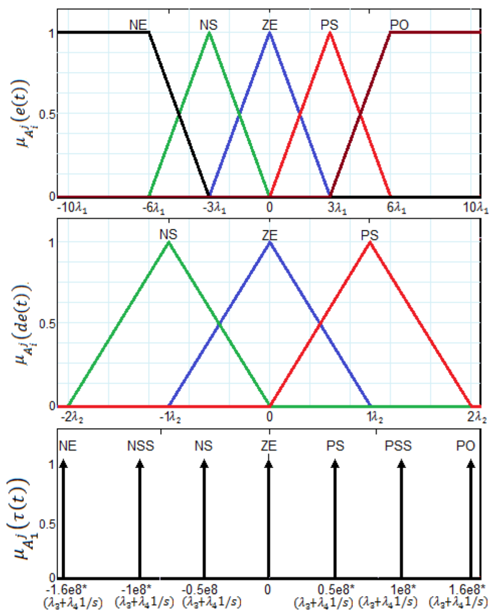

Figure 4. The fuzzy set values of MFs are calibrated by λ coefficient.

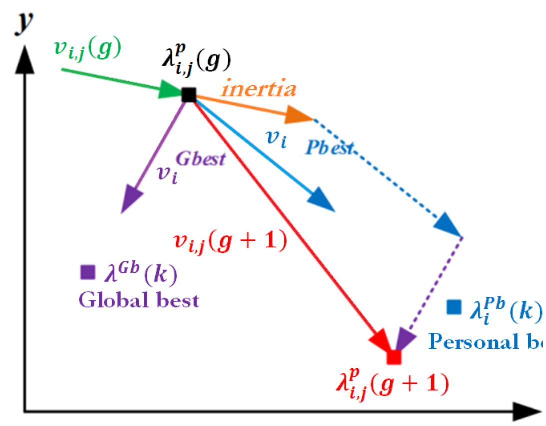

Figure 5. The displacement of λ coefficient is chosen by PSO application.

The optimized inference mechanism of fuzzy system is given by

$$\mu_B(u(t)) = max_{j=1}^{m}\left[\mu_{A_i^j}(e(t)), \mu_{A_i^j}(de(t)), \mu_{A_i^j}(\tau(t))\right] \tag{18}$$

where $\mu_{A_1^j}(e(t)) = \lambda_1(A_{e1}^j, A_{e2}^j, ..A_{ei}^j)$ is the MFs of error $e(t)$, which caused by unexpected impacts. $\mu_{A_2^j}(de(t)) = \lambda_2(A_{de1}^j, A_{de2}^j, A_{dei}^j)$ is the MFs of error velocity de/dt and $\mu_{A_1^j}(\tau(t)) = (\lambda_3 + (1/s)\lambda_4)(A_{\tau 1}^j, A_{\tau 2}^j, \ldots A_{\tau i}^j)$ is the MFs of output response $\tau(t)$. The j coefficient is the index of fuzzy set, i is the resulting fuzzy inference. The vector $\lambda = [\lambda_1, \lambda_2, \lambda_3, \lambda_4]$ is the parameter adjusting vector which is determined by the PSO algorithm. Following Equation (16), the fuzzy output can be described as bellows:

$$u_{fke} = \theta_{ke}^T \varphi_{ke}(\hat{e})\lambda \tag{19}$$

Step 2: Defined the λ optimized coefficient. The PSO optimization module completes the tuning of fuzzy sets with λ adjusting coefficient that achieves the optimal control structure. These parameters are used to rebuild the fuzzy structure in fuzzy controller module. The function optimization problem can be viewed as a 4-dimensional search space with randomly chosen velocities and the initial location of particles in this study [12]. That is tuning of fuzzy sets is to search optimization value in $\lambda_1, \lambda_2, \lambda_3, \lambda_4$. Each particle deputises for a potential suggestion to the λ value being optimized. The displacement schematic of λ coefficient is presented as in Figure 5. The population of particles is expected to have high tendency to move in high dimensional search spaces in order for detecting better solution [13-14]. If the certain particle finds out the better suggestion than the previous suggestion, the other will move to be near this location [15]. The process is re-executed for next position, until all positions have been tested.

The population size is denoted by s. Each particle $i\left(1 \le i \le s\right)$ presents a test solution with parameters j. At the k generation, each particle is located by $\lambda_i^p\left(k\right)$ position, the current speed of particle is $v_i\left(k\right)$, and the best location of whole global is $\lambda_i^{Pb}\left(k\right)$. Index of the best particle of population which represents the best suggestion is performed by symbol $\lambda^{Gb}\left(k\right)$. The particles of population update the attributes then each generation [16]. Updating the property will be realize according to Equation (20) as

$$v_{i,j}\left(ke+1\right) = w\left(k\right)v_{i,j}\left(ke\right) + c_1 r_1\left[\lambda_{i,j}^{Pb}\left(k\right) - \lambda_{i,j}^{p}\left(k\right)\right] + c_2 r_2\left[\lambda_{j}^{Gb}\left(k\right) - \lambda_{i,j}^{p}\left(k\right)\right] \quad (20)$$

where w is the inertia weight, c_1 and c_2 are the acceleration coefficient, r_1 and r_2 are the random constants in range $\left(0.1\right)$, g is the repetitions number [17]. The update of inertia weights [18] are defined by Equation (21) as

$$w\left(g\right) = \frac{\left(iter_{max} - g\right)\left(w_{max} - w_{min}\right)}{iter_{max}} + w_{min} \quad (21)$$

where $iter_{max}$ is the maximum value of multiple loop of the PSO algorithm, w_{max} is respectively the largest of inertial weight sand and w_{min} are respectively the smallest of inertial weights. The updating position can be executed by Equation (22) as follows:

$$\lambda_{i,j}^{p}\left(g+1\right) = \lambda_{i,j}^{p}\left(g\right) + v_{i,j}\left(g+1\right) \quad (22)$$

The best position is updated by Equation (23) as

$$\lambda_{i,j}^{Pb}\left(g+1\right) = \begin{cases} \lambda_{i,j}^{Pb}\left(g\right), if \; J\left(\lambda_{i,j}^{p}\left(g+1\right)\right) \ge J\left(\lambda_{i,j}^{Pb}\left(g\right)\right) \\ \lambda_{i,j}^{p}\left(g+1\right), \qquad otherwise \end{cases} \quad (23)$$

Finally, the best location of whole global is performed by Equation (24) as

$$\lambda_{j}^{Gb}\left(g+1\right) = \arg min_{\lambda_{i,j}^{Pb}} J(\lambda_{i,j}^{Pb}\left(g+1\right)), 1 \le i \le s \quad (24)$$

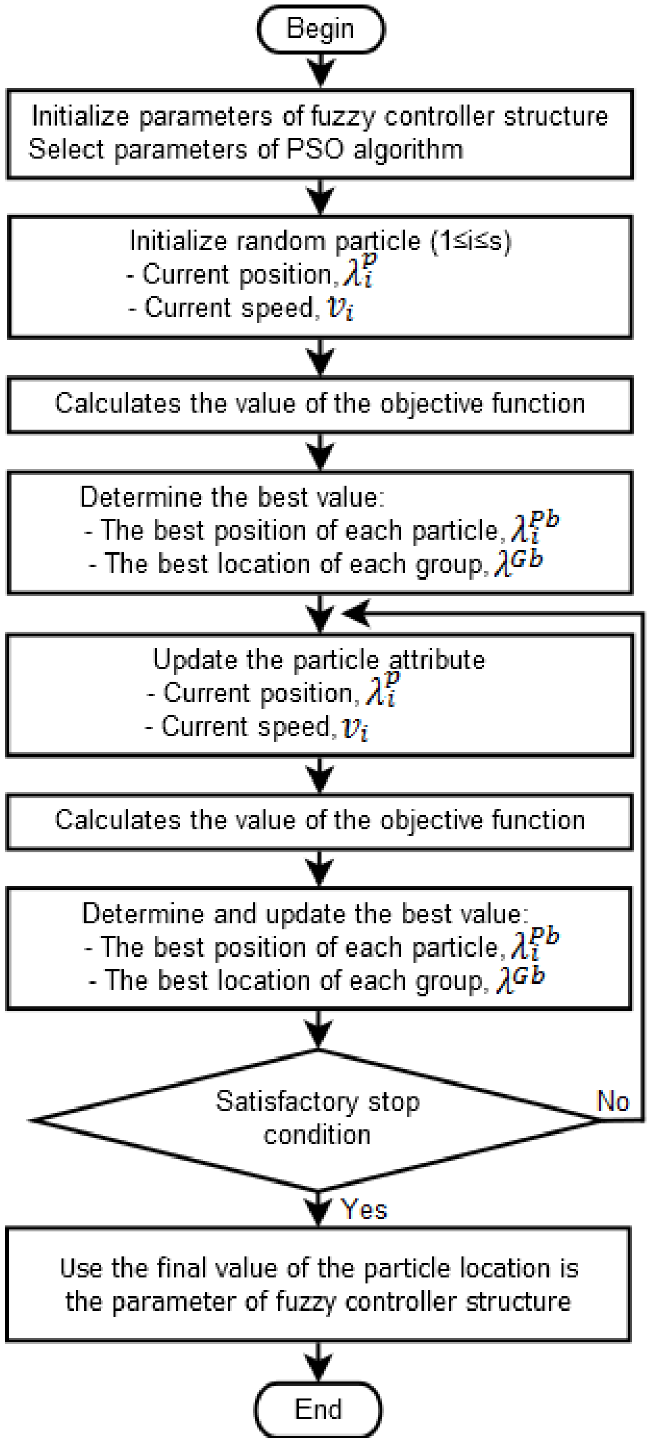

Figure 6. The optimization flowchart of fuzzy system uses the PSO algorithm.

The minimum initial values that caused by the error between response value and referent value is the optimal goal. The optimization flowchart of fuzzy system is expressed by Figure 6 [19]. The important thing to be done in the PSO optimization is the choosing fitness function [20]. Since the original PSO algorithm is designed for real-value problem, so fuzzy sets optimize is easily achieved. The fitness function is used for iterations to value the quality of all the proposed solutions to the problem in the current population. The different features of fitness function affect how easy or difficult the problem is for a PSO algorithm [21]. Suitable fitness function can be chosen according to the demand of the study. The FPSO control structure for DPS shows in Figure 7. In this paper, the fitness function is chosen by the ITAE criteria as follows:

$$ITAE = \int_0^\infty t\left|e(t)\right|dt \tag{25}$$

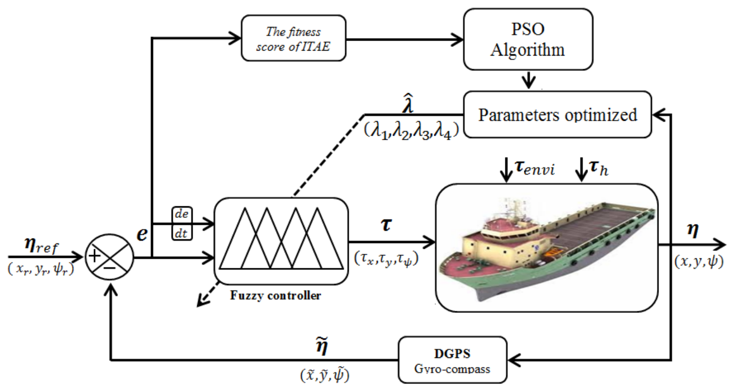

Figure. 7 The FPSO control structure for dynamic positioning system of vessel.

SIMULATION STUDIES

Configuration Parameter

In this section, the simulation applications are carried out to validate the proposed FPSO control scheme for DPS. Further, performance comparisons between the proposed FPSO controller and the fuzzy controller are conducted to assess the precision and effective of the proposed controller. FPSO controller with the optimal goal (24) is tested on a supply vessel in two cases. The main structural parameters of the supply vessel [1] are listed in Table 2 by the ratio of 1:1000.

Table 2. The structure parameters of supply vessel.

DESCRIPTION	DIMENSION
Length overall (LOA)	76.2 m
Length between perpendiculars (LPP)	48 m
Beam (B)	18.8 m
Design Draft (T)	6.25 m
Design Displacement (∇)	350 m^3
Design speed (u_0)	8 knots

$$D = \begin{bmatrix} 5.02e4 & 0 & 0 \\ 0 & 2.72e5 & -4.39e6 \\ 0 & -4.39e6 & 4.18e8 \end{bmatrix}$$

$$M = \begin{bmatrix} 5.31e6 & 0 & 0 \\ 0 & 8.28e6 & 0 \\ 0 & 0 & 3.74e9 \end{bmatrix}$$

The wave, wind, current and high frequency are considered as the most four environmental factors of the system. The kinetic of wave factor is represented by Equation (8). In simulations, the wave simulation parameters [10] are chosen as follows: wave height $H_s = 0.8m,$ wave spectrum peak frequency $\omega_p = 0rad/s$, wave direction $\psi_0 = -30^0$, spreading factor $s = 2,$ number of frequencies $N = 20,$ number of directions $M = 10$, cutoff frequency factor $\xi = 3,$ wave component energy limit $k = 0.005$ and wave direction limit $\psi_{lim} = 0$. The wind kinetic is given by Equation (11). The wind simulation parameters [10] are sorted as follows: $A_L = 2.4$, $A_T = 9.34,$ wind speed $V_\omega = 2m/s$ and the angle of impact wind $\beta_\omega = 20^0$. Beside that, Equation (14) presents these factors of current kinetic model. The simulation parameters for current factor are set to their default values accept as follows: $V_C = 2m/s,$ vessel direction $\beta_C = 30^0$, low frequency and high frequency of rotation are ignored $\psi_L = \psi_H = 0$. The high frequency spectrum of wave factor is performed by Equation (15). In simulations, the high frequency coefficients are chosen as: dominating wave frequency $w_0 = 0.8976rad/s,$ damping cofficient $\lambda = 0.1$ and the wave intensity $\sigma = \sqrt{2}$.

We carry out simulation on the supply vessel parameter in two cases. Case 1: The FPSO and fuzzy force the vessel to arrive at the desired value [3 m, 7 m, 20 degree] in around 200s from reference [0 m, 0 m, 0 degree]. Case 2: These controllers are proposed to keep vessel routine for achieving desired trajectory under unexpected impacts. Figures 8(a) and 9(b) reveal that the FPSO controller can make the vessel motion to aim at the expected position in simulation cases. The real position (x, y) and heading are kept at the target value illustrated by Figures 8(b) and 9(a). Figures 8(d) show that the control forces and moment by the FPSO and fuzzy controller are glossy and justice. The unexpected impacts are presented by Figure 8(c).

Simulation Results

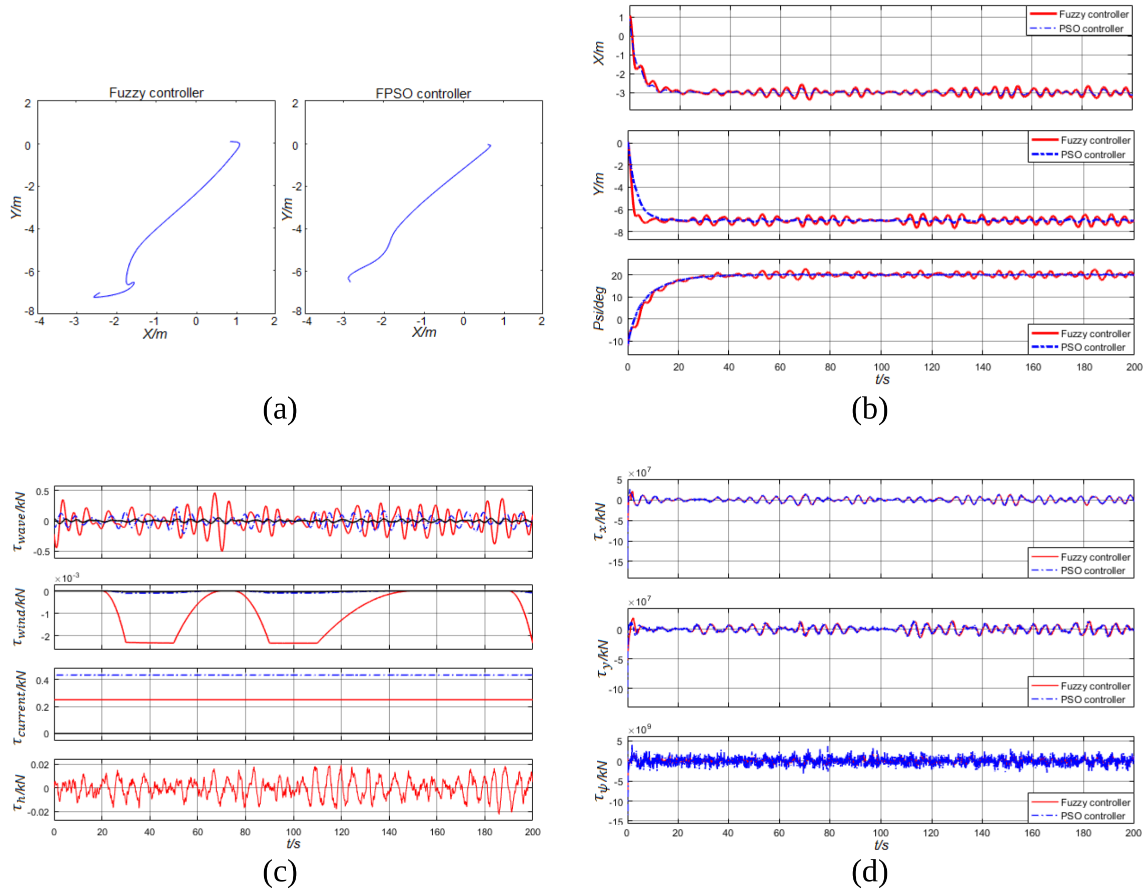

Figure 8. The simulation of cases 1 consist two controllers.
(a) Trajectory of the vessel position in xy-plane. (b) The real position (x, y) of vessel and the heading ψ of vessel. (c) Unexpected impacts (τ_{wave}, τ_{wind}, $\tau_{current}$ and τ_h) have an affect on the vessel. (d) Surge control force τ_x, sway control force τ_y and yaw control force τ_ψ.

(a)

(b)

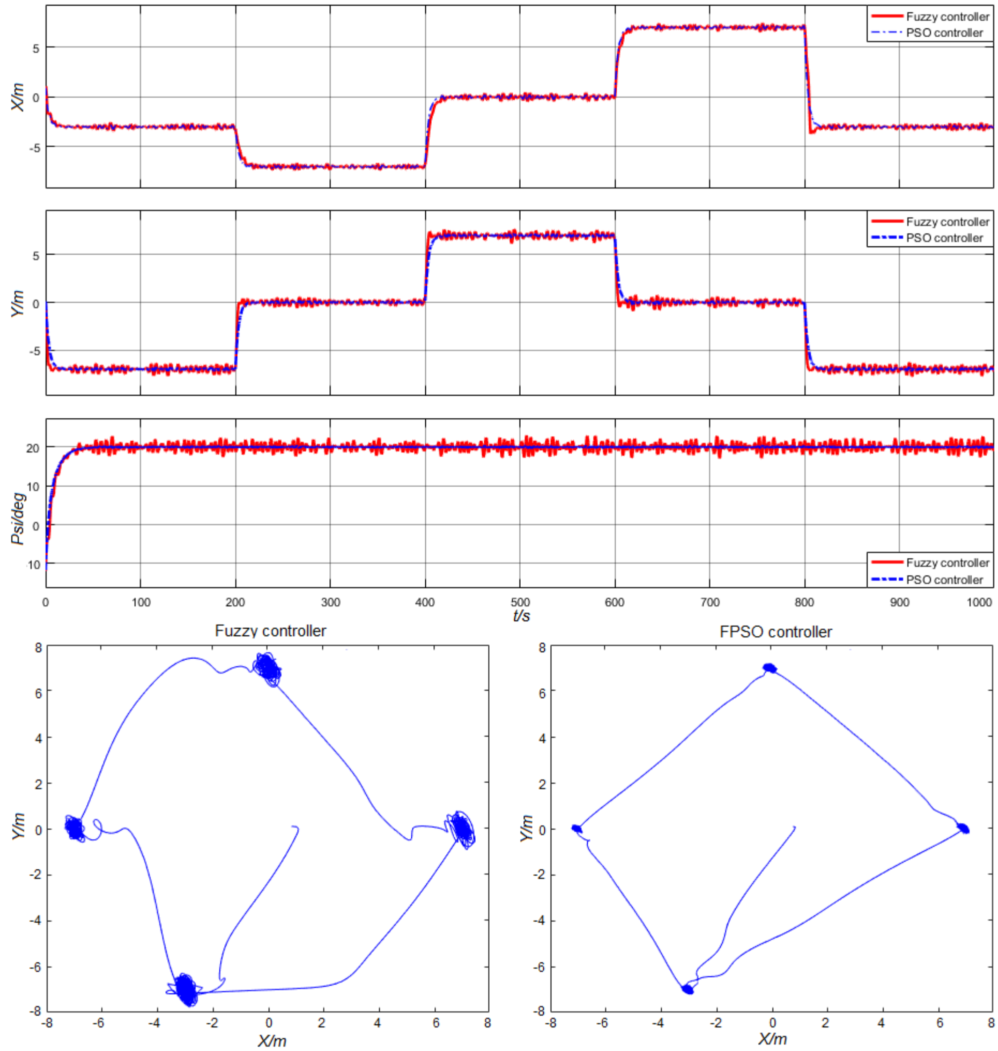

Figure 9. The simulation of cases 2 consist two controllers. (a) Real position (x, y) and the vessel heading ψ. (b) Trajectory of the vessel position in xy-plane.

If we only use a fuzzy controller [9] for keeping the balance of vessel motion, the vessel position will be vibratile at higher impact cases. Besides that, the vessel heading fluctuates strongly according to the level of unexpected impacts. The DPS controllers of the position error vectors in cases are given by Figures 8(a) and 9(b), which illustrate that the FPSO controller has a good stable performance in each of simulation case under unexpected impacts acting on the vessel in case, respectively. Having done so, it dealt with the question of causation according to Assumption 1 and Remark 1. Only using a fuzzy controller for keeping the balance of DPS, the vessel position will be stable from the low-impact case and vibratale at the higher impact cases. Besides that, the vessel heading fluctuates strongly according to the level of unexpected impacts. The satisfactory results prove that the FPSO controller has the adaptability to nonlinear systems of vessel motion and against time-varying unexpected impacts. Thereby improving the quality of control signal, that make amplitude of surge, sway and yaw fluctuation at low-level and keep the vessel balance.

CONCLUSIONS

In this paper, a FPSO controller for DPS has been suggested in the presence of dynamic structure of controller and unexpected impacts. Proposed algorithm optimize structure parameters fuzzy and reduce the nonlinear characteristics of DPS which caused by unexpected impacts. Therefore, that helps the vessel maintain accuracy position and desired heading. The proposed solution should cover the uncertain factors and parameters M and D which are related with vessel operational and environmental conditions to be more practical. In the future work, this study can be extended by using the robust algorithm to improve the DP control quality when the vessel operates in instable state for long time and constantly.

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