Robust Adaptive Fuzzy Control Using Genetic Algorithm for Dynamic Positioning System

XUAN-KIEN DANG[ID][1]**, (Member, IEEE), VIET-DUNG DO**[1,2]**, (Member, IEEE), AND XUAN-PHUONG NGUYEN**[1]

[1]Graduate School, Ho Chi Minh City University of Transport, Ho Chi Minh City 70000, Vietnam
[2]Dong An Polytechnic, Binh Duong 75000, Vietnam

Corresponding author: Xuan-Kien Dang (dangxuankien@hcmutrans.edu.vn)

ABSTRACT This paper aims to develop a genetic algorithm to adjust an fuzzy controller for Vessels' Dynamic Positioning System (Vessels' DPs). It is well-known that nonlinearities affecting the control accuracy of the DPs are related to the arrangement of different types of thrusters in the vessels, such as azimuth thrusters (electric, L-drive, and Z-drive), bow thrusters, stern thrusters, water jets, and propulsion propellers with rudders. Compared with the traditional fuzzy control methods, the proposed Robust Adaptive Fuzzy Control using Genetic Algorithm (RAFC-GA) not only overcomes the influence of nonlinearities in the DPs, but also eliminates the impact of parameter uncertainties. Therefore, the tracking performance is excellent and robustness is maintained. The RAFC-GA control method is superior to the conventional fuzzy control methods in the two following aspects: 1) to find the optimal values for the fuzzy structure parameters to satisfy the robust condition under the effect of disturbances and nonlinearities in the DPs without weakening the output tracking performance and robustness, 2) to improve the quality of the system by optimizing values for the fuzzy structure using genetic algorithm which dynamically adjusted the coverage domain width and the overlap degree of membership functions. Simulation results of the RAFC-GA are evaluated in comparison with other methods. The RAFC-GA performs the desired transient response of DPs better than others in three case studies, which proves the effectiveness of the proposed solution.

INDEX TERMS Dynamic positioning system, parameter uncertainties, optimize fuzzy, robust genetic algorithm.

I. INTRODUCTION

A. PROBLEMS AND MOTIVATIONS

Over the past few decades, there are some methods utilized to keep vessels' position in the sea, namely the use of an anchor spread, the use of a jack-up barge and dynamic positioning system (DPs). Even though each method has its own advantages, dynamic positioning (DP) has many more operations possible that were not feasible before. To be specific, it is easy for the vessels to change position using DPs thanks to its excellent maneuverability. Moreover, DPs requires no anchor handling tugs, does not depend on water depth and also are not limited by obstructed seabed. Basically, DPs is primarily concerned with the vessels' control in the horizontal plane

including surge, sway and yaw. It calculates the required control actions to maintain position and adjusts position errors by applying forces of thrusters to the vessels as demanded by the control system. Therefore, the control system of DPs plays an important role in improving the efficiency of the vessel in most sea conditions.

The first generation of DPs often uses traditional linear controllers like Proportional-Integral-Derivative (PID) controller [1], Linear Quadratic Gausian (LQG) controller [2]. Fossen *et al.* presented some nonlinear control methods for a DP control system, such as feedback linearization and backstepping [3]. Although those methods have simple structures and acceptable stability, the control efficiency is low under different conditions of the sea or the effect of uncertain factors. More importantly, we need to face with a certain challenge that the vessels usually work under the complexity

---

The associate editor coordinating the review of this manuscript and approving it for publication was Haibin Sun[ID].

and vulnerability of deep water of the sea. Hence, we need a control system which can be adaptive to changing variables, and robust to uncertain factors.

In the process of adaptive control of DPs, Aschemann *et al.* [4], Popov *et al.* [5], and Fossen *et al.* [6] presented the idea of self-adaptation control by control algorithms and observer the uncertainties of system parameters and the changes of disturbances. In addition, there are some of adaptive control algorithms based on model predictive, such as generalized predictive control (GPC) [7] and non-linear model predictive control [8]. To be clear, predictive control introduces the idea of adaptive control, which is suitable for uncertain structural and complex systems in ship motion control. In general, the adaptive control of the DP system aims to improve the quality of control in the presence of non-parametric perturbations such as disturbances and unmodeled dynamics, but it does not need any prior information about the bounds on these uncertainties or, in other words, the adaptive control has no purpose for robustness. However, DPs need not only high quality of control but also robustness. Therefore, adaptive control method does not seem reliable enough.

Clearly, in the actual working condition of the vessel, there are three main factors including uncertain parameters of system, dead-zone inputs and time-delay, and dynamic and environment disturbance directly affect to the quality and performance of DPs. Considering the nonlinearity of vessels' DPs related to the vessels arranged different types of thrusters, such as azimuth thrusters (electric, L-drive or Z-drive), bow thrusters, stern thrusters, water jets, or propulsion propellers with rudders. The system has a complex structure, including many devices, leading to the system parameters are uncertain. The dead-zone inputs and time-delay of DPs are the most important non-smooth nonlinearities of system, it can result in poor performance and even severely affect the system stability [9]. Moreover, the problem of time-delay in DPs has received considerable attention, the main kind of time-delay is encountered in actuators [10], while another obvious kind of delay is the one produced between the sensors and the activation of the control mechanism [11]. With complex of vessel dynamics, the dead-zone inputs and time-delay are considered as main factors causing the nonlinearity of DPs. Subsequently, adaptive fuzzy control approach provides an effective control which is highly desirable to handle this particular nonlinear system [12]. Regarding to DPs control, some related articles will be analyzed clearly in the next subsection.

B. RELATED WORKS

Vessels's DPs has been increasingly used in offshore oil and gas drilling, cable and pipe laying, and dredging, so that the challenge of DPs development remains an problem of significant advancements from researchers. They have been paid attention to study of DP control system, such as the nonlinear adaptive control, sliding mode control, back-stepping control, two or more control methods are combined to deal with the uncertain disturbances and parameters. Recently,

Sørensen [13] and Wang *et al.* [14] surveyed a lot of previous research materials which introduces some modern control theories to aim at improving the quality of DPs. Basically, the nonlinearity and uncertain disturbance must be taken in consideration while almost the traditional control theories are simple in structure and method, the disadvantages of these methods were that the kinetic functions of motions must be linearized under certain conditions. From the above, the modern theories, such as Fuzzy Logic Control (FLC), Neural Network Control (NNC), Cerebellar Model Articulation Control(CMAC), Neural-Fuzzy has been widely investigated from different perspectives. To clarify the fundamental research issues, we analyze more carefully the control algorithms related to DPs in next paragraph.

Related to Fuzzy control, Chang *et al.* used Takagi-Sugeno fuzzy controller to control the nonlinear DPs and solved common positive definite matrix P and linear feedback gains to satisfy the stability conditions of system by using LMI tools [15]. The performances of the nonlinear DPs based Fuzzy logic appreciated in the simulated results, but the effects of disturbances have not been mentioned in this study. A Type-2 Fuzzy Logic Controller Active disturbance rejection control (ADRC) is a new control strategy for DPs in case of the system is in the present of nonparametric perturbations, namely disturbances and unmodeled dynamics. Liu *et al.* have verified that ADRC has a high robustness and dynamic regulation ability for vessel control in the bad weather [16]. Fuzzy control algorithm is used to improve conventional active disturbance rejection controller (ADRC) adopted in the design of ship course controller, the parameters of ADRC are optimized by fuzzy adaptive algorithm [17]. Regarding to reduce the affect of unexpected impacts from environmental, Hu *et al.* presented an adaptive fuzzy controller for the DPs [18], the unexpected impacts are approximated by the adaptive fuzzy structure. Dang *et al.* analyzed the sea weather effects to the Ship Maneuvering based on Fuzzy control method to maintain stability of ship position when engaging in fishing [19]. Thus, disturbance rejection is a fairly common solution in ship motion control and Fuzzy control is a the appropriate option for study.

Regard to the nonlinearity of DPs, the thruster fault-tolerant control [20] used the Luenberger observation to detect actuator faults, the DPs is provided by a discrete - time variable - structure controller selected by the supervisor based on a fault isolation logic. The simulation tests establish for a scale model of the offshore vessel indicate that, the dynamic positioning system is guaranteed the nonlinearity caused by actuators faults. This subject needs to be considered with the influence of unexpected factors on the vessel motion such as wave, wind and time-delays of the control process. Therefore, the process of designing finite quadratic optimal controllers for DPs is much simpler. Related to external forces, Gu *et al.* applied a NNC to measure the wave amplitude and estimate the external force [21], which has an effect on the vessel, the dynamic positioning was demonstrated with simulation. However, it is necessary to take the practical test for verifying

proposed method. In order to improve the control quality in the actual environment, Xia *et al.* developed the CMAC based on the PID algorithm to approximate the nonlinear components [22], and Ta *et al.* enhanced the robustness of CMAC for DPs [23]. The responses of CMAC indicates that the controller is able to adapt to external forces, even if the vessel operates at high speed or uncertain parameters.

In recent years, Adaptive Fuzzy Control (AFC) has got a great development and lots of important results in order to deal with problems of uncertainty and disturbance of nonliner system in literatures [24]–[27], [28], and [29]. The problem of event-triggered adaptive fuzzy control for a class of MIMO switched nonlinear systems has been studied [28]. The result showed adaptive fuzzy control can guarantee that all the signals in the closed-loop system which are bounded under a class of switching signals with average dwell time. Li *et al.* utilized the small-gain technique-based adaptive fuzzy tracking scheme which can guarantee the tracking error converges to a small neighborhood of the origin with bounded system signals [29]. Moreover, adaptive reliable guaranteed the control performance of uncertain nonlinear systems by using Lyapunov function for class of event-triggered MIMO nonlinear system and nonlinear time-delay systems [28] and [29]. Related to vessels' DPs, Fang *et al.* apply adaptive Neural-Fuzzy algorithm to practice to find out the best control parameters for propulsion systems by reduced the environment disturbances which are estimated [30]. Moreover, nonlinear adaptive fuzzy output-feedback controller designed to solve the problem of unmeasured states of ships, unknown dynamic model parameters, unknown time varying environment disturbances and input saturation in [31].

Amongst the evolutionary algorithms, the revolution in the study of natural algorithms applied in theory control is still in the process of intense racing by researchers. The most common algorithms that can be named Genetic Algorithm (GA) [32], Ant Colony Optimized (ACO) [33], Artificial Bee Colony Algorithm (ABCA) [34], and Particle Swarm Optimization (PSO) [35], among them GA is one of the most widely used algorithm for estimating fuzzy weights and obtaining good shape of the membership function, that is the way to make adaptive fuzzy control systems increasing quality and performance of control process. Adaptive Fuzzy Control based on GA, structure provides a feasible approach for DP nonlinear systems with unexpected impacts due to the fuzzy's ability to approximate a nonlinear function. There are some Robust Adaptive Control via Genetic Algorithm have been presented to ensure a good trade-off between performance and robustness against uncertain parameters [36]. Besides that, the robust H_∞ tracking performance is proposed to guarantee uniformly robustness bounded [37] for the process parameters of GA. However, the application of the AFC based on GA improves the adaptability of vessel DPs, but the calculation results of the intelligent algorithm are random, and the study and application of the GA are not comprehensive. Thus, most optimization algorithms including GA which are not applied in the field of ship motion control. Therefore,

this paper suggests a novel model of robust adaptive fuzzy control to deal with the position control for a class of nonlinear vessels' DPs using GA.

C. CONTRIBUTIONS

To overcome the aforementioned problems, we propose the RAFC-GA for Vessel's DPs. The contributions of the paper are presented as follows:

1. We propose the model of adaptive fuzzy control for vessel's DPs to overcome the effect of three main factor that are uncertain parameters of system, dynamic and environment disturbance, and dead-zone inputs and time-delay are considered to be the two main factors causing nonlinearity of DPs. Based on soft fuzzy rules, the adaptive law is determined by the ideal variable λ_k which adjusts a fuzzy set of values whenever there is a vessel's position error, the result is the error come to zero.

2. We improve the quality of the system by optimizing value of a λ_k based on genetic algorithm, a fuzzy set values of MFs are calibrated. The second adaptive law are set to select the parameters of GA process and then λ_{GA_k} will calculate the MFs to optimize the intersection between fuzzy rules.

3. We added the robust function λ_{RC_k} to keep fuzzy set values of MFs are always in the allowed range even if β_i reaches ∞ so that DPs satisfies both high quality and robustness.

The rest of this paper is organized as follows. In Section II, we introduce the nonlinear motion of a vessel's DPs with some assumption and remark. The AFC-GA model are presented in Section III. Next section we deal with the robust adaptive problem by jointing the optimization based on GA and Robust scheme. Section V is dedicated to showing the simulation results, analysis, and evaluation of the RAFC-GA proposed. Finally, we conclude the paper in Section VI.

II. PROBLEM FORMULATION
A. DYNAMIC POSITIONING SYSTEM
The nonlinear motion of a vessel in DPs mode is described by Fossen [38] and reused by Do *et al.* [39]. Two separate coordinate systems presented by Fig. 1 include: the first 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 is defined as below:

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

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

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_{envi} represents the forces from environment, including wave, wind and current.
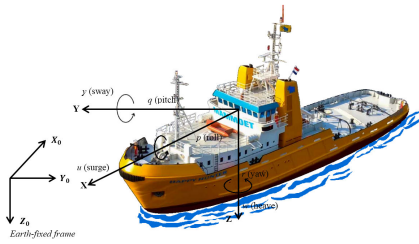
FIGURE 1. Definition of the earth-fixed and the vessel-fixed reference frames.

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 central of the vessel towards the relative frame of reference [19]. The transformation matrix $J(\psi)$ and $M \in R^{3 \times 3}$ and $D \in R^{3 \times 3}$ 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. The inertia quantities are increased by the acceleration of the surge, sway, and yaw direction of transformation as expressed as in Eq.(5)

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

In most of 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 reduced, it can be supposed that $N_v = Y_r$. The damping compositions in surge, sway, and yaw directions are defined by Eq. (6)

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

Because of the DPs parameters are updated directly following the changes in the operation-varying of the vessel, the structural parameters are added ΔM and ΔD, $M = M_0 + \Delta M$ and $D = D_0 + \Delta D$, where M_0 and D_0 represent nominal values, and ΔM and ΔD represent the uncertainties. Thus, all uncertainties errors will be taken into account and the control weights are updated continuously during the control process.

Assumption 1: If the vessel operates in a practical case under environmental impacts τ_{envi}, the parameter object will be highly nonlinear underlying physical processes.

Remark 1: The hybrid of fuzzy logic systems provides an effective control solution for the complex process which's physical parameters do not define accurately. This solution allows users to make decisions based on experience. However, the structure of the simple fuzzy controller is set up with a fixed status. Besides this, the MFs parameters are chosen by the experience of the programmer based on the idea of several captains. Clearly, the structure parameters of the controller are not in the optimal case. Therefore, applying the simple fuzzy solution to control the DPs nonlinear under environmental impacts, and as such, *Assumption 1* is more reasonable and practical.

In this paper, we aim to propose the RAFC-GA controller design for the DPs which expressed in equation (1) and equation (2). The vessel operates under the conditions of *Assumption 1*, the control process, includes the appearance of nonlinear characteristics, time-delay, and dead-zone inputs, and is affected by errors. Besides, the varying operations also make the structural parameters *M* and *D* changed, synonymous with ΔM and ΔD parameter is uncertain uncertainties. The result showed that the desired position and heading of the vessel are maintained with arbitrary accuracy, while GA suggestion is adopted to adjust the optimal fuzzy structure. Thereby, optimizing the controller structure helps the DPs fast-forward to a stability domain, and all parameters of the GA system are guaranteed the ultimate boundedness.

B. ENVIRONMENT IMPACTS

The environment impacts include the wave factor, wind factor and current factor, named τ_{envi}, which is expressed as

$$\tau_{envi} = \tau_{wave} + \tau_{wind} + \tau_{current} \tag{7}$$

The wave impact factor is described as follow:

$$\begin{aligned} \tau_{wave} &= \zeta(x, y, t) \\ &= \sum_{q=1}^{N} \sum_{r=1}^{M} \sqrt{2S(\omega_q, \psi_r)\Delta\omega\Delta\psi} \sin(\omega_q t \\ &\quad \dots + \phi_{qr} - k_q(x\cos\psi_r + y\sin\psi_r)) \end{aligned} \tag{8}$$

where ψ_r, ω_q, ϕ_{qr} and *S* represent the direction, frequency, phase angle and wave spectrum, in which the phase angle ϕ_{qr} of wave components is between 0 and 2π. The $\Delta\omega$ and $\Delta\psi$ factors represent the harmonic amplitudes of wave frequency ω_q. On the other hand, $k_q = 2\pi/\lambda_q$ is the number of waves, as λ_q is the wave length and the dispersion relation $\omega_q = \sqrt{kg}$ with *g* is the gravity acceleration. The low frequency (V_w) and direction (β_w) of wind modeled are the slowly varying quantities. The wind forces are performed by

$$\begin{aligned} \tau_{wind} &= [X_{wind}, Y_{wind}]^T \\ X_{wind} &= 0.5C_X g_R \rho_w V_R^2 A_T \\ Y_{wind} &= 0.5C_Y g_R \rho_w V_R^2 A_T \end{aligned} \tag{9}$$

where C_X and C_Y express the wind traction into the ichnography area A_T. In addition, V_R presents the wind speed and
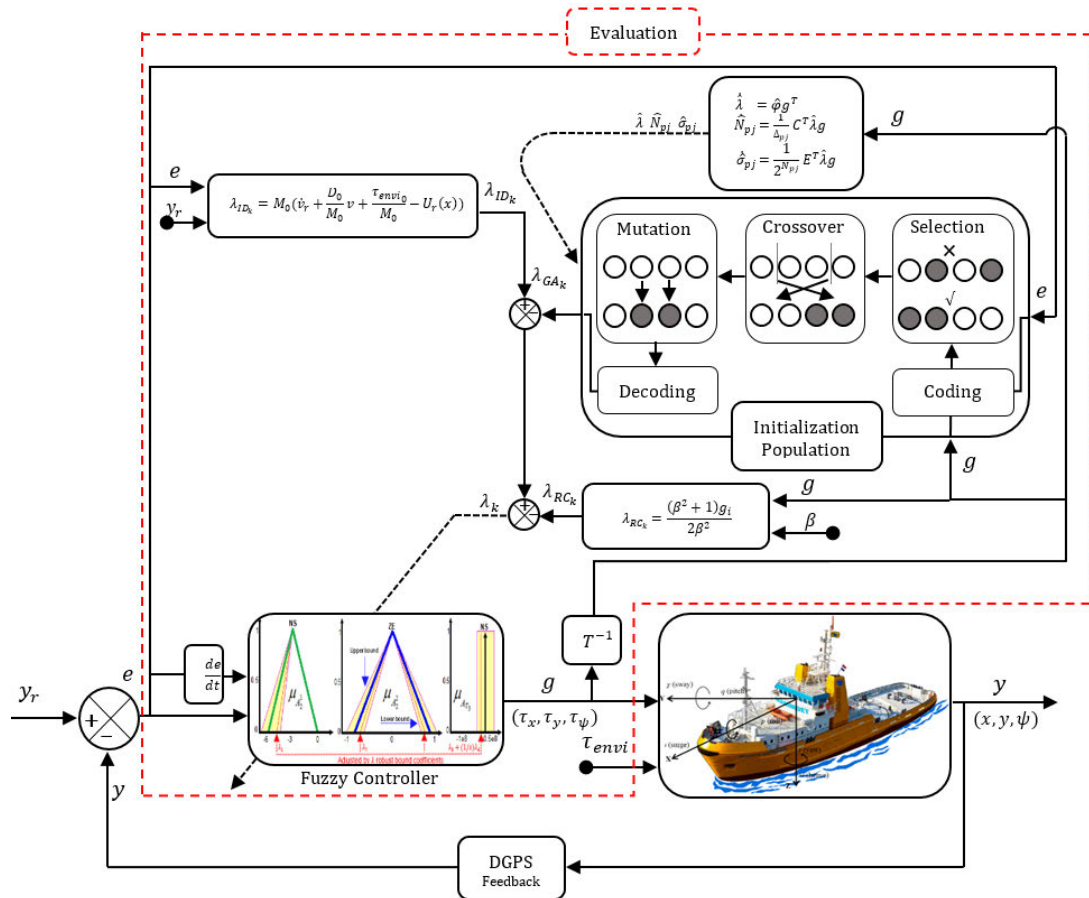
FIGURE 2. The robust adaptive fuzzy control using genetic algorithm structure for DPs.

g_R is the wind direction.

$$V_R = V_w ; \qquad g_R = \beta_w - \psi_L - \psi_H \qquad (10)$$

Besides 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 velocity of vessel coordinates is presented by

$$u_c = V_c cos (\beta_c - \psi_L - \psi_H)$$
$$v_c = V_c sin (\beta_c - \psi_L - \psi_H)$$
$$\tau_{current} = [u_c, v_c, 0]^T \qquad (11)$$

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

III. ADAPTIVE FUZZY CONTROL

We propose a adaptive fuzzy control which structure is described by Fig. 2 to overcome the problem raised at *Section II*. Due to its good response to nonlinear parameters as well as the initial structure is independent of the model parameters, so the fuzzy model was chosen for the DP control. However, a conventional fuzzy system is mainly based on the programmer's experience, which means that the structure

parameter is built to be not highly accurate and not optimal. In general, the operation process of nonlinear system generate uncertainties which can cause large erroneous for the controller, leading to DPs imbalance. Thus, if we use the controller with non-optimal parameters to fix the problem in *Section II* is not satisfactory. To overcome the disadvantages of conventional fuzzy structures, we propose an AFC controller in which the shape value of fuzzy sets adjusted by λ_k *(k = 1,2,3,4)* adaptation coefficient. The λ_k adaptation is established by the λ_{ID_k} ideal force to reduce error for the control system.

In this study, we use a fuzzy Takagi-Sugeno (TS) model for the DPs of supply vessel which has a double-inputs e, de/dt, and single-output τ [39]. The inference process system combines MFs with if-then rules and the fuzzy logic operators. The rule consequents are often taken to be linear functions of inputs. The rule notation form within B^i is a binary variable that determines the consequence of the rule given as follow [40]

$$R_i : \ If \ \hat{e}_1 \ is \ A_1^i \ldots and \ \hat{e}_n \ is \ A_n^i then \ g \ is \ B^i \qquad (12)$$

where A_1^i, A_2^i, ..A_n^i and B^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

$$g(\hat{e}) = \frac{\sum_{i=1}^{h} B^i [\prod_{j=1}^{n} \mu_{A_j^i}(\hat{e}_j)]}{\sum_{i=1}^{h} [\prod_{j=1}^{n} \mu_{A_j^i}(\hat{e}_j)]} \qquad (13)$$

for $\mu_{A_j^i}(\hat{e}_j)$ is the MFs of fuzzy system, h is the if-then rules amount, $\varphi(\hat{e}) = [\varphi^1, \varphi^2, \ldots, \varphi^h]^T \in R^h$ is the fuzzy basis vector with φ is defined as

$$\varphi(\hat{e}) = \frac{[\prod_{j=1}^{n} \mu_{A_j^i}(\hat{e}_j)]}{\sum_{i=1}^{h} [\prod_{j=1}^{n} \mu_{A_j^i}(\hat{e}_j)]} \qquad (14)$$

In an architecture of proposed control, the fuzzy set values is dynamically calibrated with the λ^T adjustable parameter vector corresponding to B^i $(i = 1,2,\ldots h)$. Then the fuzzy system (13) can be written as the linearization parametric form

$$g(\hat{e}) = \lambda^T \varphi(\hat{e}) \qquad (15)$$

The λ^T adaptive calibration for a fuzzy system is basically established by the ideal control force which described by a λ_{ID_k} coefficient. The λ_{ID_k} coefficient is defined based on the ideal dynamic parameter of DPs model. The dynamic equation Eq.(2) of the vessel motion can be expressed as

$$\dot{v} = -\frac{D_0}{M_0}v + \frac{\tau_0}{M_0} - \frac{\tau_{envi0}}{M_0} + U_r(x) \qquad (16)$$

where D_0, M_0, τ_{envi0} are nominal parameter of D, M, τ_{envi} and $U_r(x)$ denotes the uncertainties due to involve complex interactions among the control parameters. In the case of the parameters matrix D, M are well-known and ocean environment impacts τ_{envi} are defined exactly. Bahita *et al.* proposed an ideal force controller to achieve the stability of the system as follows [41]

$$\lambda_{ID_k} = M_0(\dot{v}_r + \frac{D_0}{M_0}v + \frac{\tau_{envi0}}{M_0} - U_r(x)) \qquad (17)$$

The λ_{ID_k} coefficient plays a basic role in the adaptive fuzzy structure. On the other hand, the λ_{ID_k} ideal force serves as the basic factor for the λ_k coefficient in the process of finding the optimal control parameters. I.e., the λ_{GA_k} and λ_{RC_k} coefficients have not been established at the begin time of searching process, the GA evolution cycle for finding the convergence goal is still operated by using the λ_{ID_k} basic coefficient. Nevertheless, if the fuzzy adaptive structure is used to control the DPs under impacts of the dynamic model erroneous such as sensor erroneous, unknown input or time-delay causing nonlinear characteristics, its efficiency is not high. In order to improve the control quality, we propose the GA algorithm to calibrate optimal the MFs values by λ_{GA_k} coefficient. The GA searching process of determining λ_{GA_k} optimal coefficient is described in the next section.

IV. A NOVEL ROBUST ADAPTIVE FUZZY CONTROL USING GENETIC ALGORITHM

A. THE MECHANISM OF PROPOSED MODEL

The mechanism of proposed model is shown in Fig. 2, operates as follows: The adaptive fuzzy controller is the primary controller for vessel DPs. The fuzzy sets of MFs is calibrated adaptively based on the λ_k coefficient. Thus, the erroneous caused by nonlinearity is minimized, and the λ_k coefficient is ensured to achieve the optimal goal by GA. In addition, analyzing the H_∞ robust tracking performance of λ_k coefficient during GA evolution process to achieve the robustness respond and stability in the presence of the robustness margin. The process of defining the λ_k calibration coefficient consists of three main phases are particularly presented as follows:

- Phase 1: Find the λ_{ID_k} $(k = 1,2,3,4)$ force to basically calibrate the λ_k coefficient at the GA searching begin while the λ_{GA_k} and λ_{RC_k} force are still not defined. This phase is introduced in *Section III*.
- Phase 2: Find the optimal λ_{GA_k} force by the GA evolution. The λ_{GA_k} is the primary calibration force for adjusting the λ_k coefficient.
- Phase 3: Find the λ_{RC_k} force to guarantee the DPs control does not out of the robustness bounded.

To reduce nonlinearity as well as to find optimal MFs parameters for fuzzy controller, the hybrid adaptive fuzzy control with genetic algorithm is implemented in this study (defined at Phase 2). The importance thing of designing an integrated fuzzy control and GA architecture is to consider which part of the fuzzy knowledge base (FKB) can be optimized by the GA. The response of fuzzy system is determined by two main components, i.e., the fuzzy rule base parameters are established by the group of MFs shape values and the type of MFs combined with the language label of each fuzzy rule. In the proposed controller, the GA algorithm are employed to calibrate optimal the MFs shape values via λ_k coefficient. In the GA evolution, the goal is to find the optimal parameter λ_{GA_k} $(k = 1,2,3,4)$ according to the ideal state $\lambda_{GA_k}^0$. Therefore, the adaptation laws for GA algorithm is also proposed to realize this goal.

In the process of searching the optimal MFs value, some huge values of λ_k coefficient are able to make the adaptive fuzzy system out of balance. In addition, the actual operation also makes DPs appear the dynamic disturbances such as actuator erroneous, parameter erroneous, and random erroneous. If only fuzzy adaptive structures are used for DPs nonlinear, these dynamic disturbances cannot be fully addressed. Thus, we propose a combined with a λ_{RC_k} $(k = 1,2,3,4)$ robust bounded working in parallel with the adaptive fuzzy control using the GA optimization (defined at Phase 3). The λ_{RC_k} robust bounded is responsible for maintaining the λ_k calibration values in the stable searching domain. So the fuzzy response is not only guarantee the performance quality but also guarantee ultimate bounded.

The goal of the proposed solution is to find out the λ_k calibration coefficient which is satisfies the optimal condition

under the dynamic disturbances and keeps the searching GA convergence at the robustness bounded. The operation mechanism of optimal calibration, and robustness calibration for the λ_k coefficient are introduced in the sequel.

B. ADAPTIVE FUZZY CONTROL USING GENETIC ALGORITHM

In the architecture of proposed control, the MFs setting value plays a key role in guaranteeing the performance of fuzzy logic controller. If the poor parameter of MFs are used, the system performance will be lowered, and the DPs will be out of balance. We suggest a GA's optimal solution for correcting the MFs value to improve the control quality. The GA evolution process of finding the λ_{GA_k} correction coefficient consists of seven steps are detail represented as follows [42]:

- Step 1: Define input variables, output variables and state variables of the control model, fuzzy inference tools, and MFs shape values are used.
- Step 2: Establish the input space and output space of fuzzy variable and assign the fuzzy impact levels corresponding to language variables for each fuzzy region.
- Step 3: Code the region of variable fuzzy corresponding to the MFs shape into real valued-strings. After coding stage, every chromosome is represented in the real and binary valued string.
- Step 4: Combine Hybrid-GA algorithm in two sequential parts: part 1 (real coding) and part 2 (binary coding) as a self-turning adaptation to calibrate the MFs shape value.
- Step 5: Apply newly MFs shape values to validate the performance of adaptive fuzzy controller and compute a fitness values for the chromosomes according to the criteria efficiency.
- Step 6: Check the terminated condition of GA evolution. If the convergence criterions are not satisfied, repeated on to Step 3.
- Step 7: Associate fuzzy rules and their corresponding MFs shape by using the defuzzification process to define a mapping from input space to output space.

In this section, we present a combined genetic algorithm and fuzzy control in an adaptive fuzzy control using genetic algorithm (AFC-GA) for the DPs. The scheme for defining the λ_{GA_k} optimal correction is detail described in Fig. 2, in which the λ_{GA_k} coefficient plays the leading role for setting the λ_k adaptation coefficient. In addition, the adaptation laws are determined to minimize errors occurring at the GA evolutionary process.

1) GENETIC ALGORITHM SOLUTION

In order to find out the optimal results for the adaptive fuzzy control system, a GA searching algorithm is applied to define the λ_{GA_k} convergence condition that are looking for searching space. The GA includes a group of suggestion named population. At every stage, the GA solution choose the good individuals from the current population to become

parents and uses this individuals to produce the children for next pedigree [43]. The application of genetic evolution upon individuals continues until a good enough suggestion for optimization is found. In this paper, the λ_{GA_k} optimization is determined by GA which include initialization population, selection operation, crossover operation, mutation operation and evaluation for the optimal value of fuzzy sets. So the gene evolution are expressed as follows:

Initialization Population: The GA population starts with random initialization of the N_P individuals to present the potential suggestions. Because, the λ_{GA_k} coefficient employs to represent the individuals consisting of the calibrating of MFs. Each potential suggestion is expressed by chromosomes, i.e., a binary string. A fuzzy set value is corrected by a λ_{GA_k} chromosomes gene which can hold one of the binary string values 0 and 1. The setting of individual genotype consist of two parts: coding mask and fuzzy parameter with the expression of genotype is shown in Fig. 3.
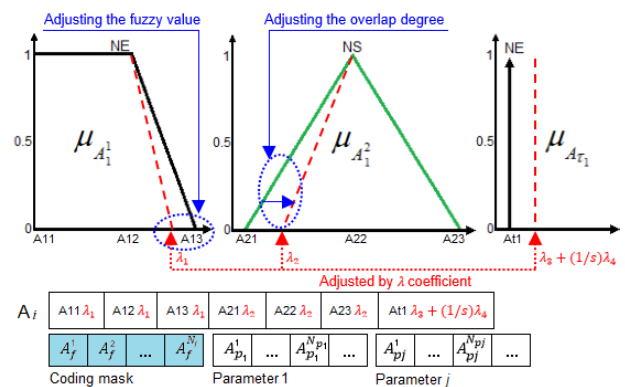

FIGURE 3. Describing the expression of individual genotype.

Coding mask A_f is a binary vector with a length of N_f. When generating the coding mask A_f, the ith position value is given by

$$A_i = \begin{cases} 1, & P\left(A_f^i = 1\right) = mf_{se}/mf, \ i = 1, 2..N_f \\ 0, & P\left(A_f^i = 0\right) = 1 - mf_{se}/mf \end{cases} \quad (18)$$

where a 0 or 1 at the ith position expresses the positive or active of the ith characteristic, mf_{se} is an original factor and expresses the amount of selected characteristic. This suggestion make the genetic evolution characteristics in lower case [44]. In addition, the generation number (N_G), crossover fraction (P_c), and mutation probability (P_m) are defined.

Selection Operation: The selection process looks for the best individuals to begin into the next population. The selection compares an individual's fitness value to other individuals and determines the individuals which will continue to breed in the next population. Through selection, the good individuals are prioritized to breed with higher rating than the bad individuals for next generation. The high pressure of selection can leads to early convergence but easily falls into the local optimal region. Beside that, a low pressure of

selection can cause by slow convergence. In the selection process, the relationship between coding mask A_f and its phenotype representation is expressed as below

$$\tilde{D} = D.diag(A_f) \quad (19)$$

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

$$N_{pj} = round\left[log_2\left(\frac{\sigma_{pj,up} - \sigma_{pj,low} + \Delta}{\Delta_{pj}} \right) \right] + 1 \quad (20)$$

where $\sigma_{pj,up}$ and $\sigma_{pj,low}$ represent the upper and lower searching bound, respectively. Δ_{pj} is an original factor and display an accurate appraisal.

Crossover Operation: Mechanism crossover is initialized randomly for creating a new gene between two parent individuals. We apply a random cut-point for exchanging genetic material between individuals of a population, thus new individuals emerge. The crossover operator is carry out on the chosen parent binary strings with a crossover fraction P_c. For creating the new individuals, the genetic material part of 1 father from the right of the cut-point is combined with the genetic material part of the mother from the left of the cut-point. These new individuals will become parents in the next generation.

Mutation Operation: Crossover process can result in the removal of good genetic material. Mutation operation is used to restore good genetic material which may be remove in the previous processes. A gene can be randomly changed, meaning that the 1-binary value will be changed to 0 or vice versa with a mutation probability P_m. In terms of mutant selection, it is sometimes possible to swap values between the two selected genes, which can keep mf_{se} from change. In this study, the mutation probability is changed in 5% range during the each generation. After the evolution strategy, the MFs selection parameters are combined in a chromosome. Then this chromosome is decoded to the real value of fuzzy sets with their corresponding MFs. So the genotype A_{pj} of parameters *j* should be decoded into phenotype σ_{pj} by

$$\sigma_{pj} = \sigma_{pj,low} + (\sigma_{pj,up} - \sigma_{pj,low})\left(\frac{\sum_{i=1}^{N_{pj}} \left(A_{pj}^{(i)} \right)^{N_{pj}-1}}{2^{N_{pj}}} \right) \quad (21)$$

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

Evaluation: The results obtained after the mutation process are evaluated again with the fitness function. The offspring results satisfying the convergence condition will stop the GA process. If not satisfied, it will be included in the selection process to continue the new genetic evolution round. For evaluating convergence criteria of GA evolution, the Integral Time Absolute Error (ITAE) is commonly applied to terminate the optimization problem. The goal of ITAE index is to minimize the absolute error and settling time for the optimal control structure [45]. In this paper, GA solution

minimizes the ITAE criteria and gives the optimal values of AFC-GA control parameters. The fitness function is chosen by the ITAE criteria as follows

$$ITAE = \int_0^\infty t\, |e(t)|\, dt \quad (22)$$

In the genetic evolution, the GA process parameters are always influenced by the peripheral factors that cause the evolutionary errors. Thus, the convergence goal can be achieved in a lower case. To overcome the aforementioned errors, the authors suggest the adaptation laws to adjust the GA's process variables to adapt to the ideal parameters of GA's process. Determining the adaptation laws for the GA evolution is presented in the next section.

2) ADAPTIVE GENETIC ALGORITHM
In the case of ideal condition, the structure parameters are exactly bounded, environmental impacts and uncertainties are absent. Assuming that the optimal parameters of ideal approximation controller $\lambda_{GA_k}^0$ is given by

$$\lambda_{GA_k}^0\left(g^0, \sigma_{pj}^0, N_{pj}^0, \lambda^0 \right) = \lambda^{0T}\varphi^0\left(\hat{e} \right) + \xi \quad (23)$$

where g^0, σ_{pj}^0, N_{pj}^0, λ^0 are the optimal parameters of g, σ_{pj}, N_{pj}, λ and ξ is an approximation error. In the practical operation, the D, M and τ_{envi} parameter matrices can not be defined exactly in a practical environment. In this paper, we develop the λ_{RC_k} robust controller for reducing the uncertainties affecting the stability of the control parameters. In addition, the DPs parameters are not able to accessible the optimal goal. Thus, the estimated parameters are used in DP control designing λ_{GA_k} as follows:

$$\lambda_{GA_k}\left(\hat{g}, \hat{\sigma}_{pj}, \hat{N}_{pj}, \hat{\lambda} \right) + \lambda_{RC_k} = \hat{\lambda}^T\hat{\varphi}\left(\hat{e} \right) + \lambda_{RC_k} \quad (24)$$

where $\hat{g}$, $\hat{\sigma}_{pj}$, $\hat{N}_{pj}$, $\hat{\lambda}$ are the estimation of optimal parameters g^0, σ_{pj}^0, N_{pj}^0, λ^0. An approximation control error $\tilde{\lambda}_k$ is defined as bellow:

$$\begin{aligned} \tilde{\lambda}_k &= \left(\lambda_{GA_k}^0 - \lambda_{GA_k} \right) \\ &= \left(\lambda^{0T}\varphi^0\left(\hat{e} \right) - \hat{\lambda}^T\hat{\varphi}\left(\hat{e} \right) + \xi - \lambda_{RC_k} \right) \\ &= \left(\tilde{\lambda}^T\varphi^0\left(\hat{e} \right) + \hat{\lambda}^T\tilde{\varphi}\left(\hat{e} \right) + \xi - \lambda_{RC_k} \right) \end{aligned} \quad (25)$$

for $\tilde{\lambda} = \lambda^0 - \hat{\lambda}$, $\tilde{\varphi} = \varphi^0 - \hat{\varphi}$ is the estimation error between the optimal parameters and the estimation parameters. By using the Taylor series expansion to transform the multi-dimension receptive-field space into a partially linear form. Linear approximation form of $\tilde{\varphi}$ in two variables N_{pj}

and σ_{pj}, respectively Eq.(26)

$$
\widetilde{\varphi} = \begin{bmatrix} \widetilde{\varphi}_1 \\ \vdots \\ \widetilde{\varphi}_k \\ \vdots \\ \widetilde{\varphi}_{nb} \end{bmatrix} = \begin{bmatrix} \left(\dfrac{\partial \varphi_1}{\partial N_{pj}} \right)^T \\ \vdots \\ \left(\dfrac{\partial \varphi_k}{\partial N_{pj}} \right)^T \\ \vdots \\ \left(\dfrac{\partial \varphi_{nb}}{\partial N_{pj}} \right)^T \end{bmatrix} \left(N_{pj}^0 - \hat{N}_{pj} \right)\Big|_{N_{pj}=\hat{N}_{pj}}
$$

$$
+ \begin{bmatrix} \left(\dfrac{\partial \varphi_1}{\partial \sigma_{pj}} \right)^T \\ \vdots \\ \left(\dfrac{\partial \varphi_k}{\partial \sigma_{pj}} \right)^T \\ \vdots \\ \left(\dfrac{\partial \varphi_{nb}}{\partial \sigma_{pj}} \right)^T \end{bmatrix} (\sigma_{pj}^0 - \widehat{\sigma}_{pj})\Big|_{\sigma_{pj}=\widehat{\sigma}_{pj}} + O_h \quad (26)
$$

In the case of linear approximation Eq.(26), the estimation of fuzzy vector is given by

$$
\varphi^0 = \widetilde{\varphi} + C^T \tilde{N}_{pj} + E^T \widetilde{\sigma}_{pj} + O_h \quad (27)
$$

where $\tilde{N}_{pj} = N_{pj}^0 - \hat{N}_{pj}$, $\widetilde{\sigma}_{pj} = \sigma_{pj}^0 - \widehat{\sigma}_{pj}$ and O_h is higher-order terms of Taylor series expansion. Next, taking derivative two sides of Eq.(10), then substituting $\widetilde{\varphi} = C^T \tilde{N}_{pj} + E^T \widetilde{\sigma}_{pj} + O_h$ and $\varphi^0 = \widehat{\varphi} + \widetilde{\varphi}$ into Eq.(25), respectively

$$
\begin{aligned}
\dot{g}(\hat{e}) = \widetilde{\lambda}_k &= \left(\lambda_{GA_k}^0 - \lambda_{GA_k} \right) \\
&= \tilde{\lambda}^T \left(\widehat{\varphi} + C^T \tilde{N}_{pj} + E^T \widetilde{\sigma}_{pj} + O_h \right) \\
&\quad + \hat{\lambda}^T \left(C^T \tilde{N}_{pj} + E^T \widetilde{\sigma}_{pj} + O_h \right) + \xi - \lambda_{RC_k} \\
&= \tilde{\lambda}^T \widehat{\varphi} + \hat{\lambda}^T \left(C^T \tilde{N}_{pj} + E^T \widetilde{\sigma}_{pj} \right) \\
&\quad + \tilde{\lambda}^T \left(C^T \tilde{N}_{pj} + E^T \widetilde{\sigma}_{pj} \right) + \lambda^{0T} O_h + \xi - \lambda_{RC_k} \\
&= \tilde{\lambda}^T \widehat{\varphi} + \hat{\lambda}^T \left(C^T \tilde{N}_{pj} + E^T \widetilde{\sigma}_{pj} \right) - \lambda_{RC_k} + U_r(x) \quad (28)
\end{aligned}
$$

We get $U_r(x) = \tilde{\lambda}^T \left(C^T \tilde{N}_{pj} + E^T \widetilde{\sigma}_{pj} \right) + \lambda^{0T} O_h + \xi$ is the expression of environment impacts and uncertainties. Consider the Lyapunov candidate for whole DP control system [46] as follows

$$
\begin{aligned}
V\left(g, \tilde{\lambda}, \tilde{N}_{pj}, \widetilde{\sigma}_{pj} \right) &= \frac{1}{2} g^T g + \frac{1}{2} \tilde{\lambda}^T \tilde{\lambda} \\
&\quad + \frac{1}{2\Delta_{pj}} \tilde{N}_{pj}^T \tilde{N}_{pj} + \frac{1}{2 \times 2^{N_{pj}}} \widetilde{\sigma}_{pj}^T \widetilde{\sigma}_{pj} \quad (29)
\end{aligned}
$$

Then computing the derivative both sides of the Eq.(29), we get

$$
\begin{aligned}
&\dot{V}\left(g, \tilde{\lambda}, \tilde{N}_{pj}, \widetilde{\sigma}_{pj} \right) \\
&= g^T \dot{g} + \tilde{\lambda}^T \dot{\tilde{\lambda}} + \Delta_{pj} \tilde{N}_{pj}^T \dot{\tilde{N}}_{pj} + 2^{N_{pj}} \widetilde{\sigma}_{pj}^T \dot{\widetilde{\sigma}}_{pj}
\end{aligned}
$$

$$
\begin{aligned}
&= g^T (\tilde{\lambda}^T \widehat{\varphi} + \hat{\lambda}^T \left(C^T \tilde{N}_{pj} + E^T \widetilde{\sigma}_{pj} \right) - \lambda_{RC_k} \\
&\quad + U_r(x)) - \tilde{\lambda}^T \dot{\hat{\lambda}} - \Delta_{pj} \tilde{N}_{pj}^T \dot{\hat{N}}_{pj} - 2^{N_{pj}} \widetilde{\sigma}_{pj}^T \dot{\widehat{\sigma}}_{pj} \quad (30)
\end{aligned}
$$

Next, substituting $g^T \tilde{\lambda}^T \widehat{\varphi} = \tilde{\lambda}^T \widehat{\varphi} g^T$, so the Eq.(30) can be rewritten as follows

$$
\begin{aligned}
&\dot{V}\left(g, \tilde{\lambda}, \tilde{N}_{pj}, \widetilde{\sigma}_{pj} \right) \\
&\quad \leq \tilde{\lambda}^T \left(\widehat{\varphi} g^T - \dot{\hat{\lambda}} \right) + \tilde{N}_{pj}^T \left(C^T \hat{\lambda} g - \Delta_{pj} \dot{\hat{N}}_{pj} \right) \\
&\qquad + \widetilde{\sigma}_{pj}^T \left(E^T \hat{\lambda} g - 2^{N_{pj}} \dot{\widehat{\sigma}}_{pj} \right) + g^T U_r(x) - g^T \lambda_{RC_k} \quad (31)
\end{aligned}
$$

Thus, we choose the parameter adaptation laws as

$$
\dot{\hat{\lambda}} = \widehat{\varphi} g^T \quad (32)
$$

$$
\dot{\hat{N}}_{pj} = \frac{1}{\Delta_{pj}} C^T \hat{\lambda} g \quad (33)
$$

$$
\dot{\widehat{\sigma}}_{pj} = \frac{1}{2^{N_{pj}}} E^T \hat{\lambda} g \quad (34)
$$

The best convergence value which is determined by GA process is the λ_{GA_k} optimal correction for fuzzy controller. In the AFC-GA approach, the τ_{envi} environment impacts and the nonlinear characteristics are estimated by the adaptive structure and optimized by GA solution, so that the performance of DP control system can be ensured at a required level. Some λ_{GA_k} values are too large that exceeds the safe operating limits of control structure caused instability of the DPs. In addition, the dynamic disturbance which occur during system operation make the system out of control. Nevertheless, the AFC-GA approach does not take hight effective for overcoming dynamic disturbances. Therefore, we consider the λ_{RC_k} coefficient with a robust algorithm to guarantee ultimate boundedness for the GA evolution process. The detailed robust adaptive fuzzy using GA solution is introduced in the next section.

C. DESIGNING THE ROBUST ADAPTIVE FUZZY CONTROL USING GENETIC ALGORITHM

The target of λ_{RC_k} correction factor is to eliminate the unbalanced factors that the adaptive fuzzy structure has not handled well. The GA adaptation laws are proposed in Eqs.(32), (33), and (34) to reduce the erroneous that may occur during the GA process of finding a optimal solutions. So the derivative of equation Eq.(31) can be rewritten as

$$
\begin{aligned}
\dot{V}\left(g, \tilde{\lambda}, \tilde{N}_{pj}, \widetilde{\sigma}_{pj} \right) &\leq g^T U_r(x) - g^T \lambda_{RC_k} \\
&= \sum_{i=1}^{n} \left(g_i U_{ri}(x) - g_i \lambda_{RC_k} \right) \quad (35)
\end{aligned}
$$

The rule of robust controller is performed by

$$
\lambda_{RC_k} = \frac{\left(\beta^2 + 1 \right) g_i}{2\beta^2} \quad (36)
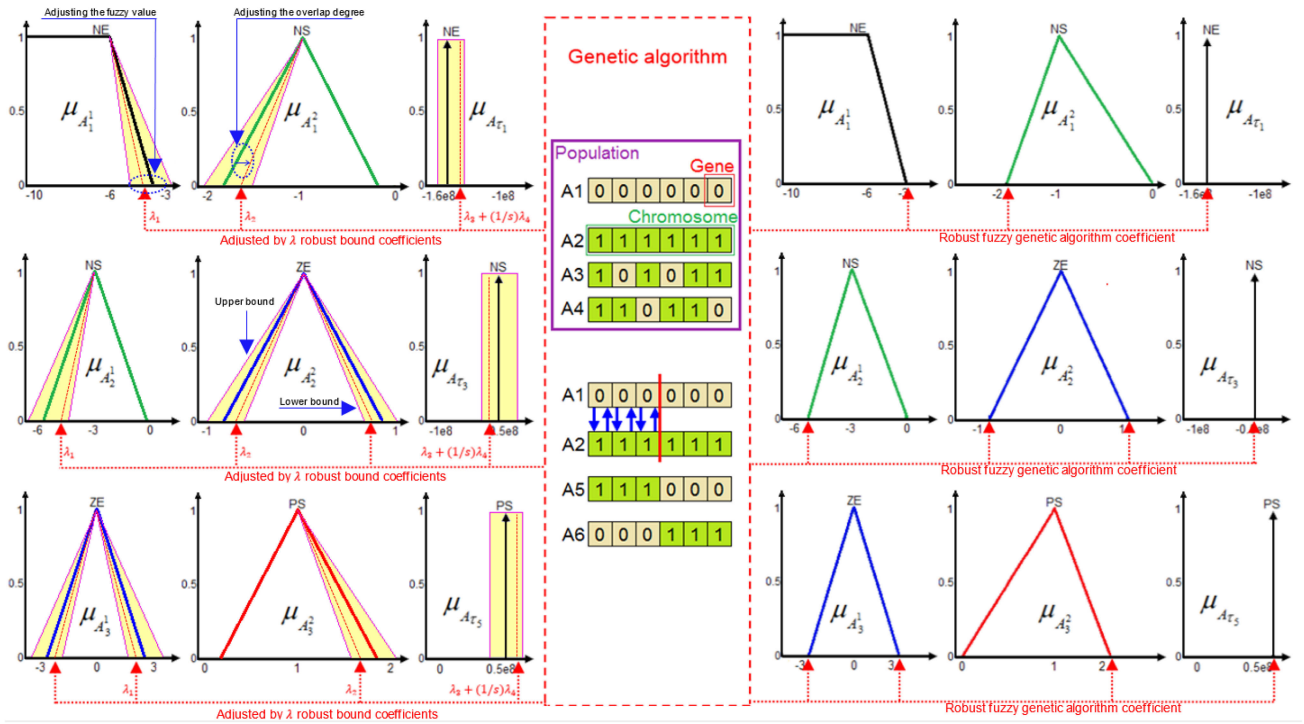$$

FIGURE 4. The MFs values are calibrated by the robust adaptive fuzzy control using genetic algorithm.

By substituting Eq.(36) into Eq.(35), the derivative of Eq.(35) is redescribed as follows

$$
\dot{V}\left(g, \tilde{\lambda}, \tilde{N}_{pj}, \tilde{\sigma}_{pj}\right)
$$

$$
\leq \sum_{i=1}^{n}\left(g_i U_{ri}(x) - g_i \frac{\left(\beta_i^2 + 1\right) g_i}{2\beta_i^2}\right)
$$

$$
\leq \sum_{i=1}^{n}\left(g_i U_{ri}(x) - \frac{1}{2}g_i^2 - \frac{1}{2\beta_i^2}g_i^2\right)
$$

$$
\leq \sum_{i=1}^{n}\left(-\frac{1}{2}g_i^2 - \frac{1}{2}\left(\frac{g_i}{\beta_i} - \beta_i U_{ri}(x)\right)^2 + \frac{\beta_i^2 U_{ri}^2(x)}{2}\right)
$$

$$
\leq \sum_{i=1}^{n}\left(-\frac{1}{2}g_i^2 + \frac{\beta_i^2 U_{ri}^2(x)}{2}\right) \tag{37}
$$

Integrating both sides of the differential Eq.(37) with respect $t = 0$ to $t = \infty$, respectively

$$
V(T) - V(0) \leq \sum_{i=1}^{n}\left(-\frac{1}{2}\int_{t=0}^{\infty}g_i^2 dt + \frac{\beta_i^2}{2}\int_{t=0}^{\infty}U_{ri}^2(x)\,dt\right) \tag{38}
$$

Based on the Lyapunov function value, $V(T) \geq 0$, the inequality in Eq.(38) can be expressed as

$$
\sum_{i=1}^{n}\frac{1}{2}\int_{t=0}^{T}g_i^2 dt \leq V(0) + \sum_{i=1}^{n}\frac{\beta_i^2}{2}\int_{t=0}^{T}U_{ri}^2(x)\,dt \tag{39}
$$

Consider the candidate Lyapunov in Eq.(29), then we have the inequalities (39) following equivalent

$$
\sum_{i=1}^{n}\frac{1}{2}\int_{t=0}^{T}g_i^2 dt
$$

$$
= g^T(0)\,g(0) + \tilde{\lambda}^T(0)\,\tilde{\lambda}(0) + \frac{1}{\Delta_{pj}}\tilde{N}_{pj}^T(0)\tilde{N}_{pj}(0)
$$

$$
+ \frac{1}{2N_{pj}}\tilde{\sigma}_{pj}^T(0)\tilde{\sigma}_{pj}(0) + \sum_{i=1}^{n}\frac{\beta_i^2}{2}\int_{t=0}^{T}U_{ri}^2(x)\,dt \tag{40}
$$

At the beginning of control process, the initial factors chosen are $g = 0$, $\tilde{\lambda} = 0$, $\tilde{N}_{pj} = 0$, and $\tilde{\sigma}_{pj} = 0$, then the robust H_∞ tracking performance can be archived as follows

$$
sup_{U_{ri} \in L_2[0,T]}\sum_{i=1}^{n}\left(\frac{\|g_i\|}{\|U_{ri}\|} \leq \beta_i\right) \tag{41}
$$

where $\|g_i\|^2 = \int_{t=0}^{T}g_i^2 dt$, $\|U_{ri}\|^2 = \int_{t=0}^{T}U_{ri}^2 dt$ and β_i are the prescribed attenuation level for uncertainties. Chosen $\beta_i = \infty$, this is the case of minimum error tracking control without disturbance attenuation.

The MFs calibration using the proposed RAFC-GA solution is described in detail by Fig. 4. The λ_k coefficient calibrates adaptively the fuzzy structure with the λ_{ID_k} basic parameter to keep the system running continuously. In addition, the quality of fuzzy adaptive controller is enhanced by the GA optimal solution via λ_{GA_k} coefficient, namely adaptive fuzzy control using genetic algorithm, thereby achieving the global optimal for the proposed controller. In the process

of GA searching, the λ_{RC_k} robust coefficient works in tandem with the AFC-GA structure to decrease the imbalance values caused by dynamic disturbances. Thereby guaranteeing the DP's performance on a robustness bounded (limited by upper bound and lower bound). To verify effectiveness of the RAFC-GA proposed solution, simulation studies with AFC-GA method comparisons on two different supply vessel are carried out. The details of configuration parameter and results are represented in the next section.

V. SIMULATION AND EVALUATION

A. CONFIGURATION PARAMETER

1) ENVIRONMENT PARAMETERS

The wave, wind and current are considered as the most three environmental factors of the system. The kinetic of wave factor is represented by Eq.(8). In simulations, the wave simulation parameters [37] are chosen as follows: wave height $H_s = 0.8m$, wave spectrum peak frequency $\omega_q = 0 rad/s$, wave direction $\psi_0 = -30^0$, spreading factor $s = 2$, number of frequencies $N = 20$, number of directions $M = 10$, cutoff frequency factor $\xi = 3$, wave component energy limit $k = 0.005$ and wave direction limit $\psi_{lim} = 0$. The wind kinetic is given by Eq.(9). The wind simulation parameters 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, Eq.(11) 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 $\psi_L = \psi_H = 0$.

2) CONVERGENCE EVALUATION OF GAs

TABLE 1. A comparison of different identifiers in terms of the optimization DPs process.

Solution	Fuzzy sets	Number of parameters	Training time	Convergence generation	Testing time
F-PSO [35]	17	33	13.05s	22th	0.5s
F-GA [39]	17	33	17.55s	24th	0.35s
RAFC-GA	17	33	15.5s	17th	0.35s

To fairly compare the simulation results obtained, RAFC-GA and other solutions apply the same number of training parameters and vessel structure modelling. The performance of RAFC-GA model is compared with that of the fuzzy particle swarm optimization (F-PSO) [35], and the fuzzy genetic algorithm (F-GA) [39] for DPs control. This study realizes the effectiveness comparison of the various models in terms of fuzzy rules, number of parameters, training time, convergence generation and testing time. The comparison results are presented in Table 1.

In this study, we use the GA evolution parameters as same as Table 2 for implementing the proposed system. The searching process of λ_k optimal coefficient is randomly generated. 90 evolutions were applied with random initial models so that every evolution process could be able to wear a different

TABLE 2. Parameter setting of GAs.

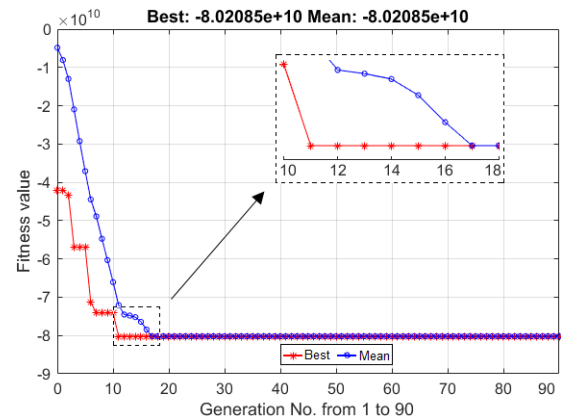| Symbol	Description	Values
N_G	Generation number	90
N_P	Population size	45
A_f	The coding mask	4
N_f	Length of binary vector	40
$N_p j$	The genotypic length	4
P_c	The crossover fraction	0.5
P_m	The mutation probability	0.05
mf_{se}	The original factor	2
	Best convergence	-8.021×10^{10}

FIGURE 5. Convergence performance of GAs.

genetic direction to evolve the DP control. Through gene evolution, the best convergence result is -8.02085×10^{10} which corresponds to λ_k (λ_{kx}, λ_{ky}, $\lambda_{k\psi}$) values. In addition, the convergence performance of GAs is described in detail by Fig. 5. The best fitness value and the mean fitness value are getting closer and obtaining better performance. Then, the GAs quickly achieves the best convergence result after 17 generations. Hence, this approach shows the effective of RAFC-GA solution for enhancing the quality of DPs control.

B. PERFORMANCE EVALUATION BY SIMULATION

We carried out the simulation of designed system in the same environment conditions and parameters of Vessels's DPs, which are done by using Matlab 2016a software. The structure of fuzzy controller is built on the m.file format to make the GA evolution process more comfortable for finding the convergence value. In addition, the GA Toolbox which determine the operation parameters for proposed system is verified by the robust rule (express as eq.(36)) to guarantee the optimal RAFC-GA parameters at the robustness bounded. The AFC-GA controller are evaluated in comparison with simulation results using the RAFC-GA controller. The simulation results are depicted by Fig. 6, Fig. 7 and Fig. 8. Fig. 6(a), Figs. 7(a) and 8(a) reveal that the RAFC-GA controller (blue line) and AFC-GA controller (red line) can make the vessel motion to aim at the expected position in simulation cases. The actual position (x, y) and heading (ψ) are kept at the target value illustrated by Fig. 6(b), Figs. 7(b) and 8(b).

TABLE 3. A performance comparison of different solution for case study 1.

Solution	Membership functions	Response time	Overshoot	Fluctuation
Fuzzy [35]	45	19s	0.25m	0.31m
F-PSO [35]	45	15s	0.22m	0.27m
F-GA [39]	45	16s	0.21m	0.28m
AFC [47]	45	17s	0.23m	0.29m
AFC-GA	45	17s	0.19m	0.25m
RAFC-GA	45	18s	0.15m	0.21m

On the other hand, Fig. 6(d), Figs. 7(d) and 8(d) show that the control forces and moments by the RAFC-GA model and AFC-GA model are glossy and justice. The environmental impacts are presented by Fig. 6(c), Figs. 7(c) and 8(c). The RAFC-GA optimization controller (presented in *Sect. IV.C*) with the stable goal (expressed at *Eq.*(41)) is tested on the supply vessel model in three cases study. The following three cases are considered to determine the efficiency of the RAFC-GA.

1) CASE STUDY 1

The simulations in case 1, the RAFC-GA and AFC-GA solutions control the vessel move to the expected value [3m, 7m, 20degree] in around 200s from the reference value [0m, 0m, 0degree]. This case study is performed on the Northern Clipper model with the overall length of 82m, breadth 18m, draught 4.6m and design mass 4.591×10^6kg [18]. Operation parameters of the Northern Clipper vessel are supplied by

$$D = \begin{bmatrix} 5.0242 \times 10^4 & 0 & 0 \\ 0 & 2.7229 \times 10^5 & -4.3933 \times 10^6 \\ 0 & -4.3933 \times 10^6 & 4.1894 \times 10^8 \end{bmatrix}$$

$$M = \begin{bmatrix} 5.3122 \times 10^6 & 0 & 0 \\ 0 & 8.2831 \times 10^6 & 0 \\ 0 & 0 & 3.7454 \times 10^9 \end{bmatrix}$$

with results of the proposed RAFC-GA solution are expressed clearly in Fig. 6. Beside that, the λ_k robust optimal coefficients are defined as follow:

$$\lambda_{kx}(1.6294e^8, 1.4121e^8, 1.5025e^8, 1.5171e^7);$$
$$\lambda_{ky}(1.6294e^8, 1.4121e^8, 1.5025e^8, 1.5171e^7);$$
$$\lambda_{k\psi}(1.7375e^{13}, 1.8917e^{13}, 1.2692e^{12}, 9.9714e^{12});$$

The erroneous of vessel trajectory that are expressed in Fig. 6a is satisfied in the overshoot and fluctuation aspect. The performance comparison of related solutions, Fuzzy and F-PSO [35], F-GA [39], AFC [47] and proposed AFC-GA and RAFC-GA, showed in Table 3. In the detail, the maximum overshoots, the value of the Fuzzy, F-PSO, F-GA, AFC, AFC-GA and the RAFC-GA are 0.25m, 0.22m, 0.21m, 0.23m, 0.19m and 0.15m, respectively. The maximum fluctuation of the proposed RAFC-GA is lower than those of the fuzzy, the F-PSO, the F-GA, the AFC, and the AFC-GA
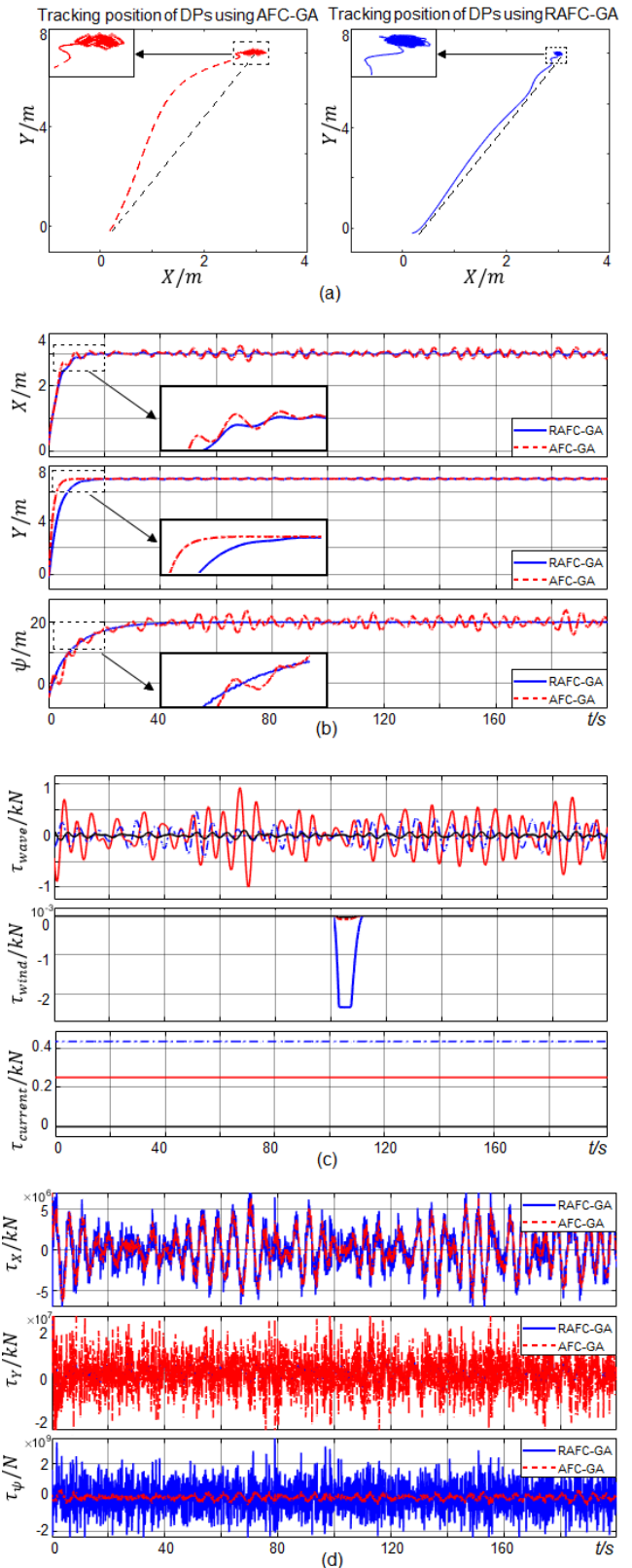

FIGURE 6. The simulation of case study 1 consist two controllers. (a) Trajectory of the vessel position in xy-plane. (b) Actual position (x, y) of vessel and the heading ψ of vessel. (c) Environment impacts τ_{wave}, τ_{wind}, and $\tau_{current}$. (d) Surge control force τ_x, sway control force τ_y and yaw control force τ_ψ.

approximately 0.11m, 0.06m, 0.07m, 0.08m and 0.04m, respectively. The RAFC-GA controller can be reached absolute smallest overshoot and fluctuation which determined the system performance better than the others while the minimum response time of the RAFC-GA is slightly larger demonstrated that the adaptive fuzzy controller using GA is used more time consuming than conventional solutions such as the F-GA and AFC.

2) CASE STUDY 2

To confirm the adaptability and robustness of the RAFC-GA controller under the impacts of parameter uncertainties and environmental disturbances, the dynamic parameters of the Northern Clipper model are randomly changed from 1 to 1.2 times [18] as large as those in case study 1, i.e.

$$D = R(1 \div 1.2)$$
$$\times \begin{bmatrix} 5.0242 \times 10^4 & 0 & 0 \\ 0 & 2.7229 \times 10^5 & -4.3933 \times 10^6 \\ 0 & -4.3933 \times 10^6 & 4.1894 \times 10^8 \end{bmatrix}$$
$$M = R(1 \div 1.2)$$
$$\times \begin{bmatrix} 5.3122 \times 10^6 & 0 & 0 \\ 0 & 8.2831 \times 10^6 & 0 \\ 0 & 0 & 3.7454 \times 10^9 \end{bmatrix}$$

In the case study 2, the same proposed RAFC-GA controller is used in the case of vessel's dynamic parameter are uncertain and the vessel is subjected to environmental disturbances. That means the other values including initialization value of simulation, controller design parameter are unchanged. So the value of λ_k coefficients are chosen as same as case study 1 as below

$$\lambda_{kx}(1.6294e^8, 1.4121e^8, 1.5025e^8, 1.5171e^7);$$
$$\lambda_{ky}(1.6294e^8, 1.4121e^8, 1.5025e^8, 1.5171e^7);$$
$$\lambda_{k\psi}(1.7375e^{13}, 1.8917e^{13}, 1.2692e^{12}, 9.9714e^{12});$$

The dynamics parameters are altered due to the effect of uncertainties that reflect the vessel inertia are also transformed. Hence, the vessel's trajectory which controlled by the proposed RAFC-GA controller is slightly fluctuated. From the Fig. 7, it can be shown that both of solutions are able to maintain the vessel around the setpoint under the nonlinear characteristic, which caused by the uncertainties of dynamic parameter. However, the tracking effects of RAFC-GA solution is better than the AFC-GA solution. The comparison results in Table 4 express that the fluctuation of RAFC-GA is less than those of the Fuzzy, the F-PSO, the F-GA, the AFC, and the AFC-GA approximately 0.11m, 0.06m, 0.06m, 0.08m and 0.03m, respectively. By using RAFC-GA solution, the overshoot value is smaller than the AFC solution 0.05m. It is obvious that the proposed RAFC-GA can meet the engineering needs under the disturbances of uncertainties and environmental operations.
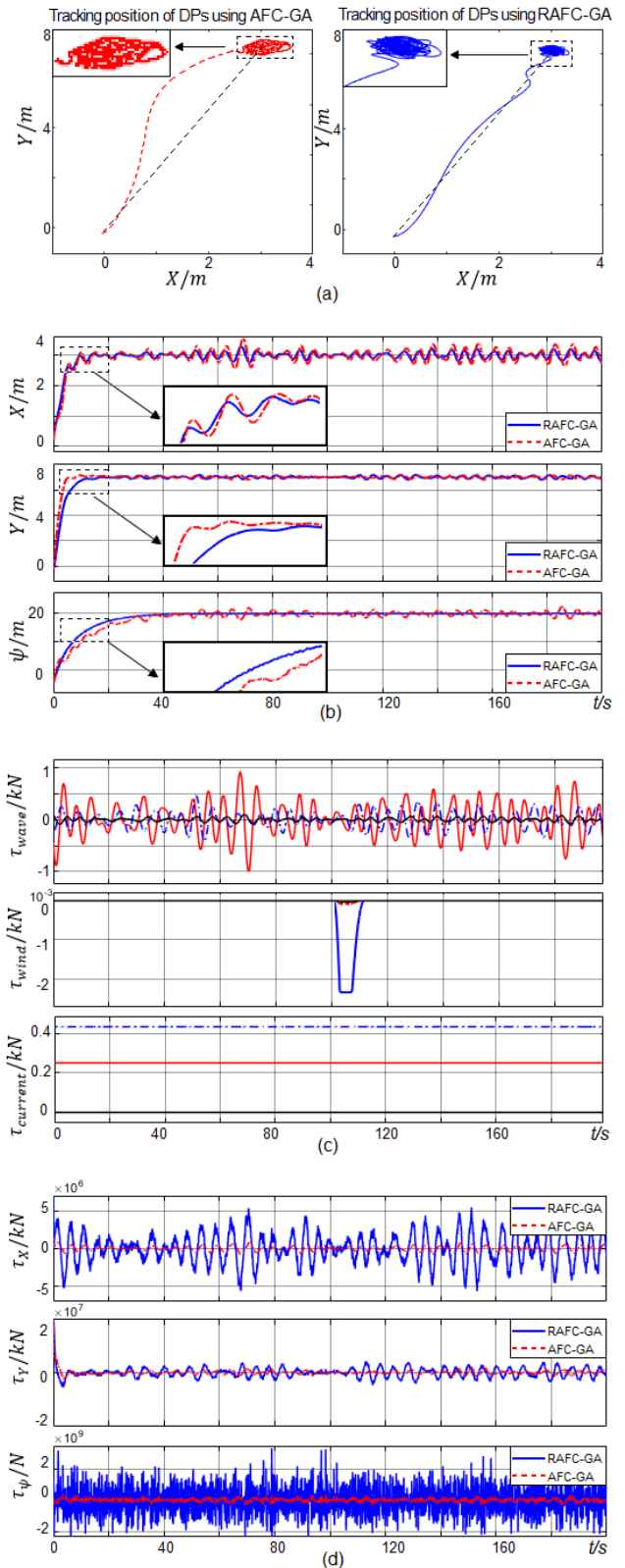

FIGURE 7. The simulation of case study 2 consist two controllers. (a) Trajectory of the vessel position in xy-plane. (b) Actual position (x, y) of vessel and the heading ψ of vessel. (c) Environment impacts τ_{wave}, τ_{wind}, and $\tau_{current}$. (d) Surge control force τ_x, sway control force τ_y and yaw control force τ_ψ.

TABLE 4. A performance comparison of different solution for case study 2.

Solution	Membership functions	Response time	Overshoot	Fluctuation
Fuzzy [35]	45	22s	0.26m	0.34m
F-PSO [35]	45	17s	0.24m	0.29m
F-GA [39]	45	17s	0.23m	0.29m
AFC [47]	45	18s	0.23m	0.31m
AFC-GA	45	19s	0.20m	0.26m
RAFC-GA	45	19s	0.18m	0.23m

TABLE 5. A performance comparison of different solution for case study 3.

Solution	Membership functions	Response time	Overshoot	Fluctuation
Fuzzy [35]	45	21s	0.27m	0.33m
F-PSO [35]	45	16s	0.24m	0.29m
F-GA [39]	45	16s	0.23m	0.28m
AFC [47]	45	18s	0.25m	0.26m
AFC-GA	45	17s	0.21m	0.25m
RAFC-GA	45	19s	0.19m	0.22m

3) CASE STUDY 3

In the third case, the λ_k coefficients which calibrate the proposed RAFC-GA solution are given as

$$\lambda_{kx}(7.7234e^7, 6.31321e^7, 6.7035e^7, 8.6171e^6);$$
$$\lambda_{ky}(6.5274e^7, 4.6431e^7, 5.7545e^7, 6.6771e^6);$$
$$\lambda_{k\psi}(3.8595e^{12}, 6.3117e^{12}, 7.3142e^{11}, 4.7824e^{12});$$

are used to control a supply vessel of 80m in length with two main propellers and three thrusters [48] for keeping the desired trajectory of vessel routine under unexpected impacts. The operation parameters of supply vessel are provided by

$$D = \begin{bmatrix} 2 \times 10^5 & 0 & 0 \\ 0 & 1 \times 10^5 & -7 \times 10^5 \\ 0 & -7 \times 10^5 & 6.39 \times 10^7 \end{bmatrix}$$

$$M = \begin{bmatrix} 7 \times 10^6 & 0 & 0 \\ 0 & 1.1 \times 10^7 & -1.3 \times 10^7 \\ 0 & -1.3 \times 10^7 & 3.193 \times 10^9 \end{bmatrix}$$

The comparison performance of case study 3 are given by Table 5. As the results, the RAFC-GA solution are limited in the response time, in which the proposed solution is 19s compared to the other solutions as F-PSO, F-GA, AFC, and AFC-GA are 16s, 16s, 18s, and 17s, respectively. The results of the DP controls in Table 5 illustrate that the overshoot value for the fuzzy is 0.27m, for the F-PSO is 0.24m, for the F-GA is 0.23m, for the AFC is 0.25m, for the AFC-GA is 0.21m and for the proposed controller is 0.19m. In fact, it is worth noting that the fluctuation of the proposed RAFC-GA is 0.22m less than the fuzzy controller and less than the AFC controller is 0.26m. Clearly, the response quality which is composed of the overshoot and the fluctuation is significantly improved. Moreover, it is clear
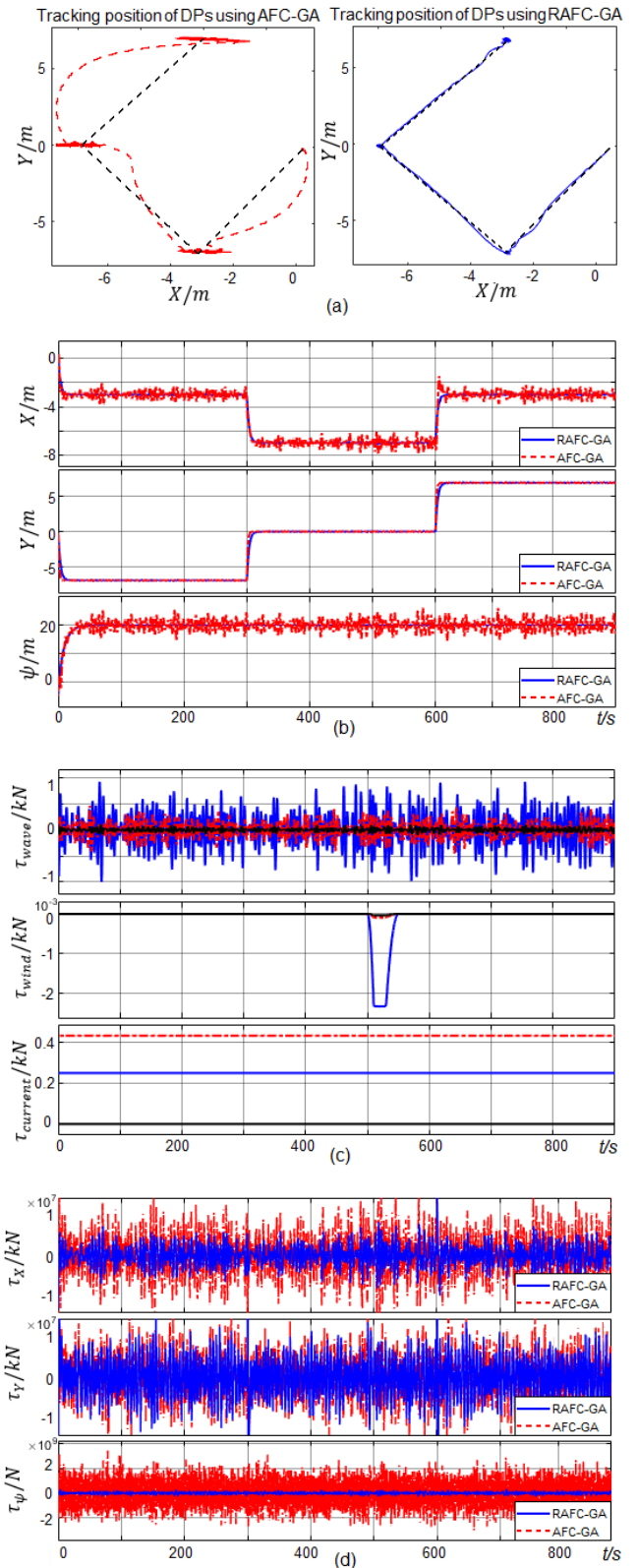

FIGURE 8. The simulation of case study 3 consist two controllers. (a) Trajectory of the vessel position in xy-plane. (b) Actual position (x, y) and the vessel heading ψ. (c) Environment impacts τ_{wave}, τ_{wind}, and $\tau_{current}$. (d) Surge control force τ_x, sway control force τ_y and yaw control force τ_ψ.

that the RAFC-GA control strategy is capable to maintain the vessel in a robustness bounded. Besides, the results of proposed RAFC-GA are given the expression in detail by Fig. 8. The vessel's trajectory is unsatisfactory when using the AFC-GA controller (red line), while the RAFC-GA controller (blue line) is more stable and less fluctuating, that means the RAFC-GA optimization control achieves a better performance. Therefore, the proposed RAFC-GA solution meets the requirements according to *Assumption 1* and *Remark 1*. If only using a AFC-GA controller for keeping the balance of DPs, the vessel's trajectory will be stable in the case of a low impact and vibrate in the case of a higher impact. Besides that, the vessel's heading oscillates according to the level of environmental disturbances. The feasible results verify that the RAFC-GA controller is capable of adapting itself to the nonlinear impacts and reducing time-varying environmental impacts. The robustness of RAFC-GA solution to the uncertainties is very obvious. On the other hand, some weaknesses have not been handled in this study. For instance, the actuators speed have not been considered the constraint of the RAFC-GA controller. Besides, the control structure does not cover the fault tolerance that occurs during the DPs process.

VI. CONCLUSION

The control system of DPs plays an important role in enhancing the efficiency of the vessel in most sea status and working conditions. In this paper, the RAFC-GA controller has been developed for the DPs in the presence of the environment impacts and uncertainties. Compared with other traditional fuzzy control methods, the proposed RAFC-GA has more advantages. To be specific, first, the optimal values of fuzzy structure parameters are found out in order to improve the quality of the system. Second, the application of H_∞ control is used to guarantee the robust boundless of GA parameters through Lyapunov stability analysis. In the future, we will apply the GA algorithm to optimize the service status of the vessel's propeller while the H_∞ controller aims to guarantee the robust boundedness for the DP operation process. Also, further experimental research is needed to improve the universality of the proposed solution.

REFERENCES

[1] F. Hubert, *Dynamic Positioning Systems: Principles, Design and Applications*. Paris, France: Technip, 1990.

[2] A. J. Sørensen, S. I. Sagatun, and T. I. Fossen, "Design of a dynamic positioning system using model-based control," *Control Eng. Pract.*, vol. 4, no. 3, pp. 359–368, Mar. 1996.

[3] T. IFossen, "Nonlinear passive weather optimal positioning control (WOPC) system for ships and rigs: Experimental results," *Automatica*, vol. 37, no. 5, pp. 701–715, May 2001.

[4] H. Aschemann, S. Wirtensohn, and J. Reuter, "Nonlinear observer-based ship control and disturbance compensation," *IFAC-PapersOnLine*, vol. 49, no. 23, pp. 297–302, 2016.

[5] I. Popov, P. Koschorrek, A. Haghani, and T. Jeinsch, "Adaptive Kalman filtering for dynamic positioning of marine vessels," *IFAC-Papers Online*, vol. 50, no. 1, pp. 1121–1126, 2017.

[6] T. I. Fossen and A. M. Lekkas, "Direct and indirect adaptive integral line-of-sight path-following controllers for marine craft exposed to ocean currents," *Int. J. Adapt. Control Signal Process.*, vol. 31, no. 4, pp. 445–463, Apr. 2017.

[7] Y. X. Su and J. Zhao, "Constrained control of ship dynamic positioning system based on generalized predictive control," *Ship Eng.*, vol. 5, pp. 49–52, 2015.

[8] G. Xia, J. Liu, X. Chen, D. Wang, and R. Yang, "EKF based model identification for a relaxed dynamic positioning ship using NMPC method," in *Proc. IEEE Int. Conf. Mechatronics Autom. (ICMA)*, Beijing, China, Aug. 2015, pp. 1313–1318.

[9] G. Xia, C. Pang, and J. Xue, "Fuzzy neural network-based robust adaptive control for dynamic positioning of underwater vehicles with input deadzone," *J. Intell. Fuzzy Syst.*, vol. 29, no. 6, pp. 2585–2595, Nov. 2015.

[10] K. J. Åström and C. G. Källström, "Identification of ship steering dynamics," *Automatica*, vol. 12, no. 1, pp. 9–22, Jan. 1976.

[11] Z. Lei and C. Guo, "Disturbance rejection control solution for ship steering system with uncertain time delay," *Ocean Eng.*, vol. 95, pp. 78–83, Feb. 2015.

[12] L. Wang, H. Li, Q. Zhou, and R. Lu, "Adaptive fuzzy control for nonstrict feedback systems with unmodeled dynamics and fuzzy dead zone via output feedback," *IEEE Trans. Cybern.*, vol. 47, no. 9, pp. 2400–2412, Sep. 2017.

[13] A. J. Sørensen, "A survey of dynamic positioning control systems," *Annu. Rev. Control*, vol. 35, no. 1, pp. 123–136, Apr. 2011.

[14] L. Wang, Q. Wu, J. L. Liu, S. J. Li, and R. R. Negenborn, "State-of-the-art research on motion control of maritime autonomous surface ships," *J. Mar. Sci. Eng.*, vol. 7, no. 12, pp. 438–470, 2019.

[15] W. J. Chang, G. J. Chen, and Y. L. Yeh, "Fuzzy control of dynamic positioning systems for ships," *J. Mar. Sci. Technol.*, vol. 10, no. 1, pp. 47–53, 2002.

[16] Y. Liu, C. Guo, and Z. Lei, "Intelligent control based on ADRC for large container ship course keeping," in *Proc. Chin. Intell. Automat. Conf.*, in Lecture Notes in Computer Science, Yangzhou, China, Aug. 2013, pp. 195–206.

[17] C. Guo, D. M. Wang, and Y. Z. Li, "Modeling and simulation for super large twin-propeller twin-rudder ship and its course ADRC," in *Proc. 16th Asia Simulation Conf. SCS Autumn Simulation Multi-Conf., AsiaSim/SCS AutumnSim*, Beijing, China, 2016, pp. 89–99.

[18] X. Hu, J. Du, and J. Shi, "Adaptive fuzzy controller design for dynamic positioning system of vessels," *Appl. Ocean Res.*, vol. 53, pp. 46–53, Oct. 2015.

[19] X. K. Dang, L. AH Ho, and V. D. Do, "Analyzing the sea weather effects to the ship maneuvering in Vietnam's sea from Binhthuan province to Ca Mau province based on fuzzy control method," *Telkomnika*, vol. 16, no. 2, pp. 533–543, 2018.

[20] F. Benetazzo, G. Ippoliti, S. Longhi, and P. Raspa, "Advanced control for fault-tolerant dynamic positioning of an offshore supply vessel," *Ocean Eng.*, vol. 106, pp. 472–484, Sep. 2015.

[21] M. Xiang Gu, Y.-H. Pao, and P. P. C. Yip, "Neural-net computing for real-time control of a ship's dynamic positioning at sea," *Control Eng. Pract.*, vol. 1, no. 2, pp. 305–314, Apr. 1993.

[22] G. Xia, X. Shi, M. Fu, H. Wang, and X. Bian, "Design of dynamic positioning systems using hybrid CMAC-based PID controller for a ship," in *Proc. IEEE Int. Conf. Mechatronics Autom.*, Niagara Falls, ON, Canada, Jul. 2005, pp. 825–830.

[23] V. P. Ta, X. K. Dang, V. H. Dong, and V. D. Do, "Designing dynamic positioning system based on H∞ robust recurrent cerebellar model articulation controller," in *Proc. 4th Int. Conf. Green Technol. Sustain. Develop. (GTSD)*, HoChiMinh, Vietnam, Nov. 2018, pp. 652–657.

[24] X. K. Dang, Z. H. Guan, H. D. Tran, and T. Li, "Fuzzy adaptive control of networked control system with unknown time-delay," in *Proc. 30th Chin. Control Conf.*, Yantai, China, 2011, pp. 4622–4626.

[25] S. D. Nguyen, H. D. Vo, and T.-I. Seo, "Nonlinear adaptive control based on fuzzy sliding mode technique and fuzzy-based compensator," *ISA Trans.*, vol. 70, pp. 309–321, Sep. 2017.

[26] W. Wang and S. Tong, "Adaptive fuzzy bounded control for consensus of multiple strict-feedback nonlinear systems," *IEEE Trans. Cybern.*, vol. 48, no. 2, pp. 522–531, Feb. 2018.

[27] H. K. Tran, J.-S. Chiou, N. T. Nam, and V. Tuyen, "Adaptive fuzzy control method for a single tilt tricopter," *IEEE Access*, vol. 7, pp. 161741–161747, 2019.

[28] X. Huo, L. Ma, X. D. Zhao, and G. D. Zong, "Event-triggered adaptive fuzzy output feedback control of MIMO switched nonlinear systems with average dwell time," *Appl. Math. Comput.*, vol. 365, pp. 1–16, Jan. 2020.

[29] L. Ma, X. Huo, X. Zhao, and G. Zong, "Adaptive fuzzy tracking control for a class of uncertain switched nonlinear systems with multiple constraints: A small-gain approach," *Int. J. Fuzzy Syst.*, vol. 21, no. 8, pp. 2609–2624, Nov. 2019.

[30] M.-C. Fang and Z.-Y. Lee, "Application of neuro-fuzzy algorithm to portable dynamic positioning control system for ships," *Int. J. Nav. Archit. Ocean Eng.*, vol. 8, no. 1, pp. 38–52, Jan. 2016.

[31] X. Lin, J. Nie, Y. Jiao, K. Liang, and H. Li, "Nonlinear adaptive fuzzy output-feedback controller design for dynamic positioning system of ships," *Ocean Eng.*, vol. 158, pp. 186–195, Jun. 2018.

[32] X. Yu and J. Liang, "Genetic fuzzy tree based node moving strategy of target tracking in multimodal wireless sensor network," *IEEE Access*, vol. 6, pp. 25764–25772, 2018.

[33] C.-F. Juang, C.-H. Lin, and T. B. Bui, "Multiobjective rule-based cooperative continuous ant colony optimized fuzzy systems with a robot control application," *IEEE Trans. Cybern.*, vol. 50, no. 2, pp. 650–663, Feb. 2020.

[34] W. Gao, H. Sheng, J. Wang, and S. Wang, "Artificial bee colony algorithm based on novel mechanism for fuzzy portfolio selection," *IEEE Trans. Fuzzy Syst.*, vol. 27, no. 5, pp. 966–978, May 2019.

[35] V.-D. Do and X.-K. Dang, "The fuzzy particle swarm optimization algorithm design for dynamic positioning system under unexpected impacts," *J. Mech. Eng. Sci.*, vol. 13, no. 3, pp. 5407–5423, Sep. 2019.

[36] C. S. Chin and W. P. Lin, "Robust genetic algorithm and fuzzy inference mechanism embedded in a sliding-mode controller for an uncertain underwater robot," *IEEE/ASME Trans. Mechatronics*, vol. 23, no. 2, pp. 655–666, Apr. 2018.

[37] J.-Q. Wang, Z.-J. Zou, and T. Wang, "Path following of a surface ship sailing in restricted waters under wind effect using robust H_∞ guaranteed cost control," *Int. J. Nav. Archit. Ocean Eng.*, vol. 11, no. 1, pp. 606–623, Jan. 2019.

[38] T. I. Fossen, *Mar. control Syst. – Guid., Navigat. control ship, rigs underwater vehicles.* Marine Cybernetics, Trondheim, Norway, 2002.

[39] V. D. Do, X. K. Dang, L. M. T. Huynh, and V. C. Ho, "Optimized multicascade fuzzy model for ship dynamic positioning system based on genetic algorithm," in *Proc. 5th EAI Interfaces Conf. Ind. Netw. Intell. Syst.*, HoChiMinh, Vietnam, 2019, pp. 165–181.

[40] E. Kim, "A fuzzy disturbance observer and its application to control," *IEEE Trans. Fuzzy Syst.*, vol. 10, no. 1, pp. 77–84, 2002.

[41] M. Bahita and K. Belarbi, "Neural stable adaptive control for a class of nonlinear systems without use of a supervisory term in the control law," *J. Eng. Sci. Technol.*, vol. 7, no. 1, pp. 97–118, 2012.

[42] P. C. Shill, A. K. Paul, and K. Murase, "Adaptive fuzzy logic controllers using hybrid genetic algorithms," *Int. J. Uncertainty, Fuzziness Knowl.-Based Syst.*, vol. 27, no. 01, pp. 41–71, Feb. 2019.

[43] N. S. Jaddi and S. Abdullah, "Hybrid of genetic algorithm and great deluge algorithm for rough set attribute reduction," *TURKISH J. Electr. Eng. Comput. Sci.*, vol. 21, pp. 1737–1750, 2013.

[44] T. Ryu, T. Kanemaru, S. Kataoka, K. Arihama, A. Yoshitake, D. Arakawa, and J. Ando, "Optimization of energy saving device combined with a propeller using real-coded genetic algorithm," *Int. J. Nav. Archit. Ocean Eng.*, vol. 6, no. 2, pp. 406–417, Jun. 2014.

[45] A. K. Maurya, M. R. Bongulwar, and B. M. Patre, "Tuning of fractional order PID controller for higher order process based on ITAE minimization," in *Proc. Annu. IEEE India Conf. (INDICON)*, New Delhi, India, Dec. 2015, pp. 2155–2160.

[46] T. Zhang, S. S. Ge, and C. C. Hang, "Stable adaptive control for a class of nonlinear systems using a modified Lyapunov function," *IEEE Trans. Autom. Control*, vol. 45, no. 1, pp. 129–132, 2000.

[47] G. Xia, J. Xue, J. Jiao, H. Wang, and H. Zhou, "Adaptive fuzzy control for dynamic positioning ships with time-delay of actuator," in *Proc. OCEANS MTS/IEEE Monterey*, Monterey, CA, USA, Sep. 2016, pp. 1–6.

[48] J. Du, X. Hu, H. Liu, and C. L. P. Chen, "Adaptive robust output feedback control for a marine dynamic positioning system based on a high-gain observer," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 26, no. 11, pp. 2775–2786, Nov. 2015.

XUAN-KIEN DANG (Member, IEEE) was born in Haiphong, Vietnam, in 1978. He received the Ph.D. degree in control science and engineering from the Huazhong University of Science and Technology, China, in June 2012. He is currently serving as the Director for the Graduate School, Ho Chi Minh City University of Transport, Vietnam. His current research interests include control theory, automation, maritime technology, underwater vehicles, optimal and robust control, and networked control systems. He had been awarded the Best Paper Award in the 4th Conference of Science and Technology, Ho Chi Minh City University of Transport, in 2018, the President Prize for Award Winner of The Excellent Paper of The 17th Asia Maritime & Fisheries Universities Forum in 2018, and the Doctoral Scholarship - Huazhong University of Science and Technology from 2008 to 2012.
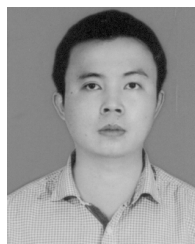
VIET-DUNG DO (Member, IEEE) was born in Ho Chi Minh City, Vietnam, in 1987. He received the master's degree in control theory and automation from the Ho Chi Minh City University of Transport, in 2016. He is currently pursuing the Ph.D. degree with the Graduate School, Ho Chi Minh City University of Transport. He is also serving as the Dean for the Faculty of Electrical and Electronic Engineering, Dong An Polytechnic, Vietnam. His current research interests include control theory, automation, maritime technology, underwater vehicles, and optimal and robust control. He had been awarded the President Prize for Award Winner of The Excellent Paper of the 17th Asia Maritime & Fisheries Universities Forum in 2018.

XUAN-PHUONG NGUYEN was born in Hanoi, Vietnam, in 1967. He received the Ph.D. degree in system analysis, control and information processing from the Scientific Research and Experimental Institute of Automotive Electronics and Electrical Equipment, Russia, in December 2011. He was conferred as an Associate Professor title in 2016. His current research interests include maritime technology, underwater vehicles, automotive electronics, and electrical systems.

● ● ●