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Robust Diving Motion Control of an Autonomous Underwater Vehicle Using Adaptive Neuro-Fuzzy Sliding Mode Technique

GIRISH V. LAKHEKAR[1], LAXMAN M. WAGHMARE[2], (Member, IEEE), PRAKASH G. JADHAV[3], AND RUPAM GUPTA ROY[4]

[1]Department of Instrumentation Engineering, Government College of Engineering, Jalgaon 425 001, India
[2]Department of Instrumentation Engineering, Shri Guru Gobind Singhji Institute of Engineering and Technology, Nanded 431 606, India
[3]Department of Chemical Engineering, Shri Guru Gobind Singhji Institute of Engineering and Technology, Nanded 431 606, India
[4]Department of Electronics and Instrumentation Engineering, National Institute of Technology, Agartala 799 046, India

Corresponding author: Girish V. Lakhekar (gv.lakhekar@gmail.com)

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ABSTRACT This paper presents an adaptive neuro-fuzzy sliding mode control (ANFSMC) scheme for diving motion control of an autonomous underwater vehicle (AUV) in the presence of parameter perturbations and wave disturbances. In the derivation of diving motion equations of an AUV, the pitch angle of the vehicle is often assumed to be small in the vertical plane. This is a quite strong restricting condition in underwater operations and may cause serious modeling inaccuracies in AUV's dynamics. The problem of nonlinear uncertain diving behavior with restricting assumption on the pitch angle directly is resolved by a neural network (NN) based equivalent control. The online NN estimator is designed to approximate a part of the equivalent control term containing nonlinear unknown dynamics and external disturbances. Subsequently, corrective control based on an adaptive fuzzy proportional-integral control is applied to eliminate the chattering phenomenon by smoothing the switching signal and also compensate structured uncertainties. The weights of NN are updated such that the corrective control signal of the ANFSMC converges towards zero. The adaptive laws are developed to compute coefficients of PID sliding manifold and adjust the gain of fuzzy switching control. The simulation results are presented to shows the efficacy of the control performance.

INDEX TERMS Autonomous underwater vehicle, adaptive neuro-fuzzy sliding mode control, diving motion, neural network, parameter perturbations and chattering phenomenon.

I. INTRODUCTION

Autonomous underwater vehicles (AUVs) have gained high demand exclusively for the investigation of artificial marine structures. Periodic inspection is necessary for the repair of underwater structures because of hazardous and unstructured seabed environments. As a result, precise navigation is a critical requirement for the operation of deep-sea AUV in exposure to high ambient pressure and along with inadequate underwater communications [1]. Especially, AUV's depth tracking control is more difficult to achieve than the other guidance control modules such as steering and forward speed control because it has dynamic behaviors related to the vertically non-symmetric hull force and restoring force [2]. The diving motion control of an AUV in a complex oceanic field is a great challenging task. This is primarily due to the highly coupled, nonlinear system dynamics and time-varying behavior with significant parametric uncertainties and unpredictable environmental conditions that exist in the sea [3]. In the vertical plane, AUV's diving behavior has been reduced to a certain multi-variable linear system [4], wherever two main assumptions were made on the AUV's dynamics. One hypothesis is that the pitch angle of the vehicle is considered to be small in diving activities, and the other one is that bounds of uncertainties are assumed to be known in advance [5], [6]. To handle the control problems with these

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characteristics, So the navigational control module desired to have the capacities of learning and adapting to the variations in the dynamics and hydrodynamic coefficients of the vehicle. With this intention, many researchers concentrated their interests in the development of several proper control techniques for controlling motion of underwater robotic vehicles such as supervisory control [7], neural network control [8], self tuning control [9], nonlinear control [10], adaptive control [5], output feedback control [11], gain scheduling control [12], robust H^{∞} control [13], sliding mode control (SMC) [14], fuzzy logic control [15], [16] (FLC), genetic algorithm-based control [17] and neuro-fuzzy control [18]. Among these control schemes, SMC provides satisfactory and effective tracking performance in the presence of model uncertainties, parameter variations, and disturbances [19], [20]. However, in practical implementation, the traditional SMC suffers from high-frequency oscillations around the sliding surface known as the chattering effect, which mainly caused due to the inclusion of the switching function in the corrective control part. In addition to that, prior knowledge of upper bounds of the perturbation vector is needed to get robustness and error convergence towards zero. Also, there is a requirement of accurate mathematical modeling of the system for computing equivalent control [21]. To deal with the challenges in context to SMC design, uncertainty and disturbance estimator (UDE) strategy found to be very promising estimation technique because of its simplicity in design as well as ease of implementation. The integration of UDE- SMC along with finite-time stabilization is widely accepted in literature [22]–[24]. Since it does not require the upper bound of uncertainty, which is the limitations of SMC. The other advantage of this combination is, it gives chatter-free control performance because of the absence of switching terms in the control law. The control design of fuzzy logic controller based on the sliding mode control theory assures chattering free performance and guaranteed closed-loop stability while simultaneously reduces the number of fuzzy rules [25], [26]. Further, a single-layered neural network is used to approximate the smooth nonlinear uncertain system functions, wherein inputs of NNs are all the states of AUV's diving model. In the case of neural network control, training time is unpredictable and may not be suitable for real-time maneuvering [27], [28]. So, several computational intelligence techniques were combined and successfully applied to the complex engineering problem in the past decade, such as online neuro-fuzzy control [29], self adaptive neuro-fuzzy inference system [30], and online genetic algorithm based optimization of fuzzy control [31]. Although intelligent control is very promising for AUV operations, it requires substantial computational power, due to the complex decision-making process. The aforementioned control issues will be resolved in this paper by designing a simplified, intelligent diving autopilot based on single-layered adaptive neuro-fuzzy sliding mode control. The structure of the controller is divided into three parts: adaptive proportional-integral-derivative (PID) sliding manifold, NN estimator, and fuzzy smoothing control. An integral term included in the linear hyperplane as proportional-derivative (PD) sliding surface definition, which resulted in a PID-like sliding surface, can provide a fast transient response with a minimum steady-state error. Adaptive laws compute the coefficients of the sliding surface. Online NN estimator based equivalent control term to estimate the nonlinear system dynamics and exogenous disturbances as the linearly combined unknown nonlinear functions and fuzzy proportional-integral switching control is designed to alleviate the chattering problem and the unknown bounds of parametric uncertainties. The proposed control scheme provides a direct solution to the nonlinear depth dynamics without any restricting condition on the AUV's pitch angle during diving progression and also offers robustness against uncertain hydrodynamics and unknown ocean disturbances. The main contributions of this paper can be summarized as follows:

- The main focus is taken on the design of an adaptive neural network controller for free-pitch-angle diving motion behavior of AUV in uncertain, complex sea environment. We construct a simplified neural network to approximate a given unknown nonlinear function dynamics and reject bounded external disturbances.
- Single neuron with a linear activation function, namely ADALINE, based equivalent control estimator designed. It uses a backpropagation (BP) algorithm for online training and also responsible for forcing the system states to a certain sliding manifold.
- The smoothing of switching control action in SMC is achieved by a single input fuzzy PI uncertainty estimator. The control design relies on the online estimated vector of structured uncertainties rather than relying on the upper bound and periodicity of perturbations.
- The closed-loop stability and robustness are guaranteed for unknown bounded dynamics, parametric uncertainties, and external disturbances. The tracking performance enhanced by using adaptive mechanisms utilized to update parameters of proposed diving autopilot.

The remainder of this paper is organized as follows: AUV's diving modeling equations are expressed in section 2. The robust composite control design for path tracking control of AUV in the dive plane is illustrated in section 3. The closed-loop stability analysis of the system is discussed in section 4. In order to demonstrate the effectiveness of the proposed control scheme, certain simulation studies are presented in section 5. Finally, we make a brief conclusion on the paper in section 6.

II. AUV MODELING

Customarily, underwater robotic vehicles (URVs) are designed to have symmetric configuration; hence, it is reasonable to presume that the body-fixed coordinate is located in the center of gravity with neutral buoyancy. In this work, we consider the MAYA AUV, as shown in Fig. 1, which has a streamlined torpedo-like body propelled by a single thruster, and its dynamics are complex, highly nonlinear,

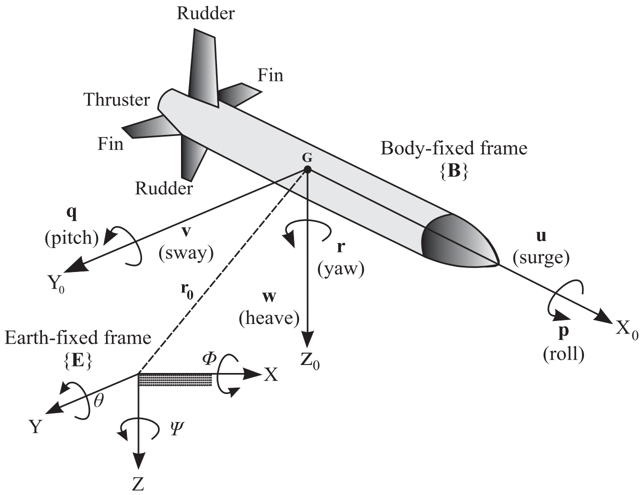

FIGURE 1. AUV in body-fixed and earth-fixed reference frame.

coupled, and time-varying. For vehicle maneuvering in the ocean environment, two stern planes and a single stern rudder underneath the hull are used [33]. The notation used in this paper is in accordance with (SNAME, 1950) and the structure of the vehicle is standard as in [32].

The simplified vertical plane dynamics of an AUV can be expressed in dimensional form as

Surge motion equation:

$$m\dot{u} + mqw = -(W - B)\sin\theta + C_X u^2 + C_{X\dot{u}}\dot{u} + T \quad (1)$$

Heave motion equation:

$$m\dot{w} - mqu = (W - B)\cos\theta + C_{Zw}uw + C_{Zq}uq + u^2 C_{Z\delta_s}\delta_s + C_{Z\dot{w}}\dot{w} + C_{Z\dot{q}}\dot{q} \quad (2)$$

$$\dot{z} = -u\sin\theta + w\cos\theta \quad (3)$$

Pitch motion equation:

$$I_y\dot{q} = B_{Z_{CB}}\sin\theta + C_{Mw}uw + C_{Mq}uq + u^2 C_{M\delta_s}\delta_s + C_{M\dot{w}}\dot{w} + C_{M\dot{q}}\dot{q} \quad (4)$$

$$\dot{\theta} = q \quad (5)$$

The variables u and w denote surge and heave velocities, respectively, while θ, q, and z represent pitch angle, pitch angular velocity, and depth position. T is the thruster force for the surge speed, W is the weight of a vehicle, and B is the buoyancy of AUV body in the sea. The movement of a vehicle in a vertical plane controlled by stern plane angle δ_s. In addition, the moment caused by $B_{Z_{CB}}$ is the vertical distance between the center of gravity z_G and the center of buoyancy z_B, which causes moment and $C_{(.)}$ are the simplified model coefficients. In the formulation of the diving model, we use the assumption that the roll and yaw angular velocities are close to zeros, and the vehicle's forward speed is to be constant u_0. The diving motion model is formally written as

$$\frac{d}{dt}x_\nu = f_\nu(x_\nu, \dot{x}_\nu) + b_\nu(x_\nu, \dot{x}_\nu)\delta_s + d_z \quad (6)$$

where, $x_\nu = [z, q, \theta] \in \Re^3$ is the state vector, $f_\nu \in \Re^3$ is a nonlinear function (includes the cross added mass terms, coriolis, centripetal and damping terms, gravitational force and moment terms), $b_\nu \in \Re^3$ is the actual input matrix and d_z is the external disturbance.

Assumption(1): The approximately known control gain matrix $\hat{b}_\nu(x_\nu, t)$ is invertible and bounded positive definite over entire state space.

Assumption(2): The uncertainty vector $\tilde{F}(x_\nu, \dot{x}_\nu, t) = \Delta f_\nu(x_\nu, t) + \Delta b_\nu(x_\nu, t)u + d_z(x_\nu, t)$ and its partial derivatives are continuous and locally uniformly bounded in Euclidian norm as $\|\tilde{F}(x_\nu, \dot{x}_\nu, t)\| \le \varrho(x_\nu, \dot{x}_\nu, t) < \infty$. The upper bound of uncertainty norm is unknown and it is also ensures that, $\tilde{F}(x_\nu, \dot{x}_\nu, t)$ has locally bounded rate of change.

Assumption(3): We assume that d_z satisfies $|d_z| \le c_z$, where c_z is a known constant.

Assumption(4): $f_\nu(x_\nu, \dot{x}_\nu, t)$ and $b_\nu(x_\nu, \dot{x}_\nu, t)$ are smooth unknown nonlinear functions with $b_\nu > 0$. Further, we assume that $|d(b^{-1})/dt| \le c_b\varphi_b$, where φ_b is a known function and c_b is the smallest one among the unknown positive constants that satisfy the above inequality.

III. CONTROLLER DESIGN

The development of the proposed ANFSMC scheme for diving control of an AUV is discussed in this section. The navigational control problem is to synthesize an intelligent diving autopilot so that it can provide path tracking solutions to the nonlinear depth dynamics along with relaxation on the AUV's pitch angle movement in ocean waves and currents.

The robust composite controller for free pitch angle diving motion behavior of an AUV in adverse circumstances is depicted in Fig. 2, wherein switching control term is approximated by simplified fuzzy logic control and other control parts based on equivalent control to provide convergence of a system's trajectory to the sliding surface within a finite time period is computed by ADALINE NN. The output of the online NN estimator is combined with fuzzy PI smoothing control to gives robust control performance against uncertainties in the model parameters, unknown external disturbances, and time-varying parameters. Basically, online NN configuration utilized to approximate nonlinear system

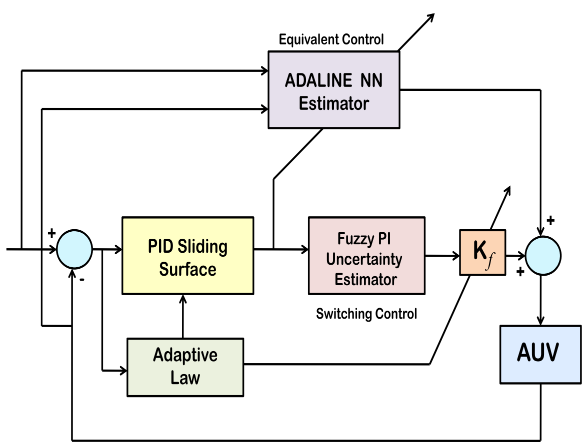

FIGURE 2. Block diagram of adaptive neuro-fuzzy sliding mode diving control for AUV.

dynamics and also reject the effect of ocean disturbances. In addition, switching control term is the fundamental cause of chattering and their design based on the bounds of uncertainties, so as to replace switching term by an adaptive fuzzy PI control to suppress chattering as well as perturbations effects. We can summarize the design procedure for the ANFSMC includes the following steps:

- Design PID sliding surface with the online tuning of sliding surface coefficients.
- Determine fuzzy PI smoothing control as an uncertainty estimator
- Design ADALINE NN to estimate nonlinear system dynamics and reject disturbances
- Online compute output gain of fuzzy PI control by an adaptive law
- Calculate the overall control signal for diving control

In this control technique, NN and FLC are applied concurrently, but each control term is primarily accountable for controlling one of the two phases of sliding mode control action. In the beginning, the fuzzy logic system is leading and drives the system towards the sliding surface. As the system moves from reaching phase to sliding phase, the output of the fuzzy decreases and the NN weights are updated accordingly, so that an exact equivalent controller is estimated to keep the system on the sliding surface. The learning rate of NN is inversely related to the sliding parameter, and therefore the NN becomes more dominant in the control action that occurs in the sliding phase. The weights of the NN are updated by using the iterative gradient algorithm, due to which reaching time is shorten and gain factor of fuzzy inference system along with surface coefficients are determined by using adaptive laws.

A. PID SLIDING SURFACE

Let us define PID sliding manifold $\sigma_{(t)}$ in the state space $\Re^2$ by the equation $\sigma(z_e, \theta, q)$ with following equation

$$\sigma_{(t)} = K_p(z_{d(t)} - z_{(t)}) + K_i\theta_{(t)} + K_d q_{(t)} = Gx_{ve} \tag{7}$$

where, the vertical tracking error z_e is the difference between depth parameter z and desired vertical position z_d. The sliding surface coefficients K_p, K_i and K_d are designed such that the sliding mode on $\sigma = 0$ is stable i.e. convergence of σ goes to zero in turn guarantees that $\tilde{z}$ converge to zero. The values of PID coefficients are strictly positive constant $[K_p, K_i \text{ and } K_d] = G \in \Re^T$. The stability and transient performance of control systems depend on the proper selection of sliding surface coefficients. PID sliding surface improves the tracking performance by reducing errors to a satisfactory value. In PID manifold, the proportional term drives the states to the neighborhood of the sliding surface, and the integral action forces the states onto the sliding surface irrespective of the bounds of the uncertainties and disturbances, while the derivative action provides a stabilizing effect to counter the possible excessive control produced by the integral action. The integral term and the derivative term play important roles in ensuring that the states move onto the sliding surface. The gains of PID sliding surface can be computed online by the following adaptive laws as,

$$\dot{K}_p = -\eta_1 \sigma e \tag{8}$$

$$\dot{K}_i = -\eta_2 \sigma \int e dt \tag{9}$$

$$\dot{K}_d = -\eta_3 \sigma \dot{e} \tag{10}$$

where, $\eta_i > 0$ is the learning rate i = 1, 2, 3. The control law based on a continuous time varying PID sliding surface, here coefficients are systematically obtained according to the adaptive laws [34]. An adaptive strategy is presented to tune the PID parameters online to control the process states onto a sliding surface that characterizes the closed-loop performance. The online tuning of PID parameters provides a quick and smooth hitting of the system states onto the sliding surface and also tracks the setpoint very well without any oscillation. However, it is capable of handling only constant parametric uncertainty, inadequate robustness against external disturbance. The PID's integral and derivative gains can be automatically tuned to satisfy the reachability condition. Hence, the stability of the closed-loop system can be guaranteed as long as the integral and derivative gains are tuned according to (9) and (10).

B. EQUIVALENT CONTROL

Filippov's construction of the equivalent dynamics is the method normally used to generate the equivalent control law. The control effort is obtained from the solution of the system's algebraic equation $\dot{\sigma} = 0$ without considering lumped uncertainty to achieve the desired performance under the nominal operating model condition, and it is referred as equivalent control.

$$u_{eq} = (Gb_v)^{-1}\left(\frac{d\phi(t)}{dt} - Gf_v(x_v, t) - Gd_z(x_v, t)\right) \tag{11}$$

The control should be selected such that a candidate Lyapunov function satisfies the stability criteria, has to be positive definite, and its derivative has to be negative semidefinite:

$$V = \frac{1}{2}\sigma^T\sigma \tag{12}$$

$$\frac{dV}{dt} = \sigma^T\dot{\sigma} \tag{13}$$

Equivalent control is valid only on the sliding surface. Therefore, an additional term should be defined to pull the system to the surface. For this purpose, the derivative of the Lyapunov function can be selected as follows:

$$\dot{V} = -\sigma^T\Gamma\sigma \leq 0 \tag{14}$$

where, Γ is the positive definite matrix, By equating (14) and (13) and carrying out necessary computations, the overall desired continuous control signal is determined as follows:

$$u_d = u_{eq} - (Gb_v)^{-1}\Gamma\sigma \tag{15}$$

For the computation of desired continuous control (15) required information about equivalent control. However, if system parameters $f_\nu(x_\nu, t)$ and b_ν are not known exactly, then the calculated equivalent control inputs will be completely different from the needed equivalent control input. So, this solution must be modified as

$$u_{eq} = (Gb_\nu)^{-1}\left(\frac{d\phi(t)}{dt} - Gf_\nu(x_\nu, t) - Gd_z(x_\nu, t)\right)$$
$$u_{eq} = (Gb_\nu)^{-1}\dot{\sigma} - u \tag{16}$$

Then, results of desired continuous control signal can be rewritten as

$$u_d = u - (Gb_\nu)^{-1}(\Gamma\sigma + \dot{\sigma}) \tag{17}$$

The above expression (17) determines u_d, which satisfies the reaching mode condition, as a function of implemented control signal u. The desired continuous control law (17) for AUV dynamics ensures the stability of motion on the sliding manifold, and after the reaching manifold, control law (17) is equal to equivalent control. For the computation of equivalent control, information about the equivalent control in its implicit form is needed ($u_{eq} = (Gb_\nu)^{-1}\dot{\sigma} - u$), so this solution is not practical for the real-time implementation. As a result, we present a design method of on-line estimator which estimates a part of equivalent control containing a nonlinear system matrix f_ν, input matrix uncertainty Δb_ν and load disturbance d_z as a linearly combined nonlinear function by the use of a NN's most powerful ability, that is, the function of approximation.

$$GN(x_\nu) = G(f_\nu(x_\nu) + \Delta b_\nu(x_\nu)u + d_z(x_\nu)) \tag{18}$$

The unknown nonlinear functions in this control will have to be estimated with single-layer NN. The linearly combined nonlinear function $(f_\nu(x_\nu) + \Delta b_\nu(x_\nu)u + d_z(x_\nu))$ is replaced by the mapping of NN function N. The actual input matrix b_ν replaced by the estimated matrix $\tilde{b}_\nu$. Then, the overall desired continuous control signal

$$u_d = -(G\tilde{b}_\nu)^{-1}\left(GN(x_\nu, t) - \frac{d\phi(t)}{dt}\right) - (G\tilde{b}_\nu)^{-1}\Gamma\sigma \tag{19}$$

Using this control input signal, the time derivative of Lyapunov function along the state trajectories is determined as

$$\frac{dV}{dt} = \sigma^T\frac{d\sigma}{dt}$$
$$\dot{V} = \sigma^T\left(f_\nu(x_\nu, t) + \Delta b_\nu(x_\nu, t)u + d_z - N(x_\nu, t)\right) - \sigma^T\Gamma\sigma \tag{20}$$

From the above equation, suppose that the NN can be trained to satisfy the following condition:

$$|\sigma^T\left(f_\nu(x_\nu, t) + \Delta b_\nu(x_\nu, t)u + d_z - N(x_\nu, t)\right)| < |\sigma^T\Gamma\sigma| \tag{21}$$

Then, $\dot{V} < 0$ holds and consequently the convergence of σ to zero is assured. With the control input in (19), the estimation error represented by J, can be determined from nonlinear AUV's diving dynamics and sliding manifold as follows:

$$J = G\left(f_\nu(x_\nu, t) + \Delta b_\nu(x_\nu, t)u + d_z - N(x_\nu, t)\right) = \Gamma\sigma + \dot{\sigma} \tag{22}$$

From (21) and estimation error obtained by (22), the NN is to be trained to minimize the function given below:

$$E = \frac{(\dot{\sigma} + \Gamma\sigma)^2}{2} \tag{23}$$

Now, the goal is to build a single layer neuron with a linear activation function, namely ADALINE NN [36], based on the BP algorithm used to estimate the equivalent control part which pushes the system state to a certain sliding manifold. The structure of NN based controller is given in Fig. 3, basically consist of the input layer and only one output node. The resulting control input u is given as

$$u = W^T x_{\nu e} \tag{24}$$

Here, $W = [w_1 \; w_2 \; w_3]^T$ and $x_{\nu e} = [z_e \; q \; \theta]^T$, the stability can be obtained by satisfying $\dot{\sigma} + \Gamma\sigma = 0$

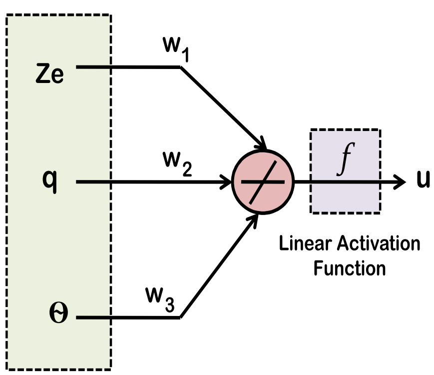

FIGURE 3. Structure of ADALINE NN.

1) COMPUTATION OF WEIGHT UPDATES

In order to determine the weight updates, the sensitivity (dE/dw_i) for weights should be known. The weights are updated as follows:

$$\dot{w}_i = -\eta_a\frac{dE}{dw_i} \tag{25}$$

By using the chain rule, the following equation can be written

$$\frac{dE}{dw_i} = \left(\frac{dE}{du}\right)\left(\frac{du}{dw_i}\right) \tag{26}$$

From (23) and (25)

$$\frac{dE}{dw_i} = \frac{1}{2}\left(\frac{d(\dot{\sigma} + \Gamma\sigma)^2}{du}\right)x_{\nu e}$$
$$\frac{dE}{dw_i} = (\dot{\sigma} + \Gamma\sigma)\left(\frac{d(\dot{\sigma} + \Gamma\sigma)}{du}\right)x_{\nu e} \tag{27}$$

Hence,

$$\frac{dE}{dw_i} = (\dot{\sigma} + \Gamma\sigma)\left(\frac{d(G\dot{x}_{\nu e} + \Gamma Gx_{\nu e})}{du}\right)x_{\nu e} \tag{28}$$

$$\frac{dE}{dw_i} = (\dot{\sigma} + \Gamma\sigma)\ G\ b_v(x_v, t)\ x_{ve} \tag{29}$$

Then, rewritten above equation in discrete form for numerical simulation, the weight update rule is given as

$$w_i^{new} = w_i^{old} - \eta_a(\dot{\sigma} + \Gamma\sigma)\ G\ b_v(x_v, t)\ x_{ve} \tag{30}$$

Note that, for linear system the equation can reduces to

$$w_i^{new} = w_i^{old} - \eta_a(\dot{\sigma} + \Gamma\sigma)\ G\ b\ x_{ve} \tag{31}$$

Since $\eta_a G b$ is a constant parameter, η_a, G, b can altogether be included in a constant $\bar{\eta_a}$ and can be reduced as

$$w_i^{new} = w_i^{old} - \bar{\eta_a}(\dot{\sigma} + \Gamma\sigma)x_{ve} \tag{32}$$

For a nonlinear system with constant input matrix B consider, the same result (32), can be obtained.

2) DISTURBANCE REJECTION

The least square error function (23) can be examined in more detail as follows:

$$\begin{aligned}\dot{\sigma} + \Gamma\sigma &= G\dot{x}_{ve} + \Gamma G x_{ve}\\ &= Gf_v(x_v, t) + GB_v(x_v, t)W^T x_{ve} + Gd_z\\ &\quad + G\,f_v(z_v^r, \dot{z}_v^r) + \Gamma G x_{ve}\end{aligned} \tag{33}$$

Taking the common terms in to parenthesis, the following expression can be obtained as

$$\dot{\sigma} + \Gamma\sigma = Gf_v(x_v, t) + (GB_v(x_v, t)W^T + \Gamma G)x_{ve} + G\,d_z + Gf_v(z_v^r, \dot{z}_v^r) \tag{34}$$

It can be seen from (34) that, when the tracking error z_e goes to zero, the weights w_i have to go infinity to suppress the effect of external disturbance. To circumvent this, it is logical to add another term to the controller structure that will deal with the disturbance rejection. This additional term handles with the disturbance without being multiplied with the state x_{ve}. The control design for disturbance compensation is as shown in Fig. 4. with this controller structure, the expression for the control input is

$$\hat{u}_{eq} = W^T x_{ve} + w_4 \tag{35}$$

By using the same weight update procedure as described above, w_4 can be updated as

$$w_4^{new} = w_4^{old} - \eta_a(\dot{\sigma} + \Gamma\sigma)G\ B(x_v, t)\ x_{ve} \tag{36}$$

The main drawbacks of the BP algorithm are its slow rate of convergence and its inability to ensure global convergence. Some heuristic methods, like adding a momentum term to the BP algorithm and standard numerical optimization techniques have been used to improve the convergence rate of the BP algorithm. The problems with this numerical optimization techniques are that the storage and memory requirements. Other algorithms for fast convergence include extended Kalman filtering (EKF), recursive least square (RLS), and Levenberg-Marquardt (LM). Though the algorithms converge faster, it requires too much computation per pattern. For simplicity and ease of implementation concerned, computation of adaptive learning rate using the Lyapunov function approach is the key contribution in the field of NN based control. It is observed that this adaptive learning rate increases the speed of convergence and resolve the issues of computation of adaptive learning rate [35].

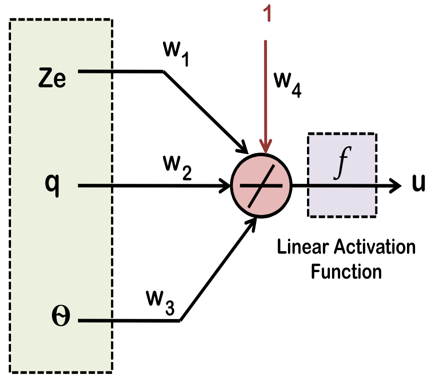

FIGURE 4. An improved structure of ADALINE NN.

3) ADAPTIVE LEARNING RATE

The simplified ADALINE NN structure has a single output with linear activation function for neurons. The network is parameterized in terms of its weights which is represented as a weighting factor $W \in \Re^m$. For approximation of a specific function problem, the training data consists of N patterns, $\{x^{p_n}, y^{p_n}\}$. Let us consider a specific pattern p_n for the input vector is x^{p_n}, then the network output is given as,

$$y^{p_n} = f(W, x^{p_n}) \tag{37}$$

The usual quadratic error cost function (23), which is minimized to train the weight vector W of NN. We consider a Lyapunov function candidate as

$$V_n = \frac{1}{2}(\tilde{y}^T.\tilde{y}) \tag{38}$$

where, $\tilde{y} = [y_d^1 - y^1, \ldots.., y_d^{p_n} - y^{p_n}, \ldots.., y_d^N - y^N]^T$. Then, it's time derivative is given as

$$\dot{V}_n = -\tilde{y}^T\frac{\partial y}{\partial W}\ \dot{W} = -\tilde{y}^T J\ \dot{W} \tag{39}$$

where, $J = \partial y/\partial W \in \Re^{N\times m}$

Theorem (1): An initial arbitrary weight $W(0)$ is updated by $W(t') = W(0) + \int_0^{t'} \dot{W}.dt$

where,

$$\dot{W} = \frac{\|\tilde{y}\|^2}{\|J^T\tilde{y}\|^2 + \varepsilon_n}J^T\tilde{y} \tag{40}$$

Then, $\tilde{y}$ converges to zero under the condition that $\dot{W}$ exists along the convergence trajectory.

Proof: Substitution (40) in to (39)

$$\dot{V}_n = -\|\tilde{y}\| \leq 0 \tag{41}$$

where, $\dot{V}_n < 0$ for all $\tilde{y} \neq 0$, If $\dot{V}_n$ is uniform continous and bounded then according to Barbalat's lemma as

$t \rightarrow \infty$, $\dot{V}_n \rightarrow 0$ and $\tilde{y} \rightarrow 0$. The weight update (40) in the instantaneous gradient-descent (GD) method.

$$\dot{W} = \frac{\|\tilde{y}\|^2}{\|J_{P_n}^T \tilde{y}\|^2 + \varepsilon_n} J_{P_n}^T \tilde{y} \tag{42}$$

where, $\tilde{y} = y_d^{p_n} - y^{p_n} \epsilon \Re$ and $J_{p_n} = \partial y^p / \partial W \in \Re^{1 \times m}$ is the instantaneous value of the Jacobian. The updated weight in difference equation form is given as

$$\begin{aligned} W(t+1) &= W(t) + \mu_n \dot{W}(t) \\ &= W(t) + \frac{\mu_n \|\tilde{y}\|^2}{\|J_{P_n}^T \tilde{y}\|^2 + \varepsilon_n} J_{P_n}^T \tilde{y} \end{aligned} \tag{43}$$

Here, μ_n is a constant which is selected heuristically. We can add a very small constant ϵ_n to the denominator to avoid numerical instability when error $\tilde{y}$ goes to zero. The expression of updating the weighting factor in the instantaneous GD method represented as,

$$\triangle W = -\eta \left(\frac{\partial E}{\partial W} \right)^T \tag{44}$$

$$= \eta J_{P_n}^T \tilde{y} \tag{45}$$

$$W(t+1) = W(t) + \eta J_{P_n}^T \tilde{y} \tag{46}$$

where, η is the learning rate. Comparing (43) with (46), we can see the remarkable similarity where the fixed learning rate in the BP algorithm is replaced by its adaptive version η_a given by

$$\eta_a = \frac{\mu_n \|\tilde{y}\|^2}{\|J_{P_n}^T \tilde{y}\|^2 + \varepsilon_n} \tag{47}$$

However, the computation of the adaptive learning rate using the Lyapunov function approach is the key part in neural network-based control [35].

C. CORRECTIVE CONTROL

In this subsection, an adaptive control law is designed to determine the consequent part of the fuzzy system, which is introduced to approximate the switching control and to eliminate the chattering effect. Furthermore, to attenuate chattering, when the error state is within the boundary layer width $|\sigma| < \phi_b$, then fuzzy PI-type smoothing control law is designed as an uncertainty estimator instead of traditional corrective/ switching control term. With the estimation of the perturbation vector, the stability and closed-loop tracking performance of the system is going to be improved. The estimator design relies on the online estimation of a lumped uncertainty vector rather than relying on the upper bounds of uncertainties. So, a priori knowledge of the bounds of uncertainties is not needed, and at each time instant, the control input compensates the uncertainty that occurs. PI uncertainty estimator [21] is defined as

$$u_{ad} = K_u \sigma + L_{est} \tag{48}$$

where, K_u is a diagonal positive definite constant matrix, σ is represented as PID sliding surface variable and L_{est} is the estimated uncertainty vector, which is predicted from the surface dynamics is expressed as

$$L_{est} = \Upsilon \int \sigma.dt \tag{49}$$

where, Υ is a positive definite diagonal constant design matrix that determines the rate of adaptation. The robust adaptive term in (48) is a proportional-integral PI controller with respect to sliding surface and is given as

$$u_{ad} = K_u \sigma + \Upsilon \int \sigma.dt = \delta_p u_{pi} \tag{50}$$

where, δ_p is a diagonal gain matrix and u_{pi} denotes PI control action included, proportional term drives the variable σ to a neighborhood around zero, and the integral action forces the convergence to zero. The integral term plays a significant role in ensuring that the states move on to the sliding surface. For improving tracking performance of AUV in a vertical plane, robust adaptive PI term replaces by single input fuzzy PI control structure with respect to sliding surface variable, which has the capability of learning and adapting to the parametric variation, with the help of Fuzzy IF-THEN rules for mapping of input σ to output variable $\hat{u}_{sw}$.

An adaptive fuzzy logic system (AFLCS) is presented in this section to compensate parametric uncertainties that occur in the oceanic environment. The fuzzy logic control module basically consists of a collection of fuzzy IF-THEN rules that can be set as follows. The fuzzy system is based on single-dimensional (1D) rule base, as given in Table 1. A typical fuzzy rule in the rule-base structure of the AFLS is given as

$$R_p^{(m)} : \text{IF } \sigma_i \text{ is } F_{\sigma_i}^{(m)} \text{ THEN } \hat{u}_{sw}(\sigma|\theta_p) \text{ is } F_{\hat{p}}^{(m)}$$

where, $i = 1, 2, 3, \ldots, 7.$, m is the fuzzy rule base index, $F_{\sigma_i}^{(m)}$ denote the fuzzy sets assigned to σ sliding surface and $F_{\hat{p}}^{(m)}$ represents the fuzzy singletons assigned to the output variable as $\hat{u}_{sw}$ of the fuzzy inference module. In fuzzy inference engine, input linguistic variables employed for triangular type membership function of sliding surface variable are NL is *Negative Large*, NM is *Negative Medium*, NS is *Negative Small*, Z is *Zero*, PS is *Positive Small*, PM is *Positive Medium*, PL is *Positive Large*. The singleton membership function for output fuzzy PI control variables are employed as L_{NL} is *Lumped Negative Large*, L_{NM} is *Lumped Negative Medium*, L_{NS} is *Lumped Negative Small*, L_Z is *Lumped Zero*, L_{PS} is *Lumped Positive Small*, L_{PM} is *Lumped Positive Medium*, L_{PL} is *Lumped Positive Large*. NL, NM,NS.. L_{NL}, L_{NS}, $\ldots L_{PL}$ are labels of fuzzy sets and their corresponding membership functions are depicted in Fig. 5, respectively.

TABLE 1. Rule base for Single input Fuzzy PI algorithm.

σ	NL	NM	NS	Z	PS	PM	PL
$\hat{u}_{sw}$	L_{NL}	L_{NM}	L_{NS}	L_Z	L_{PS}	L_{PM}	L_{PL}

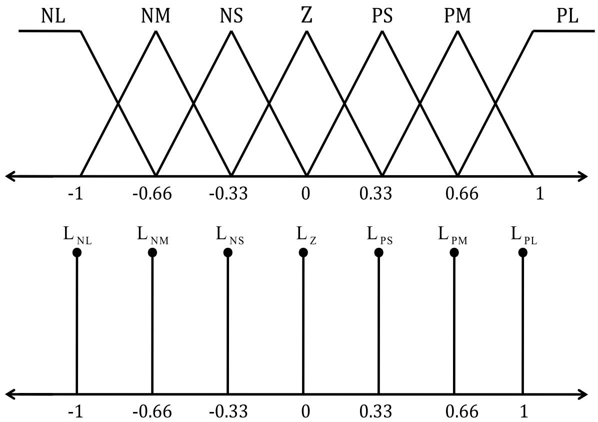

FIGURE 5. Input-output membership functions of fuzzy inference engine.

Fuzzy system can be designed by product inference engine, singleton fuzzifier and center average defuzzifier. Therefore, the output of fuzzy system can be calculated as

$$\hat{u}_{sw}(\sigma|\theta_p) = \theta_p^T\varphi(\sigma_i) = K_u\sigma + \Upsilon\int\sigma.dt \tag{51}$$

with $\theta_p^T = [K_u, \ \Upsilon] = [F_{\hat{p}}^1, \ F_{\hat{p}}^2, \ F_{\hat{p}}^3, \ldots.. \ F_{\hat{p}}^Q]^T$ is the adjustable parameter vector and $\varphi^T(\sigma_i) = [\sigma, \ \int\sigma.dt] = [\varphi^1(\sigma_i), \ \varphi^2(\sigma_i), \ \varphi^3(\sigma_i), \ldots\ldots, \ \varphi^Q(\sigma_i)]^T$ is the vector of fuzzy basis function defined as

$$\varphi_i^m(\sigma_i) = \frac{\Pi_{i=1}^n\mu_{F_{\sigma_i}^{(m)}}(\sigma_i^*)}{\Sigma_{j=1}^Q\left[\Pi_{i=1}^n\mu_{F_{\sigma_i}^{(m)}}(\sigma_i^*)\right]} \tag{52}$$

where, $\mu_{F_{\sigma_i}^{(m)}}(\sigma_i^*)$ denotes the membership function value of σ_i in $F_{\sigma_i}^{(m)}$. The fuzzy approximator can determine PI uncertainty estimator to provide smooth control signal and suppress the effect of parametric uncertainties.

The overall control law u^* is chosen as

$$\begin{aligned} u^* &= \hat{u}_{eq} + K_f\hat{u}_{sw} \\ &= -(G\hat{b}_v)^{-1}\left(G\hat{f}_v(x_v, t) + G\hat{d}_z(x_v, t) - \frac{d\hat{\phi}(t)}{dt}\right) \\ &\quad + K_f\theta_p^T\varphi(\sigma_i) \end{aligned} \tag{53}$$

In this composite control law, the ADALINE NN model is designed to construct the equivalent control law based on the estimation of nonlinear system functions and unknown disturbances. While, fuzzy inference approximator is used to compute corrective control by using the concept of PI uncertainty estimator for reducing the chattering problem as well as the effect of lumped uncertainties. The parameters of composite control law are updated as follows:

$$\dot{\theta}_p = -\gamma_\theta|\sigma_i|\varphi_i^m(\sigma_i) \tag{54}$$

$$\hat{K}_f = \frac{\hat{\beta}}{\delta_f + (1-\delta_f)e^{-\varsigma|\sigma|^p}}; \quad \dot{\hat{\beta}} = -\gamma_K\|\sigma\| \tag{55}$$

where, in the above relation γ_θ and γ_K are positive and arbitrary constants. p, δ_f and ς are small positive constants to provide the smoothness of control input. $\hat{\beta}$ denotes the estimated value of β and $\gamma_K > 0$ is the adaptation gain, ensures the convergence of tracking error despite the perturbations.

The fuzzy consequent parameter θ_p in (54) adjusted in order to improve the system's control performance. The adaptive rule is derived from steep descent rule to decrease the value of $\sigma\dot{\sigma}$ with respect to θ_p. This adaptive mechanism satisfies the objective of online learning and adjustment of fuzzy control rules. The main advantage of this adaptive online law is that it speeds up the reaching phase in sliding motion behavior.

The exponential compensator in (55) is designed to cope with the approximation error introduced by the ADALINE NN based equivalent control estimation. Since the nonlinear exponential reaching law to smoothly adapt the variations of the sliding surface, thus the chattering phenomenon can be alleviated. The result of reaching control gain exhibits fast response and robustness near the sliding surface. However, it still requires prior knowledge of the uncertainties bounds. This control issues resolved by using an adaptive fuzzy PI learning algorithm, which can be accelerated convergence of tracking error towards zero.

In the ADALINE NN model, fast convergence and computational complexity are two key issues resolved by computing the adaptive learning rate (54) using the Lyapunov function approach. The estimation error $\tilde{y}$ converges to zero under the condition that $\dot{\eta}_a$ exists along the convergence trajectory. with this adaptation scheme, the neuro-fuzzy sliding mode control module derived from designing diving autopilot for precise AUV maneuvering with the relaxation on constraints of pitch angle movement in an unstructured marine environment.

IV. STABILITY ANALYSIS

Theorem (2): By using the BP algorithm with a proper learning rate and function approximation accuracy, it is guaranteed that quadratic cost function E defined in (23) converges to zero, without bonding to local minimum. It means that, for a bounded external disturbance $d_z(t)$ and unknown nonlinear AUV dynamics, it is guaranteed that closed loop path tracking is stable with zero steady state tracking error in dive plane.

Proof: According to Lyapunov stability criteria, we have to show that $\dot{E} < 0$. The derivative of the error function with respect to time is given by

$$\frac{dE}{dt} = \frac{\partial E}{\partial w_1}\frac{\partial w_1}{\partial t} + \frac{\partial E}{\partial w_2}\frac{\partial w_2}{\partial t} + \frac{\partial E}{\partial w_3}\frac{\partial w_3}{\partial t} + \frac{\partial E}{\partial w_4}\frac{\partial w_4}{\partial t} \tag{56}$$

The expression for continuous changes of the weights is

$$\frac{dw_i}{dt} = -\eta_a\frac{dE}{dw_i} \tag{57}$$

substituting (57) into (56)

$$\begin{aligned} \frac{dE}{dt} &= -\eta_a\left(\frac{dE}{dw_1}\right)^2 - \eta_a\left(\frac{dE}{dw_2}\right)^2 \ldots\ldots \\ &\quad \ldots.. - \eta_a\left(\frac{dE}{dw_3}\right)^2 - \eta_a\left(\frac{dE}{dw_4}\right)^2 \end{aligned} \tag{58}$$

From (25), substitute the values of vector x_{ve} in to (29) and resulting scalar equations as follows:

$$\frac{dE}{dw_1} = (\dot{\sigma} + \Gamma\sigma)\ Gb_\nu(x_\nu, t)\ z_e \tag{59}$$

$$\frac{dE}{dw_2} = (\dot{\sigma} + \Gamma\sigma)\ Gb_\nu(x_\nu, t)\ q \tag{60}$$

$$\frac{dE}{dw_3} = (\dot{\sigma} + \Gamma\sigma)\ Gb_\nu(x_\nu, t)\ \theta \tag{61}$$

Again, take the derivative of above expressions with respect to the weights, then following equations are obtained

$$\frac{d^2E}{dw_1^2} = (Gb_\nu(x_\nu, t)\ z_e)^2 \tag{62}$$

$$\frac{d^2E}{dw_2^2} = (Gb_\nu(x_\nu, t)\ q)^2 \tag{63}$$

$$\frac{d^2E}{dw_3^2} = (Gb_\nu(x_\nu, t)\ \theta)^2 \tag{64}$$

Furthermore, the second derivative of the error function with respect to w_4 is

$$\frac{d^2E}{dw_4^2} = (Gb_\nu(x_\nu, t))^2 \tag{65}$$

From (62)-(65), it is clearly observed that the curvature of the error surface through each weight variable is always positive term represented as Ξ_i. Then, derivative of error function in (58) can be rewritten as

$$\frac{dE}{dt} = -\eta_a \sum_{i=1}^{4} \Xi_i \tag{66}$$

Note that (66), is a negative definite function completes the proof. Means, it is guaranteed that tracking error in vertical plane converges to zero.

Theorem (3): Consider the tracking control problem of an AUV represented by (6) in vertical plane. If the proposed controller is combination of equivalent and corrective control as given in (53) with the adaptive laws represented in (47), (54) and (55) for updating learning rate, fuzzy consequent and hitting gain, then the path tracking error vector asymptotically converges to zero in diving motion.

Proof: Let a Lyapunov function V_L be defined as

$$V_L = \frac{1}{2}\sigma^2 + \frac{1}{2\gamma_f}\tilde{L}^T\tilde{L} + \frac{1}{2\eta_1}\tilde{K_P}^T\tilde{K_P} + \frac{1}{2\eta_2}\tilde{K_I}^T\tilde{K_I} + \frac{1}{2\eta_3}\tilde{K_D}^T\tilde{K_D} + \frac{1}{2}\tilde{y}^T\tilde{y} + \frac{1}{2\gamma_\theta}\tilde{\theta_P}^T\tilde{\theta_P} + \frac{1}{2\eta_K}\tilde{K_f}^T\tilde{K_f} \tag{67}$$

The time derivative of Lyapunov function is,

$$\dot{V}_L = \sigma\dot{\sigma} + \frac{1}{\gamma_f}\tilde{L}^T\dot{\tilde{L}} + \frac{1}{\eta_1}\tilde{K_P}^T\dot{\tilde{K_P}} + \frac{1}{\eta_2}\tilde{K_I}^T\dot{\tilde{K_I}} + \frac{1}{\eta_3}\tilde{K_D}^T\dot{\tilde{K_D}} - \tilde{y}\frac{\partial\tilde{y}}{\partial W}\dot{\tilde{W}} + \frac{1}{\gamma_\theta}\tilde{\theta_P}^T\dot{\tilde{\theta_P}} + \frac{1}{\eta_K}\tilde{K_f}^T\dot{\tilde{K_f}} \tag{68}$$

$$\begin{aligned}\dot{V}_L &= \sigma G\left(\dot{x}_{vd} - f_\nu(x_\nu, \dot{x}_\nu) - b_\nu(x_\nu, \dot{x}_\nu)\delta_s - d_z\right) + \frac{1}{\gamma_f}\tilde{L}^T K_f f_{PI}(\sigma) + \frac{1}{\eta_1}\tilde{K_P}^T(-\eta_1\sigma e) + \frac{1}{\eta_2}\tilde{K_I}^T \\ &\quad\times(-\eta_2\sigma\int edt) + \frac{1}{\eta_3}\tilde{K_D}^T(-\eta_3\sigma\dot{e}) - \tilde{y}\frac{\partial\tilde{y}}{\partial W} \\ &\quad\times\frac{\|\tilde{y}\|^2}{\|J^T\tilde{y}\|^2+\varepsilon_n}J^T\tilde{y} + \frac{1}{\gamma_\theta}\tilde{\theta_P}^T(-\gamma_\theta|\sigma_i|\varphi_i^m(\sigma_i)) + \frac{1}{\eta_K}\tilde{K_f}^T \\ &\quad\times\frac{\left[\sigma(\delta_f + (1-\delta_f)e^{-\varsigma|\sigma|^p})\dot{\beta} - \beta\varsigma p(1-\delta_f)e^{-\varsigma|\sigma|^p}|\sigma|\right]}{(\delta_f + (1-\delta_f)e^{-\varsigma|\sigma|^p})^2}\end{aligned} \tag{69}$$

$$\begin{aligned}\dot{V}_L &= \sigma G\left(\dot{x}_{vd} - f_\nu(x_\nu, \dot{x}_\nu) - b_\nu(\hat{u}_{eq} + \hat{u}_{sw}) - d_z\right) + \frac{K_f}{\gamma_f}\|\tilde{L}\||\sigma| - \tilde{K_P}^T\sigma e - \tilde{K_I}^T\sigma\int edt - \tilde{K_D}^T\sigma\dot{e} \\ &\quad - \|\tilde{y}\|^2\frac{\|J^T\tilde{y}\|^2}{\|J^T\tilde{y}\|^2+\varepsilon_n} - \tilde{\theta_P}^T|\sigma|\varphi_i^m(\sigma) - \frac{|\sigma|\tilde{K_f}^T}{\gamma_K} \\ &\quad\times\frac{[\gamma_K\sigma\kappa(\sigma) + K_r e^{-\varsigma|\sigma|^p}]}{\kappa(\sigma)^2}\end{aligned} \tag{70}$$

$$\begin{aligned}\dot{V}_L &= \sigma G\Bigg(\dot{x}_{vd} - f_\nu(x_\nu, \dot{x}_\nu) - b_\nu\Bigg(-(G\hat{b}_\nu)^{-1}\Bigg(G\hat{f}_\nu(x_\nu) + G\hat{d}_z(x_\nu) - \frac{d\hat{\phi}(t)}{dt}\Bigg) + K_f f_{PI}(\sigma)\Bigg) - d_z\Bigg) \\ &\quad + G_f\|\tilde{L}\||\sigma| - \sigma\left(\tilde{K_P}^T e + \tilde{K_I}^T\int edt + \tilde{K_D}^T\dot{e}\right) \\ &\quad - \alpha_n\|\tilde{y}\|^2 - K_m|\sigma|\tilde{\theta_P}^T - K_s|\sigma|\kappa(x_\nu)\end{aligned} \tag{71}$$

$$\begin{aligned}\dot{V}_L &= -\sigma GK_f f_{PI}(\sigma) + G_f\|\tilde{L}\||\sigma| - \sigma|\sigma| - \alpha_n|\sigma|^2 \\ &\quad - K_m|\sigma|\tilde{\theta_P}^T - K_s|\sigma|\kappa(x_\nu)\end{aligned} \tag{72}$$

$$\begin{aligned}\dot{V}_L &= -|\sigma|\left(K_c - G_f\|\tilde{L}\| + K_m\tilde{\theta_P}^T + K_s\kappa(x_\nu) + \sigma\right) \\ &\leq -\left(K_c + K_m\tilde{\theta_P}^T + K_s\kappa(x_\nu)\right)|\sigma| \\ &\leq -\varpi|\sigma|\end{aligned} \tag{73}$$

Here, the global asymptotic stability is guaranteed since the derivative of the Lyapunov function is a negative definite.

Remark 1: In diving motion equations of AUV, depth state equation is in a certain nonlinear form, which is difficult to handle by traditional control methods. So far, AUV?s motion behaviors in vertical plane have frequently been constrained to a small-pitch-angle movement, in which the depth motion is usually linearized as $\dot{z} = -u_0 \sin\theta + d_z = -u_0\theta$ with u_0 the forward constant speed of the vehicle. Nevertheless, small-pitch-angle movement is a somewhat strong restricting condition in numerous real-time applications.

Remark 2: The proposed intelligent sliding mode control law is also applicable to another highly coupled, nonlinear, time-varying under-actuated systems, such as unmanned aerial vehicles, missiles, unmanned airships, etc.

Remark 3: The coefficients of PID sliding surface control are adjusted online through adaptive law presented in [34], which offers finite-time convergence of error towards origin.

Remark 4: In conventional SMC [14], a corrective control term may cause the chattering extremely across the sliding hyperplane, owing to delay and unmodeled dynamics. As a result, wear and tear action on the thrusters in order that the system can be damaged within a small time period. The chattering problem can be eliminated by replacing the switching control term by an adaptive PI term [21], which provides smooth control signal.

Remark 5: An adaptive PI term as an uncertainty estimator can be updated recursively in on line practice as mentioned in [37]. Using uncertainty estimator, the influence of time-varying uncertainty compensated through estimation of the internal perturbation. While, online NN estimator is used to approximate nonlinear system function and to minimize the effect of ocean waves and wind.

Remark 6: The performance of the PI uncertainty estimator improved by using a single input fuzzy PI control structure based on a reduced rule base for enhancing static and dynamic control performance. Without violating the convergence property of path tracking error and stability.

Remark 6: The robust composite proposed control law in this article does not require any information on the lumped uncertainties as compared with, which is almost difficult to estimate in practical application.

Remark 7: Unlike some previous works reported in [20] and [37]; almost all kinds of parametric uncertainties and disturbances were considered in simulations, owing to deep-sea underwater operations performed by AUV in diverse operating conditions were taken in to account in numerical simulation, without any presumptions on the periodicity or the bound of such perturbations.

Comments: The control problems exist in the SMC design, and their solutions through ANFSMC method are summarized below:

- It is worth noting that the control performance of traditional SMC heavily depends on the sliding surface. If the sliding surface of SMC is not designed properly, it may lead to unacceptable tracking performance. The selection of optimum sliding surface is tedious and a complicated task, which prescribed desirable dynamical characteristics.
- SMC is basically composed of equivalent control and switching control to provide convergence of a system's trajectory to the sliding surface within a finite time and reaching towards equilibrium point by maintaining the controlled system dynamic on a sliding surface. The computation of equivalent control requires exact knowledge of the system dynamics and parameters, and obviously, only an approximate value can be arrived at for partly known or uncertain systems. While, a discontinuous control strategy is formed to ensure the finite time reachability of the switching manifolds.
- SMC suffers from the undesired high-frequency oscillations known as chattering phenomena, which is created by the discontinuous control law and is very harmful to actuators used in practical systems. The key technical problems in SMC design are chattering, removal of the effects of unmodeled dynamics, disturbances and uncertainties along with adaptive learning, and robustness enhancement. In addition to that, the formulation of SMC requires the norm of uncertainties and disturbances properly, which is used for the determination of switching control gain. Therefore, perturbation estimation techniques are needed to overcome the problem of the knowledge of perturbation upper bounds.
- The use of intelligent computation techniques can solve problems of SMC, such as chattering and alleviate difficulties in the computation of the equivalent control. A set of switching manifold coefficients are tuned online by adaptive PID control law, which provides desirable set-point tracking performance. It should be pointed out that NNs offer a model-free approach for path tracking control with bounded disturbance rejection, which appears attractive; one should not underestimate the efforts of getting the solutions through NNs. As well, fuzzy PI designed to compensate for the effect of parametric uncertainties and provide a smooth control signal. The adaptive exponential reaching law utilized to improve the reaching time and ensuring the settling of states at its desired value. The proposed control approach has the advantage that it only requires a bound to exist, while the magnitude of this bound does not need to be known.

V. SIMULATION STUDIES

To demonstrate the effectiveness and robustness of the proposed controller, an intensive series of simulation studies has been carried out on a nonlinear AUV model in a dive plane for trajectory tracking control. The main purpose of this work is to design adaptive neuro-fuzzy autopilot for the free-pitch-angle diving behavior of an AUV in the presence of model parameter uncertainty and disturbances. For simulation studies, diving dynamics of MAYA AUV were considered, and their model parameters presented in manuscript. The control performance of traditional SMC, FSMC, and ANFSMC has been compared under two different reference path tracking problems, such as set point regulation and sinusoidal trajectory tracking control. In numerical simulation, the initial conditions of the AUV in diving motion behavior are considered as $[q(0)\ \theta(0)\ z(0)]^T = [0\ 0\ 0]^T$ and initial velocities are $[u(0)\ v(0)\ r(0)]^T = [1.5\ 0\ 0]^T$ with control parameters in Table 2. The motivation for simulation studies is to illustrate the benefits of the control scheme to drive an AUV in the dive plane smoothly and freely, without any restricting conditions.

A. SET-POINT CONTROL

With consideration of the above control parameter settings and AUV specifications along with their non-dimensional hydrodynamic coefficients given in Table 3, we first applied the proposed controller to MAYA AUV with step input command $z_d = 5m$ under nominal condition. The simulation responses of dive plane coordinates along with the control signal are shown in Fig. 6. It can be seen that smooth depth trajectory tracking and pitch angle regulation are achieved in

TABLE 2. Control setting values.

η_1	η_2	η_3	K_P	K_I	K_D	γ_θ	γ_K	ς	δ_f	ε_n	K_d
0.15	0.3	0.04	60	7	40	2.3	1.5	0.01	0.15	0.02	0.4

TABLE 3. Specifications and non-dimensional hydrodynamic coefficients of MAYA AUV.

Parameter	Symbol	Values	Unit
Mass	M	53	kg
Length	L	1.8	m
Diameter	D	0.234	m
Depth Range	Z_m	200	m
Weight	W	519.93	N
Total Average Power	P	130	W
Buoyancy	B	524.3	N
RF Communication	R_c	2.4	GHz
Rotational Mass	I_y	9.921	$kg\ m^2$
Density of Sea Water	ρ	1025	$kg\ m^3$
Forward Velocity	U_0	1.5	$m/\ s^2$

Non-dimensional hydrodynamic coefficients in the body frame

X_{uu} = -0.12	$X_{\dot{u}}$ = -0.00062	Z_g = 0.52e-2
Z_w = -0.10272890	$Z_{\dot{w}}$ = -0.029828	Z_b = -0.172e-2
Z_{δ_s} = -0.040282	M_w = -0.0083288	M_{δ_s} = -0.0078662
$M_{\dot{w}}$ = -0.00082247	M_q = -0.0019069	B_{ZCB} = -3.5942

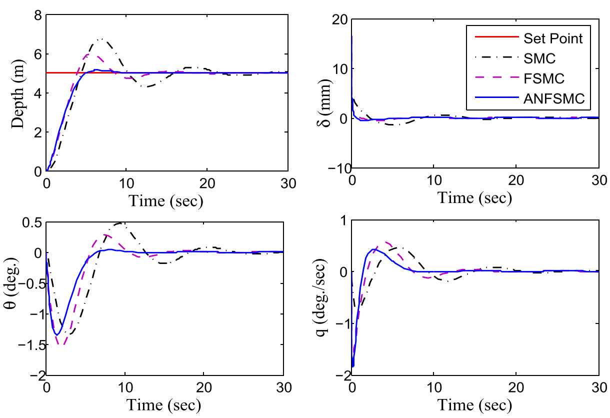

FIGURE 6. Set point tracking response of AUV in diving motion behavior.

less than 10 s. The maximum camber (control input) required is approximately 8mm, which can be easily provided through control fins. It is clearly noticed that the heave velocity goes to zero, when the desired path is regulated. While, in the case of SMC and FSMC, depth tracking response shows oscillations and reach to the desired level at 28 s and 18 s respectively. Also required control input signal of FSMC and SMC are nearby 9 mm and 10 mm respectively, to drive AUV in dive plane through the control fins. The proposed control scheme offers a smooth and better tracking response in comparison with traditional SMC and FSMC.

To evaluate the tracking performance of the closed-loop system with the proposed controller, we applied it to AUV with set point variation, 20% model uncertainty, and sampled Gaussian noise as an external disturbance. The tracking

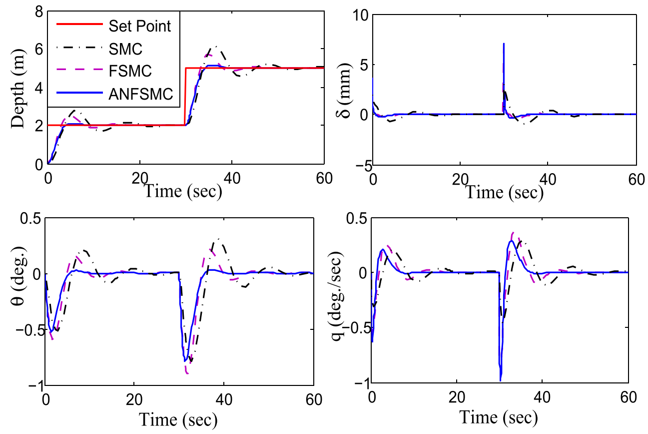

FIGURE 7. Response of AUV in step input command variation.

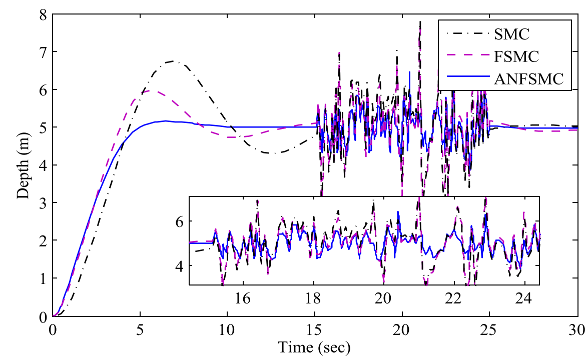

FIGURE 8. Depth tracking response in presence of disturbance and uncertainty.

response of ANFSMC shows smooth better tracking control performance in setpoint variation as compared with other traditional control techniques, as seen in Fig. 7. In setpoint variation, we can see that there is a notable difference in the settling of desired depth position and pitch angle regulation in diving motion. Whereas, FSMC and SMC exhibit oscillatory behavior in tracking of desired depth position and required more settling time. In order to show the effectiveness of the proposed control scheme introduces sampled Gaussian noise and model parameter uncertainty, which can be significantly reduced by ANFSMC as compared with SMC and FSMC in depth parameter regulation, as depicted in Fig. 8. In general, ANFSMC appeared to be less sensitive to the disturbances and parametric variations in contrast to the SMC and FSMC. To show the accuracy and effort of the proposed controller quantitatively, we examined performance measures such as ISE and IAE of step input command responses, step command variation in dive plane, and under the influence of external disturbance and parameter variation. In quantitative analysis, a smaller value of performance measures

TABLE 4. Quantitative analysis of set point tracking control of AUV in dive plane.

Case(I): Set-point tracking control in dive plane									
	ISE			IAE			RMS		
Depth (m)	SMC	FSMC	ANFSMC	SMC	FSMC	ANFSMC	SMC	FSMC	ANFSMC
2	3.8343	0.5243	0.3425	12.2423	3.2484	2.8412	0.1453	0.1312	0.1204
5	3.2754	0.4123	0.2513	12.1454	2.8323	2.3464	0.1438	0.1304	0.1201
Case(II): Under the influence of gaussian noise and uncertainty									
	ISE			IAE			RMS		
Depth (m)	SMC	FSMC	ANFSMC	SMC	FSMC	ANFSMC	SMC	FSMC	ANFSMC
5	5.9352	3.8784	1.9853	14.3421	5.8752	3.9481	0.3106	0.2437	0.2089

TABLE 5. Quantitative analysis of sinusoidal tracking control of AUV in dive plane.

Case(I): Sinusoidal trajectory tracking control in dive plane									
	ISE			IAE			RMS		
Depth (m)	SMC	FSMC	ANFSMC	SMC	FSMC	ANFSMC	SMC	FSMC	ANFSMC
$z_d = 2\sin(\pi t)$	4.2478	1.2435	0.5328	13.5384	3.8788	3.1567	0.1725	0.3821	0.3104
Case(II): Under the influence of sinusoidal disturbance and uncertainty									
	ISE			IAE			RMS		
Depth (m)	SMC	FSMC	ANFSMC	SMC	FSMC	ANFSMC	SMC	FSMC	ANFSMC
$z_d = 2\sin(\pi t)$	6.8289	3.8567	2.5684	16.8673	6.2597	4.0586	0.4021	0.3821	0.3104

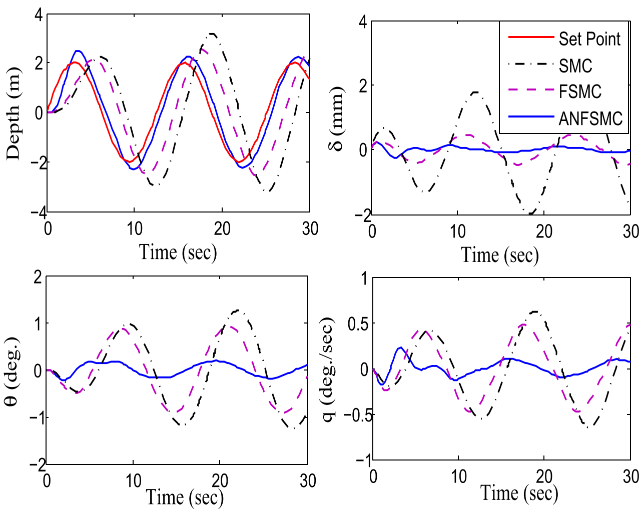

FIGURE 9. Sinusoidal trajectory tracking response of AUV in dive plane.

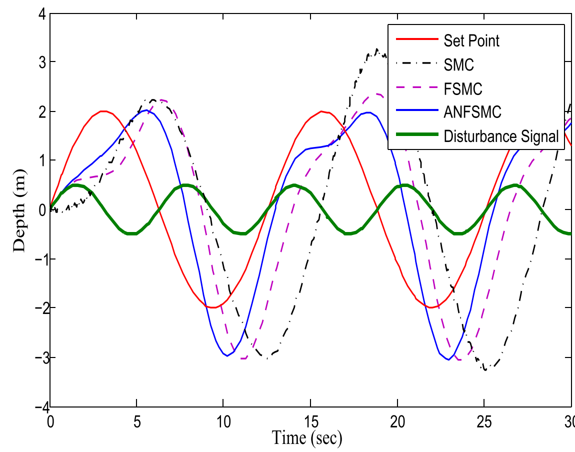

FIGURE 10. Sinusoidal trajectory tracking in presence of disturbance and uncertainty.

shows that better controller performance characteristics. It is observed that ISE and IAE values of the proposed controller for the above-mentioned conditions are considerably reduced in magnitude than other control techniques dealt with in this paper, as tabulated in Table. 4.

B. SINUSOIDAL TRAJECTORY TRACKING CONTROL

In the second stage of numerical simulation, sinusoidal reference signal $z_d = 2\sin(\pi t)$ applied to the diving model of AUV gives corresponding results of tracking, as seen in Fig. 9, considering that the initial state coincides with the initial desired state. As observed in sine wave trajectory tracking, ANFSMC is able to provide trajectory tracking with a small associated error and no chattering at all. It is clearly noticed that the traditional SMC and FSMC had a large deviation from the desired path along with some oscillation. Despite the external disturbance forces and 20 % parameter variation with respect to diving model parameters, the ANFSMC allows the underwater robotic vehicle to track the desired trajectory with a less tracking error, and the undesirable chattering effect did not appear in Fig. 10, the disturbance signal employed in simulation as $d_{(t)} = 0.5\sin(\pi t)$.

From these simulation results, SMC is not recommended unless its design doesn't base on the model dynamics and has a large deviation error with oscillatory behavior. To overcome this problem, the model-independent FSMC technique introduced to reduce oscillatory behavior and reaching time. Meanwhile, tracking response can be enhanced by combining NN and FSMC with gain adaptation scheme, able to handle ocean disturbance and parametric uncertainty. The trajectory tracking control performance in the dive plane is also confirmed by quantitative analysis, as given in Table 5. From performance indices, it is to be noted that the proposed control scheme provides minimum tracking errors in diving motion behavior in comparison with conventional SMC and FSMC.

VI. CONCLUSION

A combined form of the robust intelligent control method for diving motion control of an AUV was proposed in this article. The efficacy of the controller was demonstrated with the assistance of numerical simulations on vehicle motion control in a dive plane. The proposed control scheme utilized the benefits of sliding mode, neural network, fuzzy logic, and adaptive PID techniques, while the shortcomings attributed to these methods are remedied by each other.From obtained simulation results, the strengths of the proposed method are attributed as follows:

- Development of single-input fuzzy PI uncertainty estimator for online estimation of lumped uncertainty vector included hydrodynamic added mass and linear/ quadratic drag coefficients rather than depend on the bounds of uncertainties.
- Development of an equivalent control law using an ADALINE NN to estimate unknown nonlinear system function and also reject ocean disturbances.
- The problem of the chattering effect eliminated and also breaks the restricting conditions on pitch angle movement in diving motion.
- The stability and error converge of the closed-loop tracking control system were guaranteed by means of Lyapunov stability criterion without any assumptions on the bounds of perturbations.
- The proposed diving autopilot has a simple control structure and design method; therefore, it can be used for practical implementation with a low-cost microprocessor.

Simulation results confirm that the proposed controller performs remarkably well in terms of robustness, tracking error convergence, and disturbance attenuation. The tracking performance has been verified through quantitative analysis.

REFERENCES

[1] D. Fryxell, P. Oliveira, A. Pascoal, C. Silvestre, and I. Kaminer, "Navigation, guidance and control of AUVs: An application to the MARIUS vehicle," *Control Eng. Pract.*, vol. 4, no. 3, pp. 401–409, Mar. 1996.

[2] P. A. DeBitetto, "Fuzzy logic for depth control of unmanned undersea vehicles," in *Proc. IEEE Symp. Auto. Underwater Vehicle Technol. (AUV)*, Cambridge, MA, USA, Jul. 1994, pp. 233–241, doi: 10.1109/AUV.1994.518630.

[3] L. Lapierre, "Robust diving control of an AUV," *Ocean Eng.*, vol. 36, no. 1, pp. 92–104, Jan. 2009.

[4] B. Jalving, "The NDRE-AUV flight control system," *IEEE J. Ocean. Eng.*, vol. 19, no. 4, pp. 497–501, Oct. 1994.

[5] J.-H. Li and P.-M. Lee, "Design of an adaptive nonlinear controller for depth control of an autonomous underwater vehicle," *Ocean Eng.*, vol. 32, nos. 17–18, pp. 2165–2181, Dec. 2005.

[6] J. H. Li and P. M. Lee, "A neural network adaptive controller design for free-pitch-angle diving behavior of an autonomous underwater vehicle," *Robot. Auto. Syst.*, vol. 52, nos. 2–3, pp. 132–147, Aug. 2005.

[7] D. Yoerger, J. Newman, L. Lapierre, and J.-J. Slotine, "Supervisory control system for the JASON ROV," *IEEE J. Ocean. Eng.*, vol. JOE-11, no. 3, pp. 392–400, Jul. 1986.

[8] J. Yuh, "A neural net controller for underwater robotic vehicles," *IEEE J. Ocean. Eng.*, vol. 15, no. 3, pp. 161–166, Jul. 1990.

[9] K. R. Goheen and E. R. Jefferys, "Multivariable self-tuning autopilots for autonomous and remotely operated underwater vehicles," *IEEE J. Ocean. Eng.*, vol. 15, no. 3, pp. 144–151, Jul. 1990.

[10] B. Geranmehr and S. R. Nekoo, "Nonlinear suboptimal control of fully coupled non-affine six-DOF autonomous underwater vehicle using the state-dependent Riccati equation," *Ocean Eng.*, vol. 96, pp. 248–257, Mar. 2015.

[11] A. Pisano and E. Usai, "Output-feedback control of an underwater vehicle prototype by higher-order sliding modes," *Automatica*, vol. 40, no. 9, pp. 1525–1531, Sep. 2004.

[12] C. Silvestre, A. Pascoal, and I. Kaminer, "On the design of gain-scheduled trajectory tracking controllers," *Int. J. Robust Nonlinear Control*, vol. 12, no. 9, pp. 797–839, Jul. 2002.

[13] Z. Feng and R. Allen, "Reduced order H^{∞} control of an autonomous underwater vehicle," *Control Eng. Pract.*, vol. 12, no. 12, pp. 1511–1520, Dec. 2004.

[14] D. Yoerger and J. Slotine, "Robust trajectory control of underwater vehicles," *IEEE J. Ocean. Eng.*, vol. JOE-10, no. 4, pp. 462–470, Oct. 1985.

[15] K. Ishaque, S. S. Abdullah, S. M. Ayob, and Z. Salam, "A simplified approach to design fuzzy logic controller for an underwater vehicle," *Ocean Eng.*, vol. 38, no. 1, pp. 271–284, Jan. 2011.

[16] P. S. Londhe, M. Santhakumar, L. M. Waghmare, and B. M. Patre, "Task space control of an autonomous underwater vehicle manipulator system by robust single-input fuzzy logic control scheme," *IEEE J. Ocean. Eng.*, vol. 42, no. 1, pp. 13–28, May 2016.

[17] A. Moura, R. Rijo, P. Silva, and S. Crespo, "A multi-objective genetic algorithm applied to autonomous underwater vehicles for sewage outfall plume dispersion observations," *Appl. Soft Comput.*, vol. 10, no. 4, pp. 1119–1126, Sep. 2010.

[18] J.-S. Wang and C. S. G. Lee, "Self-adaptive recurrent neuro-fuzzy control of an autonomous underwater vehicle," *IEEE Trans. Robot. Autom.*, vol. 19, no. 2, pp. 283–295, Apr. 2003.

[19] G. Campa, M. Innocenti, and F. Nasuti, "Robust control of underwater vehicles: Sliding mode control vs. Mu synthesis," in *Proc. IEEE Ocean. Eng. Soc.*, vol. 3, Sep./Oct. 1998, pp. 1640–1644.

[20] M. Santhakumar and T. Asokan, "Investigations on the hybrid tracking control of an underactuated autonomous underwater robot," *Adv. Robot.*, vol. 24, no. 11, pp. 1529–1556, Jan. 2010.

[21] M. Zeinali and L. Notash, "Adaptive sliding mode control with uncertainty estimator for robot manipulators," *Mechanism Mach. Theory*, vol. 45, no. 1, pp. 80–90, Jan. 2010.

[22] H. Pan, W. Sun, H. Gao, and X. Jing, "Disturbance observer-based adaptive tracking control with actuator saturation and its application," *IEEE Trans. Autom. Sci. Eng.*, vol. 13, no. 2, pp. 868–875, Apr. 2016.

[23] H. Pan and W. Sun, "Nonlinear output feedback finite-time control for vehicle active suspension systems," *IEEE Trans. Ind. Informat.*, vol. 15, no. 4, pp. 2073–2082, Apr. 2019.

[24] G. V. Lakhekar, L. M. Waghmare, and R. G. Roy, "Disturbance observer-based fuzzy adapted S-surface controller for spatial trajectory tracking of autonomous underwater vehicle," *IEEE Trans. Intell. Veh.*, vol. 4, no. 4, pp. 622–636, Dec. 2019.

[25] F. Song and S. M. Smith, "Design of sliding mode fuzzy controllers for an autonomous underwater vehicle without system model," in *Proc. OCEANS MTS/IEEE Conf. Exhib.*, Providence, RI, USA, Sep. 2000, pp. 835–840, doi: 10.1109/OCEANS.2000.881362.

[26] J. Guo, F.-C. Chiu, and C.-C. Huang, "Design of a sliding mode fuzzy controller for the guidance and control of an autonomous underwater vehicle," *Ocean Eng.*, vol. 30, no. 16, pp. 2137–2155, Nov. 2003.

[27] J. H. Li, P. M. Lee, S. W. Hong, and S. J. Lee, "Stable nonlinear adaptive controller for an autonomous underwater vehicle using neural networks," *Int. J. Syst. Sci.*, vol. 38, no. 4, pp. 327–337, 2007.

[28] L.-J. Zhang, X. Qi, and Y.-J. Pang, "Adaptive output feedback control based on DRFNN for AUV," *Ocean Eng.*, vol. 36, nos. 9–10, pp. 716–722, Jul. 2009.

[29] T. W. Kim and J. Yuh, "Application of on-line neuro-fuzzy controller to AUVs," *Inf. Sci.*, vol. 145, nos. 1–2, pp. 169–182, Aug. 2002.

[30] J.-S. Wang, C. S. G. Lee, and J. Yuh, ''Self-adaptive neuro-fuzzy systems with fast parameter learning for autonomous underwater vehicle control,'' in *Proc. ICRA. Millennium Conf. IEEE Int. Conf. Robot. Automat.*, San Francisco, CA, USA, vol. 4, Apr. 2000, pp. 3861–3866.
[31] K. N. Tiwari, L. M. Waghmare, and P. Krishnankutty, ''Single input fuzzy logic controller tuning for steering control of autonomous underwater vehicle: Genetic algorithm approach,'' in *Proc. Indian Control Conf. (ICC)*, Hyderabad, India, Jan. 2016, pp. 335–340.
[32] T. I. Fossen, *Guidance and Control of Ocean Vehicles*. Hoboken, NJ, USA: Wiley, 1994, pp. 448–451.
[33] E. A. de Barros, A. Pascoal, and E. de Sa, ''AUV dynamics: Modelling and parameter estimation using analytical, semi-empirical, and CFD methods,'' *IFAC Proc. Volumes*, vol. 37, no. 10, pp. 369–376, Jul. 2004.
[34] M. Li, F. Wang, and F. Gao, ''PID-based sliding mode controller for nonlinear processes,'' *Ind. Eng. Chem. Res.*, vol. 40, no. 12, pp. 2660–2667, Jun. 2001.
[35] L. Behera, S. Kumar, and A. Patnaik, ''On adaptive learning rate that guarantees convergence in feedforward networks,'' *IEEE Trans. Neural Netw.*, vol. 17, no. 5, pp. 1116–1125, Sep. 2006.
[36] Y. Yildiz, K. Abidi, and A. Sabanovic, ''A novel approach to neuro-sliding mode controllers for systems with unknown dynamics,'' in *Proc. IEEE Int. Conf. Ind. Technol.*, Maribor, Slovenia, vol. 1, Dec. 2003, pp. 304–308.
[37] G. V. Lakhekar and L. M. Waghmare, ''Robust maneuvering of autonomous underwater vehicle: An adaptive fuzzy PI sliding mode control,'' *Intell. Service Robot.*, vol. 10, no. 3, pp. 195–212, Jul. 2017.

GIRISH V. LAKHEKAR received the B.E. degree in instrumentation engineering from Dr. Babasaheb Ambedkar Marathwada University, Aurangabad, India, in 2007, and the M.Tech. and Ph.D. degrees in instrumentation engineering from Swami Ramanand Teerth Marathwada University, Nanded, India, in 2009 and 2019, respectively. He is currently an Assistant Professor with the Department of Instrumentation Engineering, Government College of Engineering, Jalgaon, India. He has published seven articles in international journals and nine papers in national/international conferences. His active research interests include control of underwater robotic vehicles, sliding mode control, advanced process control, and cognitive radio. He is a Life Member of the Indian Society for Technical Education (ISTE) and the Institution of Engineers (IE).

LAXMAN M. WAGHMARE (Member, IEEE) received the B.E. and M.E. degrees from the Shri Guru Gobind Singhji Institute of Engineering and Technology, Nanded, India, in 1986 and 1990, respectively, and the Ph.D. degree in instrumentation engineering from IIT Roorkee, Roorkee, India, in 2001. He is currently a part of a research project sponsored by the Naval Research Board (DRDO) in progress. He is a Professor with the Department of Instrumentation Engineering, Shri Guru Gobind Singhji Institute of Engineering and Technology, Nanded. He is also the Dean of science and technology with Swami Ramanand Teerth Marathwada University, Nanded. He has one book and more than 130 publications in national/international conferences and journals to his credit. His research interests include intelligent control, process control, and image processing. He is a member of professional societies such as the Instrument Society of India (ISI), the Institution of Engineers (IE), the Institution of Engineering and Technology (IET), and the Indian Society for Technical Education (ISTE). He was a recipient of the K. S. Krishnan Memorial National Award for the Best System Oriented Research Paper (published in *IETE Journal of Research*).

PRAKASH G. JADHAV received the B.E. degree in chemical engineering from Dr. Babasaheb Ambedkar Marathwada University, Aurangabad, India, in 1990, the M.Tech. degree in environmental engineering from IIT Bombay, Mumbai, India, in 2002, and the Ph.D. degree in chemical engineering from Swami Ramanand Teerth Marathwada University, Nanded, India, in 2014. He is currently a Professor with the Department of Chemical Engineering, Shri Guru Gobind Singhji Institute of Engineering and Technology, Nanded. His active research interests include applications of process control, industrial pollution control, and chemical process operation.

RUPAM GUPTA ROY received the B.E. degree in instrumentation engineering from Dr. Babasaheb Ambedkar Marathwada University, Aurangabad, India, in 2007, and the M.Tech. degree in instrumentation engineering from the National Institute of Technology (NIT), Agartala, India, in 2013. He is currently an Assistant Professor with the Department of Electronics and Instrumentation Engineering, NIT, Agartala. His active research interests include applications of sliding mode control, process instrumentation, and industrial automation.