Optimized Multi-cascade Fuzzy Model for Ship Dynamic Positioning System Based on Genetic Algorithm

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Abstract. In this paper, we aim to develop a multi-cascade fuzzy model for the ship dynamic positioning system influenced by environment to enhance its quality. The cascades of fuzzy model are selected corresponding to the level of output feedback error. The optimized tuning of the structure parameter for fuzzy-case 2 and fuzzy-case 4 is realized by the genetic algorithm. Then, the simulation studies which compare our proposed control strategy with fuzzy control strategy using Matlab are carried out, and the simulation result proves the effectiveness of the multi-cascade fuzzy model.

Keywords: Dynamic positioning system · Environmental impact · Multi-cascade fuzzy · Genetic algorithm

1 Introduction

Offshore exploration and exploitation of ocean resources have led to the increasing demands for ship dynamic positioning (DP) system. In a DP system, a computer coordinates the propulsion system consisting of thrusters and propellers to keep the vessel in position. The environmental factors, which have an effect on a hull, are regularly changing. So the vessel moves under various conditions that make the object highly nonlinear. In the early 1960s, the first ship dynamic positioning system uses traditional proportional-integral-derivative control [1]. Subsequently, the modern theories are employed for improving the quality of controller are applied. Among them, the fuzzy algorithm is one of the most widely used theories in DP control because it has robust characteristics for the nonlinear object. Chang et al. apply an application of Takagi-Sugeno (TS) fuzzy to represent the nonlinear DP system [2]. Via parallel distributed compensation rule, the DP control system can be merged by the linear controllers of all rules. However, it is necessary to take practical test cases such as environmental impacts for verifying the advantage of proposed solution. In order to improve the control quality, Chen et al. provide an approximation technique based on adaptive control in combination with type-2 fuzzy model [3]. The proposed adaptive type-2 fuzzy model is able to reduce the hydrodynamic disturbances. But the rigorous

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theoretical examination is necessary. Ho et al. combine the orthogonal function approach and the hybrid Taguchi-genetic algorithm to define quadratic finite horizon optimal controller design fuzzy problems [4]. The standard algebraic process in suggestion approach allows easy calculation. Therefore, the process of designing finite quadratic optimal controllers for DP is much simpler. Hu et al. present an adaptive fuzzy controller for the DP system under unexpected impacts from environmental operation [5]. The unexpected impacts are approximated by the adaptive fuzzy structure. The proposed solution scheme does not require knowledge of vessel dynamic model parameters and time-varying environmental disturbances. Fang et al. apply a Neural-Fuzzy algorithm into practice to find out the best of ship propulsion systems [6]. In this case, the environmental disturbances are estimated and reduced by the neural structure. However, the real-time signal treatment of sensor with a Kalman suggests and the thruster power lags are critical aspects that should be carefully analysis. The fuzzy method has been widely used for identifying nonlinear system, only simple structure tests. For an uncertain DP system structure, it requires more work to determine the optimal fuzzy rules. On the other side, the goal of control should be confirmed under the operating condition of different seas to enhance the quality structure of controller.

This paper provides an optimized multi-cascade fuzzy model for the nonlinear DP system. The designed controller is composed of four fuzzy cascades which are selected from simple to complex edition which correspond to the level of output error, due to environmental impact. The unknown parameters caused by environmental factors that are estimated by the fuzzy sets. Subsequently, a real-coded genetic algorithm (GA) is applied in an iterative fashion together with a rule base of fuzzy algorithm in order to optimize and simplify the model, respectively. The proposed results is demonstrated for system identification and a classification problem.

The paper is organized as follows. In the next section, the problem formulation and preliminaries are discussed. The multi-cascade fuzzy model controller is proposed in Sect. 3. Section 4 presents the fuzzy genetic algorithm design controller. The supervisor design is given in Sect. 5. The simulation results are provided to validate the designed controller in Sect. 6, followed by the conclusions of the paper in Sect. 7.

2 Problem Formulation and Preliminaries

The DP motion of vessel is described by three degrees of freedom [1]. Two separate coordinate systems presented by Fig. 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 DP system with three degrees of freedom, namely, surge, sway, yaw and external force acting are shown in equations as below:

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

$$M\dot{v} + Dv = \tau + J^T(\eta)\tau_e \tag{2}$$

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 control vector τ produced by propeller and thruster systems. Vector τ_e represents the impact forces from environmental factors, including wave, wind and current.

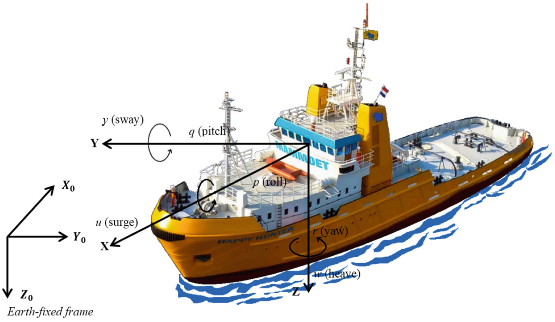

Fig. 1. Definition of the earth-fixed and the vessel-fixed reference frames.

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 centre 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

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

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

where m is the vessel mass, I_Z is the moment of inertia about the body-fixed Z-axis, x_G represents the location of G in x-axis direction, u_0 is velocity component at mid-vessel. Rewriting (1) and (2) in matrix form [7], yields the following

$$\begin{bmatrix} \dot{\eta} \\ \dot{v} \end{bmatrix} = \begin{bmatrix} 0 & J(\eta) \\ 0 & -M^{-1}D \end{bmatrix} \begin{bmatrix} \eta \\ v \end{bmatrix} + \begin{bmatrix} 0 \\ M^{-1} \end{bmatrix} \tau + \begin{bmatrix} 0 \\ M^{-1}J^T(\eta) \end{bmatrix} \tau_e \tag{5}$$

We defined the following vatiables

$$\begin{aligned} x(t) &= [\eta, v]^T = [x_1, x_2, x_3, x_4, x_5, x_6]^T \\ u(t) &= \tau = [u_1, u_2, u_3]^T \\ \tau_e(t) &= [\tau_{e1}, \tau_{e2}, \tau_{e3}]^T \end{aligned} \tag{6}$$

Let us compute the parameters of products matrices $M^{-1}D$, M^{-1} and $M^{-1}J^T(\eta)$ as

$$M^{-1}D = \begin{bmatrix} d_{11} & 0 & 0 \\ 0 & a_{22} & a_{23} \\ 0 & a_{32} & a_{33} \end{bmatrix} M^{-1} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & m_{01} & m_{02} \\ 0 & m_{20} & m_{10} \end{bmatrix} \tag{7}$$

$$M^{-1}J^T(\eta) = \begin{bmatrix} \cos(x_3(t)) & \sin(x_3(t)) & 0 \\ -m_{33}\sin(x_3(t)) & m_{33}\cos(x_3(t)) & -m_{32} \\ -m_{23}\sin(x_3(t)) & -m_{23}\cos(x_3(t)) & m_{22} \end{bmatrix} \tag{8}$$

Next, substituting (7)–(8) into (5) gives the result as

$$\begin{aligned} \begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \\ \dot{x}_4 \\ \dot{x}_5 \\ \dot{x}_6 \end{bmatrix} &= \begin{bmatrix} 0 & 0 & 0 & \cos x_3 & -\sin x_3 & 0 \\ 0 & 0 & 0 & \sin x_3 & \cos x_3 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & -d_{11} & 0 & 0 \\ 0 & 0 & 0 & 0 & -a_{22} & -a_{23} \\ 0 & 0 & 0 & 0 & -a_{32} & -a_{32} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & m_{01} & m_{02} \\ 0 & m_{20} & m_{10} \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 0 \\ u_1 \\ u_2 \\ u_3 \end{bmatrix} \\ &+ \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ \cos(x_3(t)) & \sin(x_3(t)) & 0 \\ -m_{33}\sin(x_3(t)) & -m_{33}\cos(x_3(t)) & -m_{33} \\ -m_{23}\sin(x_3(t)) & -m_{23}\cos(x_3(t)) & -m_{23} \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 0 \\ \tau_{e1} \\ \tau_{e1} \\ \tau_{e1} \end{bmatrix} \end{aligned} \tag{9}$$

The state equation of DP system can be rewritten in more compact form as

$$\dot{x} = Ax(t) + Bu(t) + E\tau_e(t) \tag{10}$$

In this paper we make the following assumptions:

Assumption 1: The force of environmental factors τ_e are time-varying and unknown. On the other hand, the structure of controllers are built with a fixed status. Therefore, DP system of vessel with unknown parameters and fixed status becomes the significant challenge of the DP control design.

Remark 1: The vessel motion operates in a practical case under environment impacts, so the object parameter is highly nonlinear underlying physical processes. Thereby carrying out the DP control with fixed status on the nonlinear object does not give high precision. As such, the Assumption 1 is reasonable and more practical.

In this paper, the controller is to design a multi-cascade fuzzy model for the DP system of vessel (1) and (2) under the Assumption 1 such that the vessel is maintained at the desired values of its position and heading with arbitrary accuracy, while GA suggestion is adapted to calibrate the fuzzy-case 2 and fuzzy-case 4. Thereby enhancing the quality of system and optimizing the controller structure for vessel motion.

3 Multi-cascade Fuzzy Model

In this study, we design a multi-cascade controller which comprises four fuzzy cases for the DP system which constitutes a nonlinear object. Structurally, the designed controllers form a cascade architecture. A fuzzy-TS dynamic model has been proposed by Do et al. to represent local linear input/output relations of DP systems [8]. The inference process system combines membership functions (MFs) with if-then rules and the fuzzy logic operators. The TS model consists of rules where the rule consequents are often taken to be linear functions of the inputs given as follow [9]:

Plan rule R_i

$$\text{If } z_1 \text{ is } F_{k1}^i \text{ and} \ldots \text{and } z_n \text{ is } F_{kn}^i \text{ Then } \dot{x}(t) = A_i x(t) + B_i u(t) + E\tau_e(t) \tag{11}$$

where $F_{k1}^i, F_{k2}^i, ..F_{kn}^i$ are the fuzzy sets [10], for $i = 1, 2, \ldots, n$, $A_i \in R^{n\times n}$ and $B_i \in R^{n\times m}$ are the input and state matrix, n is the number of If-Then rules, and $z_1,\ z_2,\ \ldots,\ z_n$ are the premise variables. The overall fuzzy system is given by

$$\begin{aligned} \dot{x}(t) &= \frac{\sum_{i=1}^{n} \mu_i(z(t))(A_i x(t) + B_i u(t))}{\sum_{i=1}^{n} \mu_i(z(t))} + E\tau_e(t) \\ &= \sum_{i=1}^{n} h_i(z(t))(A_i x(t) + B_i u(t)) + E\tau_e(t) \end{aligned} \tag{12}$$

$$\begin{aligned} \mu_i(z(t)) &= \prod_{j=1}^{n} F_{ij}\left(z_j(t)\right) \\ h_i(z(t)) &= \frac{\mu_i(z(t))}{\sum_{i=1}^{n} \mu_i(z(t))} \\ z(t) &= [z_1(t), z_2(t), \ldots, z_n(t)] \end{aligned} \tag{13}$$

for $F_{ij}(z_j(t))$ is the rank of MFs of $z_j(t)$ in F_j. In this paper, we assumes that $\mu_i(z(t)) \geq 0$ with $i = 1, 2, \ldots, n$ and

$$\sum_{i=1}^{n} \mu_i(z(t)) \geq 0, \bigvee t \tag{14}$$

We get $h_i(z(t)) \geq 0$, for $i = 1, 2, \ldots, n$ and

$$\sum_{i=1}^{n} h_i(z(t)) = 1 \tag{15}$$

Therefore, from (5) we have the following

$$\begin{aligned} \dot{x}(t) &= Fx(t) + Gu(t) + E\tau_e(t) \\ &= \sum_{i=1}^{n} h_i(z(t))(A_i x(t) + B_i u(t)) + \left\{ \left(F(x) - \sum_{i=1}^{n} h_i(z(t)) A_i x(t) \right) \right. \\ &\quad \left. + \left(G(x) - \sum_{i=1}^{n} h_i(z(t)) B_i x(t) \right) u(t) \right\} + E\tau_e(t) \end{aligned} \tag{16}$$

where $\left\{ \left(F(x) - \sum_{i=1}^{n} h_i(z(t)) A_i x(t) \right) + \left(G(x) - \sum_{i=1}^{n} h_i(z(t)) B_i x(t) \right) u(t) \right\}$ indicates the estimation error between the DP system (5) and the fuzzy system (11). Let us assume that the following fuzzy system is carried out to control the internal system (15) design as:

Plan rule R_i:

$$\text{If } z_1(t) \text{ is } F_{k1}^i \text{ and} \ldots \text{and } z_n(t) \text{ is } F_{kn}^i, \text{Then } u(t) = K_j x(t), \text{for } j = 1, 2, \ldots, r \tag{17}$$

where K_j is the control adjustment. Hence, the following overall fuzzy controller is represented as:

$$u(t) = \frac{\sum_{j=1}^{r} \mu_j(z(t)) K_j x(t)}{\sum_{j=1}^{n} \mu_j(z(t))} = \sum_{j=1}^{r} h_j(z(t)) K_j x(t) \tag{18}$$

where $h_j(z(t))$ is defined in (13) (for $j = 1, 2, \ldots, r$). Next, substituting (18) into (16) yields, the closed-loop DP nonlinear control system as follows:

$$\begin{aligned}\dot{x}(t) &= Fx(t) + Gu(t) + E\tau_e(t) \\ &= \sum_{i=1}^{n}\sum_{j=1}^{r} h_i(z(t))h_j(z(t))\left(A_i + B_iK_j\right)x(t) + \left(F(x) - \sum_{i=1}^{n} h_i(z(t))A_ix(t)\right) \\ &\quad + \sum_{i=1}^{n} h_i(z(t))\sum_{j=1}^{r} h_j(z(t))(G - B_ix(t))K_jx(t) + E\tau_e(t) \\ &= \sum_{i=1}^{n}\sum_{j=1}^{r} h_i(z(t))h_j(z(t))\left(A_i + B_iK_j\right)x(t) + \Delta f + \Delta g + E\tau_e(t)\end{aligned} \tag{19}$$

Defining and applying

$$\Delta f = \left(F(x) - \sum_{i=1}^{n} h_i(z(t))A_ix(t)\right) \tag{20}$$

and

$$\Delta g = \sum_{i=1}^{n} h_i(z(t))\sum_{j=1}^{r} h_j(z(t))(G - B_ix(t))K_jx(t) \tag{21}$$

The environmental factors make the control signal to be erroneous. So the building of MFs is an important thing to ensure the quality of fuzzy controller. If the passive parameter of MFs are used, the system performance will be lowered, and the object will be even out of balance. The GA is an effective tool for structure optimization of the controllers. Hence, integration and synthesis of fuzzy schematic and GA have been proposed to reduce the nonlinear characteristic. However, if the vessel operates under normal environmental conditions, the complex fuzzy controller (optimized by GA) is not effective, leading to slow response time. In the paper, we propose a multi-cascade fuzzy model which is divided into four fuzzy control cases corresponding to the level of environmental impact. In the no environmental impact case, the first fuzzy model is defined by a simple architecture which is described by 3×3 memberships function (fuzzy-case 1). So the closed-loop DP nonlinear control is rewritten as

$$\dot{x}_1(t) = K_s\sum_{i=1}^{3}\sum_{j=1}^{3} h_i(z(t))h_j(z(t))\left(A_i + B_iK_j\right)x(t) + \Delta f + \Delta g + E\tau_e(t) \tag{22}$$

where K_s is the fuzzy model selection, is defined by the supervisor module. In the low environment impact, the structure of second fuzzy is the same in first case. However, the value of fuzzy sets is optimized by GA (fuzzy-case 2). The DP control is given by

$$\dot{x}_2(t) = K_s\sum_{i=1}^{3}\sum_{j=1}^{3} h_i(z(t))h_j(z(t))\left(A_i + B_iK_j\lambda\right)x(t) + \Delta f + \Delta g + E\tau_e(t) \tag{23}$$

where λ is the adjusting fuzzy structure coefficient. In the case of medium environment impact, we propose the architecture of third fuzzy model which is defined by 5×3 memberships function (fuzzy-case 3). The DP control is rewritten as

$$\dot{x}_3(t) = K_s \sum_{i=1}^{5} \sum_{j=1}^{3} h_i(z(t))h_j(z(t))\left(A_i + B_i K_j\right)x(t) + \Delta f + \Delta g + E\tau_e(t) \tag{24}$$

As in the case of high level environmental impact, the structure of fourth fuzzy model would be optimized by GA in the same as the second fuzzy model (fuzzy-case 4). So the DP control is expressed as follow:

$$\dot{x}_4(t) = K_s \sum_{i=1}^{5} \sum_{j=1}^{3} h_i(z(t))h_j(z(t))\left(A_i + B_i K_j \lambda\right)x(t) + \Delta f + \Delta g + E\tau_e(t) \tag{25}$$

In the next section, the design of fuzzy structure which is optimized by GA is discussed in detail. Since the fuzzy sets are set up by experience according to the Remark 1. Thereby, the object membership function is fixed to the control signal for the nonlinear DP system is not optimized with time-varying object.

4 Fuzzy Genetic Algorithm Design

In the cascade structure, the second fuzzy controller case (3×3) and fourth fuzzy controller case (5×3) will be fixed by the optimal algorithm. This paper presents a combined genetic algorithm and fuzzy logic method, a fuzzy genetic algorithm (fuzzy-GA) for the DP system is designed to achieve the control goal stated in Sect. 2. So Fig. 2 represents the flowchart of optimizing fuzzy system. Thereby solving problems presented by Remark 1. Building control consists of a two-stage process.

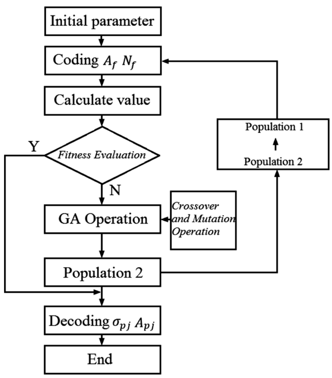

Fig. 2. Optimization flowchart of fuzzy system uses the GA.

Process 1: Determine the fuzzy system with optimized parameter. The fuzzy modulator has a double-input, $e_x(t)$, $d_{e_x(t)}/d(t)$ and a single-output, $\tau(t)$ [11]. These fuzzy sets adjusted flexibly by λ coefficient to optimize the control structure. In the fuzzy-GA controller, the value and overlap degree of MFs, which are optimized by the GA, are used. Following Eq. 18, the fuzzy output can be redescribed as belows:

$$u_{(t)} = \sum_{j=1}^{r} h_j(z(t))K_j x(t)\lambda \tag{26}$$

Process 2: Adjusting the optimized fuzzy parameter. The GA optimization module completes the calibrating of fuzzy sets with vector $\lambda(\lambda_1, \lambda_2, \lambda_3, \lambda_4)$ adjusting coefficients that synthesise the optimum control structure. Adjusting a structure of fuzzy system can be viewed as an optimization subject in 4-search space as many options of the controller could be achieving better response. The adjustment of normal solutions do not ensure an optimal goal and in the adjusted structure controller needs demonstrate through the erroneous. The GA includes a group of solutions named population and continuity modifies to them. At every stage, the GA chooses an λ individuals from the current population to become parents and uses these individuals to make children for the next pedigree [12]. The detail of coding and decoding system, crossover and mutation operation and fitness evaluation are given in the next sections.

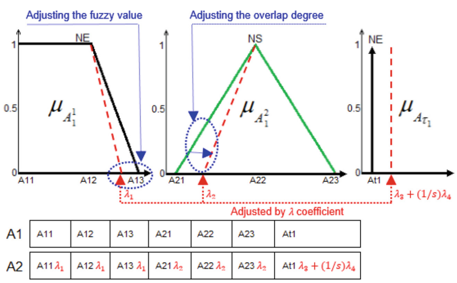

Fig. 3. Describing the coding values of MFs.

4.1 Coding and Decoding

Coding is the genetic representation of solutions [13]. The nominate solutions are displayed by strings of determine length, which named chromosomes. Figure 3 presents a method of genotype for individuals. Code mask A_f is a binary vector with a length of N_f, where a 0 or 1 at the ith position represents the absence or presence of the ith feature. The value of ith position is given by

$$A_i = \begin{cases} 1, & P\left(A_f^i = 1\right) = mf_{se}/mf, i = 1, 2\ldots N_f \\ 0, & P\left(A_f^i = 1\right) = 1 - mf_{se}/mf \end{cases} \tag{27}$$

where mf_{se} is an original factor and expresses the amount of selected characteristic. This suggestion make the characteristics of genetic evolution in lower cases. The relationship between code mask A_f and its phenotype representation is

$$\tilde{D} = D.diag\left(A_f\right) \tag{28}$$

where D and $\tilde{D}$ present the preset parameter and the parameter after characteristic selection, respectively. The N_{pj} expresses the genotypic length of ith parameter for the fuzzy set. N_{pj} is given by

$$N_{pj} = round\left[log_2\left(\frac{\sigma_{pj,up} - \sigma_{pj,low} + \Delta}{\Delta_{pj}}\right)\right] + 1 \tag{29}$$

where $\sigma_{pj,up}$ and $\sigma_{pj,low}$ show the upper and lower searching bound, respectively. Δ_{pj} is an original factor and display an accurate appraisal. The genotype A_{pj} of parameters j should be decoded into phenotype σ_{pj} by

$$\sigma_{pj} = \sigma_{pj,low} + \left(\sigma_{pj,up} - \sigma_{pj,low}\right)\left(\frac{\sum_{i=1}^{N_{pj}}\left(A_{pj}^{(i)}\right)^{N_{pj}-1}}{2^{N_{pj}}}\right) \tag{30}$$

where $A_{pj}^{(i)}$ represents the ith position value of A_{pj}.

4.2 Crossover and Mutation Operation

Homologous crossover operator is carried on this study, which is an initial random for creating a new variety of genes between two individuals. The amount of crossover is defined by the amount of optimal solution. In mutation operation, the proposed control realizes two different method for fuzzy factors and code mask. In terms of optimal solution, a gene could be randomly changed. Two genes can be chosen and crossed their parameter now and then, which can keep mf_{se} from change.

4.3 Fitness Evaluation

The minimum initial values that caused by the error between response value and referent value is the optimal goal. So the fitness function is used for iterations to value the quality of all the proposed solutions to the problem in the current population. The fuzzy-GA control structure for DP system shows in Fig. 4. In this paper, the fitness function is chosen by the ITAE criteria [15] as follows:

$$ITAE = \int_0^\infty t|e(t)|dt \tag{31}$$

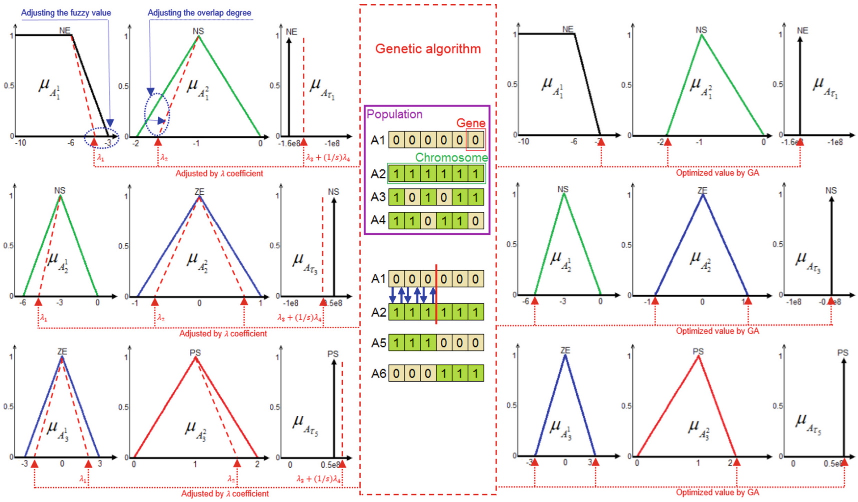

Fig. 4. The fuzzy set values of MFs are calibrated by GA [14].

5 Supervisor Design

The supervisor consists of two subsystems: Estimator, and a switch logic. Figure 5 shows the structure of the supervisor using two different process models [16]. Inputs to the supervisor are the process input, τ, and measured process states, η. The supervisor output is the switching signal, K_S.

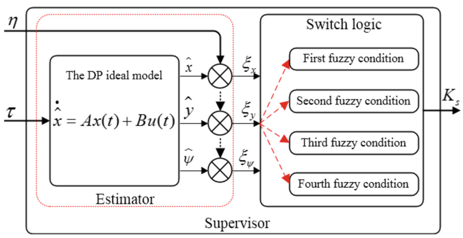

Fig. 5. The supervisor structure for cascade multi fuzzy model.

In the proposed method, namely multi-cascade fuzzy model, control signal for real model (environmental impact) is adjusted by the K_S factor. This adjustment is based on the output error ξ between ideal model (without peripheral factors) and real model. The response of real model is controlled to adapt to the ideal model. Therefore, the error caused by peripheral factors is minimized [17]. The structure of multi-cascade fuzzy model is shown in Fig. 6. Ideally, we eliminate the impact of environmental factors, it is mean $E\tau_e(t) = 0$. So the equation of ideal model are as

$$\dot{\hat{x}} = Ax(t) + Bu(t) \tag{32}$$

From Eq. 16, the equation of ideal model rewritten as

$$\dot{\hat{x}}(t) = \sum_{i=1}^{n}\sum_{j=1}^{r} h_i(z(t))h_j(z(t))\left(A_i + B_iK_j\right)x(t) + \Delta f + \Delta g \tag{33}$$

The control signal of real model is selected by K_s, which is the key ideal of supervisor function. This selection is computed according to the output error ξ, i.e., the error between the real model and the ideal model. The output error ξ is shown as

$$\xi = \dot{x}(t) - \dot{\hat{x}}(t) = P(t).U(t) - \hat{P}(t).U(t) \tag{34}$$

The error ξ helps to estimate the value and level of relative environmental impacts. The proposed method aims to remove the unexpected value ξ. The control signal of the real model is adjusted by selecting K_S to adapt the real model to the ideal. That is, $\xi \to 0$ when t $\to \infty$, and then

$$P(t).U(t) = \hat{P}(t).U(t) \tag{35}$$

The switch logic [18] signal of the real model can be presented by

$$\dot{x} = A_{K_s}(x, \tau_e) \tag{36}$$

$$e_p = C_p(x, \tau_e), p \in P \tag{37}$$

where x defines the state vector of process, the multi-fuzzy model and the multi-estimator, and τ_e is the vector of environmental impacts. A_{K_s} and C_p are functions that denote the dynamics of the switch logic system and output functions, respectively.

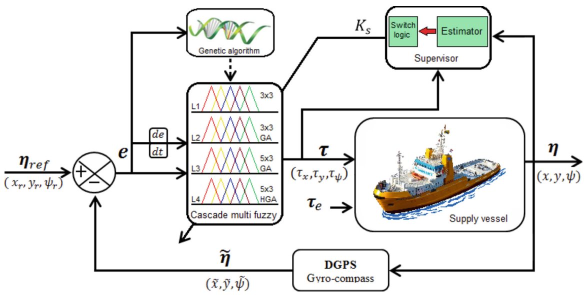

Fig. 6. The optimized multi-cascade fuzzy model structure for DP system of vessel.

6 Simulation Studies

6.1 Configuration Parameter

Performance comparisons between the proposed optimized multi-cascade fuzzy model and the fuzzy controller are conducted to assess the precision and effectiveness of the proposed controller. Multi-cascade fuzzy model (Sect. 3) with the optimal goal (Eq. 31) is tested on the supply vessel with length overall 52.08 m, length between perpendiculars 46 m, beam 12.07 m, design draft 5.52 m and design speed 11 knots [1].

$$D\begin{bmatrix} 5.024e4 & 0 & 0 \\ 0 & 2.722e5 & -4.393e6 \\ 0 & -4.393e6 & 4.189e8 \end{bmatrix}; M = \begin{bmatrix} 5.312e6 & 0 & 0 \\ 0 & 8.283e6 & 0 \\ 0 & 0 & 3.745e9 \end{bmatrix}$$

Case 1: The optimized multi-cascade fuzzy model and fuzzy force the vessel to arrive at the desired value [3 m, 7 m, 20°] in around 200 s from reference [0 m, 0 m, 0°]. Case 2: These controllers are proposed to keep vessel routine for achieving desired trajectory under environmental impacts. Figures 7(a) and 8(c) reveal that the optimized multi-cascade fuzzy model 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 Figs. 7(b) and 8(a). On the other hand, Figs. 7(d) and 8(b) show that the control forces and moment by the optimized multi-cascade fuzzy model and fuzzy controller are glossy and justice. The environmental impacts are presented by Fig. 7(c) [19]. The environment impacts include wave, wind and currents τ_e which expressed by

$$\tau_e = \tau_{wave} + \tau_{wind} + \tau_{current} \tag{38}$$

here, the wave impact is described as follow [1]:

$$\tau_{wave} = \zeta_{qr}(x, y, t) = \zeta_{aqr} sin\left(\omega_q t + \phi_{qr} - k_q(x cos\,\psi_r + y sin\,\psi_r)\right) \tag{39}$$

where wave height $H_s = 0.8$ m, wave spectrum peak frequency $\omega_p = 0$ rad/s, wave direction $\psi_0 = -30^0$, spreading factor $s = 2$, number of frequencies $N = 20$, number of directions $M = 10$, cutoff frequency factor $\zeta = 3$, wave component energy limit $k = 0.005$ and wave direction limit $\psi_{lim} = 0$. The wind forces are performed by

$$\begin{aligned} V_R &= V_w \\ g_R &= \beta_w - \psi_L - \psi_H \end{aligned} \tag{40}$$

The wind simulation parameters are sorted as follows: $A_L = 2.4$, $A_T = 9.34$, wind speed $V_\omega = 2$ m/s and the angle of impact wind $\beta_\omega = 20^0$.

$$\begin{aligned} u_c &= V_c cos(\beta_c - \psi_L - \psi_H) \\ v_c &= V_c sin(\beta_c - \psi_L - \psi_H) \\ \tau_{current} &= [u_c, v_c, 0]^T \end{aligned} \tag{41}$$

Besides that, the simulation parameters for current factor are set to their default values accept as follows: $V_C = 2$ m/s, vessel direction $\beta_C = 30^0$, low frequency and high frequency of rotation are ignored $\psi_L = \psi_H = 0$.

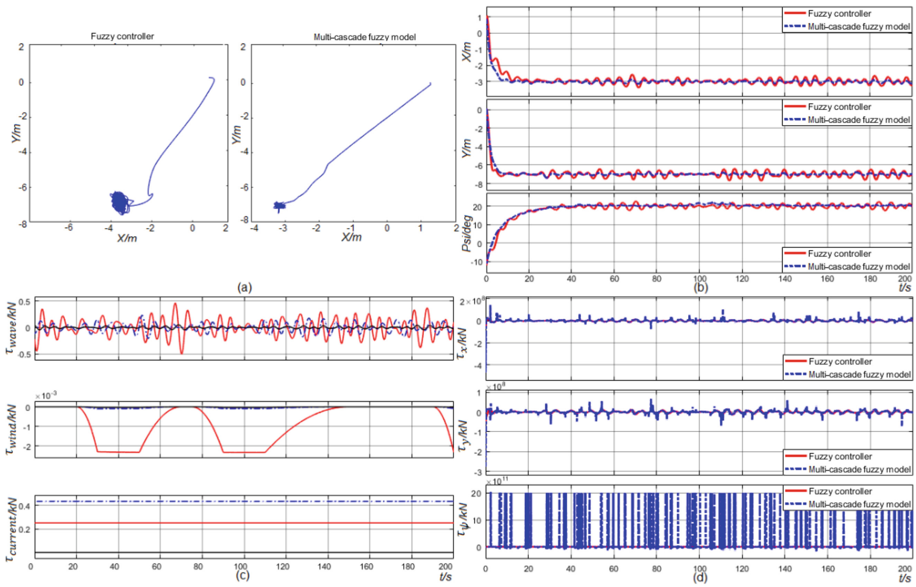

Fig. 7. The simulation of cases 1 consist of two controllers. (a) Trajectory of the vessel position in *xy*-plane. (b) The real position (x, y) of vessel and the heading ψ of vessel. (c) Environmental impacts (τ_{wave},τ_{wind} and $\tau_{current}$) have an effect on the vessel. (d) Surge control force τ_x, sway control force τ_y and yaw control force τ_ψ.

6.2 Simulation Results

The DP controllers of the position error vectors in cases are given by Figs. 7(a) and 8 (c), which illustrate that the optimized multi-cascade fuzzy model has a good stable performance in each of simulation case under environmental 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 balance of the DP system, the vessel position will be stable from the low-impact case and vibratile at the higher impact cases. Besides that, the vessel heading fluctuates strongly according to the level of environmental impacts. The satisfactory results prove that the optimized multi-cascade fuzzy model has the adaptability to nonlinear systems of vessel motion and against time-varying environmental 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.

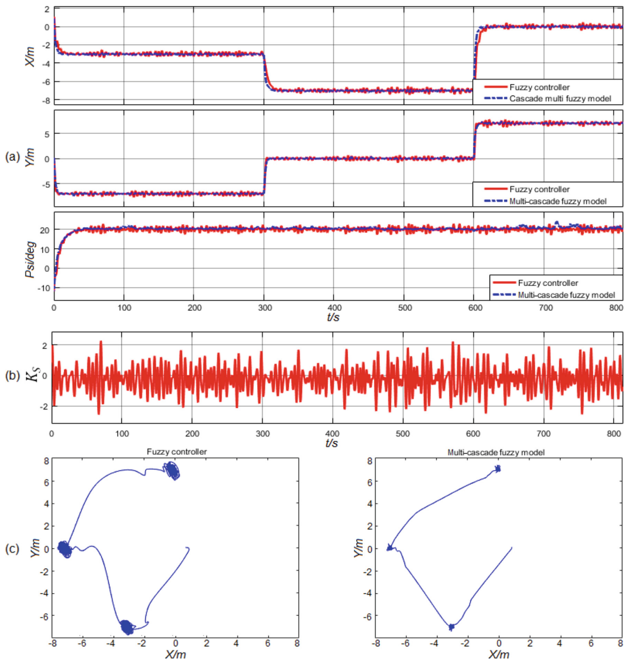

Fig. 8. The simulation of cases 2 consist of two controllers. (a) Real position (x, y) and the vessel heading ψ. (b) Output supervisor K_s which adjust multi-cascade fuzzy model structure. (c) Trajectory of the vessel position in xy-plane.

7 Conclusions

In this paper, an optimized multi-cascade fuzzy model has been developed for the DP system in the presence of environmental impacts. Our proposed control strategy is able to keep the vessel at the desired values of its position and heading with accuracy. Proposed algorithm optimize structure parameters fuzzy and reduce the nonlinear characteristics of the DP system which caused by environmental impacts. Calibrating control structure of fuzzy system was intuitive to perform. The main advantage of the proposed controller, compared to the conventional fuzzy control, it is optimal to variations in its displacement and the environmental conditions. This study can be extended by using the robust algorithm to improve the DP control quality when the vessel operates in unstable state for constantly.

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