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A fuzzy wavelet neural network-based approach to hypersonic flight vehicle direct nonaffine hybrid control

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Abstract A direct nonaffine hybrid control methodology is proposed for a generic hypersonic flight models based on fuzzy wavelet neural networks (FWNNs). The addressed strategy extends the previous indirect nonaffine control approaches stemming from simplified models of affine formulations. To cope with nonaffine effects on control design, analytically invertible models are constructed and then novel hybrid controllers are developed directly using nonaffine models. Furthermore, by employing FWNNs to devise adaptive terms, inversion errors are canceled via fuzzy neural approximations. In addition, robust terms are designed to achieve larger stable region in comparison with earlier work using Lyapunov synthesis. Finally, numerical simulation results from a hypersonic flight vehicle model are given to clarify the efficiency of the proposed direct nonaffine control scheme in the presence of parametric uncertainties.

Keywords Hypersonic flight vehicle · Direct nonaffine control · Fuzzy wavelet neural networks · Analytically invertible models · Inversion errors

List of symbols

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1 Introduction

Hypersonic flight vehicles (HFVs) have spurred considerable attention owing to its promising prospect for a reliable and cost-efficient access to near-space for both civilian and military applications [\[1](#page-11-0),[2\]](#page-11-1). To capture all of the potential effects on HFVs controllability, we must take into consideration aerodynamics, aerodynamic heating, and flexible airframe, as well as the interactions among these disciplines. For this reason, the vehicle model we developed is highly coupled and nonlinear. This makes hypersonic flight control a challenging research area. Moreover, owing to the inconstant of the vehicle characteristics including aerodynamics and thrust level with varying flight conditions, significant uncertainties affect the vehicle model [\[3](#page-11-2)[–7](#page-11-3)]. Besides, HFVs usually experience extreme aerothermal loads that cause dynamic forces and moments to rapidly change, which further increase the model uncertainties.

The nonlinear and coupled motion model for HFVs implies that the vehicle model is completely nonaffine in the control inputs (For example, " $\dot{x} = f(x, u)$ " is nonaffine and " $\dot{x} = g(x) + F(x)u$ " is affine, where *x* is the state, *u* is the control input, $f($, $g()$ and $F()$ are given functions.). Noting that it is extreme difficult to directly design controls using such a highly coupled nonaffine system, lots of efforts are made to simplify HFV's nonaffine models as affine ones, followed by affine control designs for HFVs [\[8](#page-11-4)[–13\]](#page-11-5). In [\[14](#page-11-6)[,15](#page-11-7)], simplified affine models are firstly constructed applying the input/output linearization technique based on Lie derivative notations, and then affine sliding mode controllers are presented for HFVs to provide robust tracking of reference trajectories. Moreover, under rigorous assumptions/restrictions, HFVs' motion models are directly simplified as affine ones of the formulations $\dot{y}_i = f_i(y_i) + g_i(y_i)u_i$ ($f_i()$ and $g_i() \neq 0$ are given functions, u_i and y_i are the control input and state, respectively.) [\[16](#page-11-8)[–19](#page-11-9)], on this basis, various affine control methodologies are addressed. However, model simplifications mean that we neglect certain key dynamic characteristics of HFVs, probably resulting in invalidation of control systems [\[20\]](#page-11-10). Besides, additional techniques have to be attached to improve these controllers' robust performance against system uncertainties especially the ones caused by model simplifications.

Noticing the fact that HFVs' motion models are nonlinear in the control inputs, nonaffine control designs for them also spur considerable interests. In [\[21](#page-11-11)], an indirect nonaffine control method is investigated, that is, the HFV's nonaffine model is firstly equivalently converted into an affine one by adding and subtracting the same term $k_i u_i$ (u_i is the control input, and k_i is a positive constant to be designed.) in each subsystem of HFV's model, and then an affine controller is devised. Another indirect nonaffine control strategy [\[22,](#page-11-12)[23\]](#page-11-13) is exploited by transforming the nonaffine motion model into an affine one based on Mean Value Theorem, which yields an unknown control direction problem that is handed by introducing a Nussbaum-type function.

Despite excellent tracking performance obtained by the previous studies, it is worth pointing out that there is still a considerable lack of effort in direct nonaffine control designs. Therefore, in this paper, we propose a novel direct nonaffine control methodology for HFVs. The special contributions are as summarized follows.

- (1) A direct nonaffine hybrid control is presented based on the invertible theory, which avoids model simplifications and exhibits fine practicability and reliability.
- (2) To guarantee the addressed hybrid controllers with satisfactory robustness against pragmatic uncertainties, fuzzy wavelet neural networks (FWNNs) are applied to estimate unknown flight dynamics. Furthermore, the computational costs for online

learning parameters are reduced by developing modified regulation laws.

(3) In contrast to the existing methods, larger stable region of the closed-loop control system is achieved owing to the developed robust terms.

The rest of this paper is structured as follows. Problem formulations are presented in Sect. [2.](#page-2-0) Section [3](#page-4-0) shows the design procedure of hybrid controller. Simulation results are given in Sect. [4,](#page-9-0) and the conclusions are shown in Sect. [5.](#page-10-0)

2 Problem formulation

2.1 Vehicle model

In this study, we use a longitudinal motion model developed by Parker, formulated as [\[7](#page-11-3)]

$$
\dot{V} = T\cos(\theta - \gamma)/m - D/m - g\sin\gamma
$$
 (1)

$$
\dot{h} = V \sin \gamma \tag{2}
$$

$$
\dot{\gamma} = L/(mV) + T \sin(\theta - \gamma)/(mV) - (g/V) \cos \gamma
$$
\n(3)

$$
\dot{\theta} = Q \tag{4}
$$

$$
\dot{Q} = (M + \ddot{\psi}_1 \ddot{\eta}_1 + \ddot{\psi}_2 \ddot{\eta}_2) / I_{yy}
$$
\n(5)

$$
k_1 \ddot{\eta}_1 = -2\zeta_1 \omega_1 \dot{\eta}_1 - \omega_1^2 \eta_1 + N_1 -\tilde{\psi}_1 M / I_{yy} - \tilde{\psi}_1 \tilde{\psi}_2 \ddot{\eta}_2 / I_{yy}
$$
 (6)

$$
k_2 \ddot{\eta}_2 = -2\zeta_2 \omega_2 \dot{\eta}_2 - \omega_2^2 \eta_2 + N_2 - \tilde{\psi}_2 M / I_{yy} - \tilde{\psi}_2 \tilde{\psi}_1 \ddot{\eta}_1 / I_{yy}
$$
 (7)

In the above model, velocity *V*, altitude *h*, flightpath angle γ , pitch angle θ and pitch rate Q are the rigid body states, η_1 and η_2 are the flexible states. The attack angle $\alpha = \theta - \gamma$. The thrust force *T*, drag force *D*, lift force *L*, pitching moment *M* and the generalized force N_1 and N_2 are defined as [\[7](#page-11-3)]

$$
T \approx \beta_1 (h, \bar{q}) \Phi \alpha^3 + \beta_2 (h, \bar{q}) \alpha^3
$$

+ $\beta_3 (h, \bar{q}) \Phi \alpha^2 + \beta_4 (h, \bar{q}) \alpha^2$
+ $\beta_5 (h, \bar{q}) \Phi \alpha + \beta_6 (h, \bar{q}) \alpha$
+ $\beta_7 (h, \bar{q}) \Phi + \beta_8 (h, \bar{q})$,

$$
D \approx \bar{q} SC_D^{\alpha^2} \alpha^2 + \bar{q} SC_D^{\alpha} \alpha + \bar{q} SC_D^{\delta^2} \delta^2
$$

+ $\bar{q} SC_D^{\delta_c} \delta_c + \bar{q} SC_D^0$,

$$
M \approx z_T T + \bar{q} S \bar{c} C_{M,\alpha}^{\alpha^2} \alpha^2 + \bar{q} S \bar{c} C_{M,\alpha}^{\alpha} \alpha + \bar{q} S \bar{c} C_{M,\alpha}^0
$$

+ $\bar{q} S \bar{c} c_c \delta_c$,

$$
L \approx \bar{q} SC_L^{\alpha} \alpha + \bar{q} SC_L^{\delta_c} \delta_c + \bar{q} SC_L^0
$$
,

$$
N_1 = N_1^{\alpha^2} \alpha^2 + N_1^{\alpha} \alpha + N_1^0,
$$

\n
$$
N_2 = N_2^{\alpha^2} \alpha^2 + N_2^{\alpha} \alpha + N_2^{\delta_e} \delta_e + N_2^0, \quad \bar{q} = \bar{\rho} V^2 / 2,
$$

\n
$$
\bar{\rho} = \bar{\rho}_0 \exp(-(h - h_0)/h_s),
$$

where the control inputs Φ and δ_e denote fuel equivalence ratio and elevator angular deflection, respectively. For more detailed definitions of other parameters and coefficients, the reader could refer to [\[7\]](#page-11-3) or Nomenclature

Remark 1 Some sample plots [\[7](#page-11-3)] of aerodynamic data derived from the above vehicle model are shown in Fig. [1.](#page-3-0) Obviously, the HFVs' model is completely nonaffine, which is due to that the above motion model contains these nonlinear terms " δ_e^2 ," " α^{3} " and " α^2 ." (For back-stepping designs, α is treated as a virtual control input.) For this reason, in what follows, we directly employ the vehicle nonaffine model to devise controllers. Furthermore, to represent the entire model's features, the pole-zero map [\[7\]](#page-11-3) is depicted in Fig. [2.](#page-4-1)

2.2 Control objective

To facilitate the subsequent control designs, the motion model of HFVs is formally decomposed into the velocity subsystem (i.e., Eq. [\(1\)](#page-2-1)) and the altitude subsystem $(i.e., Eqs. (2)–(5)).$ $(i.e., Eqs. (2)–(5)).$ $(i.e., Eqs. (2)–(5)).$ $(i.e., Eqs. (2)–(5)).$ $(i.e., Eqs. (2)–(5)).$

The velocity subsystem (1) is rewritten as a succinct nonaffine formulation:

$$
\begin{cases}\n\dot{V} = f_V(V, \Phi) \\
y_V = V \\
u_V = \Phi\n\end{cases}
$$
\n(8)

where $f_V(V, \Phi)$ is an unknown differentiable function; u_V and y_V are the control input and output of velocity subsystem, respectively.

Building upon the previous studies [\[22,](#page-11-12)[23\]](#page-11-13), the altitude subsystem (3) – (5) can be transformed as the following nonaffine form:

$$
\begin{cases}\n\dot{z}_1 = z_2\\ \n\dot{z}_2 = z_3\\ \n\dot{z}_3 = F_h(x, \delta_e)\\ \ny_h = z_1 = \gamma\\ \nu_h = \delta_e\n\end{cases} \tag{9}
$$

Fig. 1 The responses of drag, lift and moment along with the varying of α and δ_e . **a** The response of drag. **b**, the response of lift, **c** the response of moment

where $F_h(x, \delta_e)$ is an unknown differentiable function and $\mathbf{x} = [\gamma, \theta, Q]^{\mathrm{T}} \in \mathbb{R}^3$; u_h and y_h mean the control input and output of altitude subsystem, respectively.

The pursued control objective is that velocity *V* and altitude *h* follow their reference trajectories *V*ref and *h*ref in the presence of parametric uncertainties by developing direct nonaffine hybrid controllers Φ and δ_{e} .

2.3 FWNN approximate

FWNN is combined wavelet theory with fuzzy logic and neural networks (NNs). Because fuzzy logics can improve wavelet neural approximation performance, FWNN exhibits excellent performance and global approximation [\[24](#page-11-14)[,25](#page-11-15)]. Thus, we employ it as an accurate function approximator in this study.

For the simplify of formulation, by employing a singleton fuzzifier, product inference and weighted average defuzzifier, the output of FWNN can be described as

Fig. 2 Pole-zero maps of the Jacobian linearization of the adopted HFV model. Inputs $u = [\Phi, \delta_e]$, outputs $y = [V, \gamma]$

$$
y = \boldsymbol{W}^{\mathrm{T}} \boldsymbol{\psi}(\ell) \tag{10}
$$

where $\ell = [\ell_1, \ell_2, \cdots, \ell_n]^T \in \mathbb{R}^n$ is the input vector and $W^T = [w_1, w_1, \dots, w_N]^T \in \Re^N$ is the weight matrix; $\boldsymbol{\psi}(\ell) = [\psi_1(\ell), \psi_2(\ell), \cdots, \psi_N(\ell)]^T$ is the fuzzy wavelet basis function vector and ψ_i ⁽⁾ has the following formulation:

$$
\psi_j = \prod_{i=1}^n g_{ji}(\ell_i)\phi_j / \sum_{j=1}^N \phi_j \tag{11}
$$

where $g_{ji}(\ell_i) = 1 - b_{ji}^2(\ell_i - c_{ji})^2$ and $\phi_j =$ $\prod_{i=1}^{n} \mu_{A_{ji}}(\ell_i)$ is the firing strength with the membership function $\mu_{A_{ji}}(\ell_i)$ given by $\mu_{A_{ji}}(\ell_i) = \exp(-\ell_i)$ $(-b_{ji}^2(\ell_i - c_{ji})^2)$; b_{ji} and c_{ji} are dilation and translation parameters, respectively.

Traditionally, Taylor expansion linearization technique is usually applied to convert the nonlinear fuzzy wavelet basis function into a partially linear function of ψ_i , b_{ji} and c_{ji} [\[24\]](#page-11-14). Then, parameters ψ_i , b_{ji} and *c ji* are all online regulated for the sake of achieving desired approximation performance. This leads to high computational burden and reduces the real-time performance of control system. Therefore, an advanced learning scheme is adopted to directly turn $\varphi = ||\psi(\ell)||^2$ by setting appropriate values for b_{ji} and c_{ji} . In this way, there is only one learning parameter φ . Thus, the online computational load is low.

3 Hybrid control design

3.1 Velocity control design

Assumption 1 [\[21](#page-11-11)] $\partial f_V(V, \Phi)/\partial \Phi$ is continuous and positive.

Define velocity tracking error $\tilde{V} = V - V_{\text{ref}}$. Then using (8) , \tilde{V} is derived as

$$
\dot{\tilde{V}} = \dot{V} - \dot{V}_{\text{ref}} = f_V(V, \Phi) - \dot{V}_{\text{ref}} \tag{12}
$$

From [\(12\)](#page-4-2), a hybrid pseudocontrol v_V is developed as

$$
v_V = \hat{f}_V(V, \Phi) \tag{13}
$$

where $\hat{f}_V(V, \Phi)$ denotes the approximate of $f_V(V, \Phi)$. Define the inversion error $\delta_V = f_V(V, \Phi) - \hat{f}_V(V, \Phi)$ and then Eq. [\(12\)](#page-4-2) becomes

$$
\tilde{\dot{V}} = \delta_V + \hat{f}_V(V, \Phi) - \dot{V}_{ref}
$$
\n(14)

Assumption 2 It is concluded from Assumption [1](#page-4-3) that $\partial f_V(V, \Phi)/\partial \Phi$ also is continuous and positive.

The hybrid controller v_V is designed as

$$
v_V = v_{V1} + v_{V2} - v_{V3} + v_{V4}
$$
 (15)

where $v_{V1} = \dot{V}_{ref}$ and $v_{V2} = -K_{V1}\tilde{V} - K_{V2}\int_0^t \tilde{V}(\tau)$ d τ ; $K_{V1} \in \mathbb{R}^+$ and $K_{V2} \in \mathbb{R}^+$ are constants to be chosen; v_{V4} is a robust term and v_{V3} will be devised to cancel δ_V .

The control input Φ is derived from [\(13\)](#page-4-4) as follows

$$
\Phi = \hat{f}_V^{-1}(V, \nu_V) \tag{16}
$$

Substituting (13) and (15) into (14) , we have

$$
\tilde{V} = \delta_V + \nu_V - \dot{V}_{ref}
$$
\n
$$
= \delta_V + \nu_{V1} + \nu_{V2} - \nu_{V3} + \nu_{V4} - \dot{V}_{ref}
$$
\n
$$
= -K_{V1}\tilde{V} - K_{V2}\int_0^t \tilde{V}(\tau)d\tau + \delta_V - \nu_{V3} + \nu_{V4}
$$
\n(17)

with

$$
\delta_V - v_{V3} = f_V(V, \hat{f}_V^{-1}(V, v_{V1} + v_{V2} - v_{V3} + v_{V4})) - \hat{f}(V, \hat{f}_V^{-1}(V, v_{V1} + v_{V2} - v_{V3} + v_{V4})) - v_{V3}
$$

 \mathcal{D} Springer

$$
= f_V(V, \hat{f}_V^{-1}(V, \nu_{V1} + \nu_{V2} - \nu_{V3} + \nu_{V4})) - \nu_{V1} - \nu_{V2} - \nu_{V4}
$$
\n(18)

By defining $v_{VI} \triangleq v_{V1} + v_{V2}$ and $v_V^* \triangleq$ $\hat{f}_V(V, f_V^{-1}(V, v_V_I)),$ we obtain $f_V^{-1}(V, v_V_I)$ $=\hat{f}_V^{-1}(V, v_V^*) \Rightarrow v_{VI} = f_V(V, \hat{f}_V^{-1}(V, v_V^*)).$ Then, Eq. [\(18\)](#page-4-7) becomes

$$
\delta_V - \nu_{V3} = f_V(V, \hat{f}_V^{-1}(V, \nu_V)) - \nu_{V1} - \nu_{V4}
$$

= $f_V(V, \hat{f}_V^{-1}(V, \nu_V))$
 $-f_V(V, \hat{f}_V^{-1}(V, \nu_V^*)) - \nu_{V4}$ (19)

By Mean Value Theorem, Eq. [\(19\)](#page-5-0) is further rewritten as

$$
\delta_V - \nu_{V3} = f_V(V, \hat{f}_V^{-1}(V, \nu_V)) \n-f_V(V, \hat{f}_V^{-1}(V, \nu_V^*)) - \nu_{V4} \n= f_V(\bar{\nu}_V)(\nu_V - \nu_V^*) - \nu_V4 \n= f_V(\bar{\nu}_V)(\nu_{V1} - \nu_{V3} + \nu_V4 \n- \hat{f}_V(V, f_V^{-1}(V, \nu_V))) - \nu_V4 \n= f_V(\bar{\nu}_V)(\bar{\nu}_V - \nu_V3 + \nu_V4) - \nu_V4
$$
\n(20)

where $\bar{v}_{VI} = v_{VI} - \hat{f}_V(V, f_V^{-1}(V, v_{VI})) = f_V(V, \hat{f}_V^{-1})$ (V, v_V^*) – v_V^* is an unknown term; $f_V(\bar{v}_V)$ = $\frac{\partial f_V}{\partial \Phi} \frac{\partial \Phi}{\partial v_V} \Big|_{v_V = \bar{v}_V} = \frac{\partial f_V}{\partial \Phi} \frac{\partial \hat{f}_V}{\partial \Phi} \Big|_{\Phi = \hat{f}_V^{-1}(V, \bar{v}_V)}$ > 0 and $\bar{v}_V = \theta_V v_V + (1 - \theta_V)v_V^*$ with $\theta_V \in [0, 1].$

Substituting [\(20\)](#page-5-1) into [\(17\)](#page-4-8) yields

$$
\dot{\tilde{V}} = -K_{V1}\tilde{V} - K_{V2}\int_0^t \tilde{V}(\tau)d\tau + f_V(\tilde{\upsilon}_V)(\tilde{\upsilon}_{Vl} - \upsilon_{V3}) + f_V(\tilde{\upsilon}_V)\upsilon_{V4}
$$
\n(21)

If \bar{v}_{VI} is known, we can set $v_{V3} = \bar{v}_{VI}$ to stabilize [\(8\)](#page-2-2). However, \bar{v}_{VI} is usually unknown and hereon we employ one FWNN to approximate it. Based on the universal approximation theorem $[24,25]$ $[24,25]$ $[24,25]$, there must exist an ideal weight vector $W_V^* \in \mathbb{R}^N$ such that

$$
\bar{v}_{Vl} = W_V^{*T} \psi_V(\ell_V) + \varepsilon_V \tag{22}
$$

where $\ell_V = V$ is the input of FWNN and $\psi_V(\ell_V)$ has the same formulation as [\(11\)](#page-4-9); ε_V is an approximation error and there is a constant $\varepsilon_{VM} \in \mathbb{R}^+$ such that $|\varepsilon_V| \leq \varepsilon_{VM}.$

Define $\varphi_V = ||\boldsymbol{W}_V^*||^2 \in \Re$ and v_{V3} is devised as

$$
\upsilon_{V3} = \frac{1}{2} \tilde{V} \hat{\varphi}_V \psi_V^{\mathrm{T}}(\ell_V) \psi_V(\ell_V)
$$
 (23)

where $\hat{\varphi}_V$ denotes the estimate of φ_V .

For the single online parameter $\hat{\varphi}_V$, we design the following adaptive law:

$$
\dot{\hat{\varphi}}_V = \frac{\eta V}{2} \tilde{V}^2 \boldsymbol{\psi}_V^{\mathrm{T}}(\boldsymbol{\ell}_V) \boldsymbol{\psi}_V(\boldsymbol{\ell}_V) - 2\hat{\varphi}_V \tag{24}
$$

with $\eta_V \in \mathfrak{R}^+$.

Employing [\(22\)](#page-5-2) and [\(23\)](#page-5-3), $\bar{v}_{VI} - v_{V3}$ equals to

$$
\bar{v}_{VI} - v_{V3} = W_V^{*T} \psi_V(\ell_V) + \varepsilon_V
$$

$$
-\frac{1}{2} \tilde{V} \hat{\varphi}_V \psi_V^T(\ell_V) \psi_V(\ell_V)
$$
 (25)

Considering [\(25\)](#page-5-4), Eq. [\(21\)](#page-5-5) becomes

$$
\dot{\tilde{V}} = -K_{V1}\tilde{V} - K_{V2}\int_0^t \tilde{V}(\tau)d\tau \n+ f_V(\bar{v}_V)W_V^{*T}\psi_V(\ell_V) + f_V(\bar{v}_V)\varepsilon_V \n- \frac{1}{2}f_V(\bar{v}_V)\tilde{V}\hat{\varphi}_V\psi_V^T(\ell_V)\psi_V(\ell_V) \n+ f_V(\bar{v}_V)v_{V4}
$$
\n(26)

The robust term v_{V4} is chosen as

$$
v_{V4} = -\frac{\tilde{V}}{2\rho_V^2}
$$
 (27)

where $\rho_V \in \mathbb{R}^+$ is a constant to be selected.

Taking into consideration (27) , it is derived from (26) that

$$
\dot{\tilde{V}} = -K_{V1} \tilde{V} - K_{V2} \int_0^t \tilde{V}(\tau) d\tau \n+ f_V(\bar{\upsilon}_V) W_V^{*T} \psi_V(\ell_V) + f_V(\bar{\upsilon}_V) \varepsilon_V \n- \frac{1}{2} f_V(\bar{\upsilon}_V) \tilde{V} \hat{\varphi}_V \psi_V^T(\ell_V) \psi_V(\ell_V) \n- f_V(\bar{\upsilon}_V) \frac{\tilde{V}}{2\rho_V^2}
$$
\n(28)

Theorem 1 *Consider the closed-loop system consisting of plant* [\(8\)](#page-2-2) *under Assumptions* [1](#page-4-3) *and* [2](#page-4-10) *with controller* [\(15\)](#page-4-5) *and adaptive law* [\(24\)](#page-5-8)*. Then, all the signals involved are semi-globally uniformly ultimately bounded.*

Proof Define estimate error $\tilde{\varphi}_V = \hat{\varphi}_V - \varphi_V$. Define the following Lyapunov function:

$$
V_V = \frac{\tilde{V}^2}{2} + \frac{K_{V2}}{2} \left(\int_0^t \tilde{V}(\tau) d\tau \right)^2 + \frac{\bar{f}_V \tilde{\varphi}_V^2}{2\eta_V} \qquad (29)
$$

where $f_V \in \mathbb{R}^+$ is a constant to be ingeniously selected such that $f_V \leq f_V(\bar{v}_V)$ when $\tilde{\varphi}_V \tilde{\varphi}_V \geq 0$ or else $f_V > f_V(\bar{v}_V)$. We further have $f_V \tilde{\varphi}_V \tilde{\varphi}_V / \eta_V \leq$ $f_V(\bar{v}_V)\tilde{\varphi}_V\tilde{\varphi}_V/\eta_V$.

The time derivative of V_V is given by

$$
\dot{V}_V = \tilde{V}\dot{\tilde{V}} + K_{V2}\tilde{V} \int_0^t \tilde{V}(\tau) d\tau + \frac{\tilde{f}_V}{\eta_V} \tilde{\varphi}_V \dot{\tilde{\varphi}}_V \n\leq \tilde{V}\dot{\tilde{V}} + K_{V2}\tilde{V} \int_0^t \tilde{V}(\tau) d\tau \n+ \frac{f_V(\tilde{\upsilon}_V)}{\eta_V} \tilde{\varphi}_V \dot{\tilde{\varphi}}_V
$$
\n(30)

Substituting (24) and (28) into (30) leads to

$$
\dot{V}_V \leq -K_{V1}\tilde{V}^2 + f_V(\bar{v}_V)\tilde{V}W_V^{*T}\psi_V(\ell_V) \n+ f_V(\bar{v}_V)\tilde{V}\varepsilon_V \n- \frac{1}{2}f_V(\bar{v}_V)\tilde{V}^2\hat{\varphi}_V\psi_V^T(\ell_V)\psi_V(\ell_V) \n- f_V(\bar{v}_V)\frac{\tilde{V}^2}{2\rho_V^2} \n+ \frac{1}{2}f_V(\bar{v}_V)\tilde{V}^2\tilde{\varphi}_V\psi_V^T(\ell_V)\psi_V(\ell_V) \n- \frac{2f_V(\bar{v}_V)\tilde{\varphi}_V\hat{\varphi}_V}{\eta_V} \n= -K_{V1}\tilde{V}^2 + f_V(\bar{v}_V)\tilde{V}W_V^{*T}\psi_V(\ell_V) \n+ f_V(\bar{v}_V)\tilde{V}\varepsilon_V \n- \frac{1}{2}f_V(\bar{v}_V)\tilde{V}^2\varphi_V\psi_V^T(\ell_V)\psi_V(\ell_V) \n- f_V(\bar{v}_V)\frac{\tilde{V}^2}{2\rho_V^2} \n- \frac{2f_V(\bar{v}_V)\tilde{\varphi}_V\hat{\varphi}_V}{\eta_V}
$$
\n(31)

Notice that $\tilde{V}W^{\ast T}_{V} \psi_{V}(\ell_{V}) \leq \frac{\tilde{V}^{2}}{2} \left\| W^{\ast T}_{V} \psi_{V}(\ell_{V}) \right\|$ $^{2}+$ $\frac{1}{2} = \frac{\tilde{v}^2}{2} ||W_V^*||^2 ||\psi_V(\ell_V)||^2 + \frac{1}{2} = \frac{\tilde{v}^2}{2} \varphi_V \psi_V^T$
 $(\ell_V)\psi_V(\ell_V) + \frac{1}{2}, 2\tilde{\varphi}_V\hat{\varphi}_V \ge \tilde{\varphi}_V^2 - \varphi_V^2$ and $\tilde{V}\varepsilon_V \le$ $\left|\tilde{V}\right|\varepsilon_{VM} = 2$ $\frac{\tilde{V}}{2}$ $\varepsilon_{VM} \leq \frac{\tilde{V}^2}{4} + \varepsilon_{VM}^2$. Therefore, inequality [\(31\)](#page-6-1) becomes

$$
\dot{V}_V \le -K_{V1}\tilde{V}^2 - \frac{f_V(\bar{v}_V)\tilde{\varphi}_V^2}{\eta_V} + \frac{f_V(\bar{v}_V)\tilde{V}^2}{4} \n- f_V(\bar{v}_V)\frac{\tilde{V}^2}{2\rho_V^2} + \frac{f_V(\bar{v}_V)\varphi_V^2}{\eta_V} + \frac{1}{2}f_V(\bar{v}_V) \n+ f_V(\bar{v}_V)\varepsilon_{VM}^2
$$
\n(32)

Setting $\rho_V = \sqrt{2}$, we have

$$
\dot{V}_V \le -K_{V1}\tilde{V}^2 - \frac{f_V(\bar{v}_V)\tilde{\varphi}_V^2}{\eta_V} + \frac{f_V(\bar{v}_V)\varphi_V^2}{\eta_V}
$$

$$
+\frac{1}{2}f_V(\bar{v}_V) + f_V(\bar{v}_V)\varepsilon_{VM}^2\tag{33}
$$

Define the following compact sets:

$$
\Omega_{\tilde{V}} = \left\{ \tilde{V} \left| \left| \tilde{V} \right| \right\} \right\}
$$
\n
$$
\leq \sqrt{\left(\frac{f_V(\bar{v}_V)\varphi_V^2}{\eta_V} + \frac{1}{2}f_V(\bar{v}_V) + f_V(\bar{v}_V)\varepsilon_{VM}^2 \right) / K_{V1}} \right\}
$$
\n
$$
\Omega_{\tilde{\varphi}_V} = \left\{ \tilde{\varphi}_V \left| \left| \tilde{\varphi}_V \right| \leq \sqrt{\left(\frac{\varphi_V^2}{\eta_V} + \frac{1}{2} + \varepsilon_{VM}^2 \right) / \left(\frac{1}{\eta_V} \right)} \right\} \right\}
$$
\n(34)

If *V* $\notin \Omega_{\tilde{V}}$ or $\tilde{\varphi}_V \notin \Omega_{\tilde{\varphi}_V}$, we have $V_V < 0$. Hence, \tilde{V} and $\tilde{\varphi}_V$ are semi-globally uniformly ultimately bounded. Moreover, by choosing adequately large K_{V1} , the velocity tracking error \tilde{V} can be arbitrarily small. This completes the proof. 

3.2 Altitude control design

Assumption 3 [\[21](#page-11-11)] $\partial F_h(x, \delta_e)/\partial \delta_e$ is continuous and positive.

Define altitude tracking error $\tilde{h} = h - h_{ref}$ and the reference command $\gamma_d = \arcsin(-\kappa_h h/V + h_{\text{ref}}/V)$ with $\kappa_h \in \mathbb{R}^+$. When $\gamma \to \gamma_d$, we have $\kappa_h \tilde{h} = -\tilde{h}$, that is, $\tilde{h}\tilde{h} = -\tilde{h}^2/\kappa_h \le 0$ and \tilde{h} can converge to zero when $t \rightarrow \infty$. In what follows, the design objective becomes to let $\gamma \rightarrow \gamma_d$ by devising a hybrid control δ_e .

Define flight-path angle tracking error *eh* and error function *Eh* as

$$
\begin{cases} e_h = \gamma - \gamma_d = z_1 - \gamma_d \\ E_h = \left(\frac{d}{dt} + \mu_h\right)^3 \int_0^t e_h(\tau) d\tau \end{cases}
$$
(35)

where $\mu_h \in \mathfrak{R}^+$ and the polynomial $(s + \mu_h)^3$ is Hurwitz.

Define

$$
\begin{cases}\n\xi_1 = \dot{e}_h \\
\xi_2 = \dot{\xi}_1 \\
\xi_3 = \dot{\xi}_2\n\end{cases}
$$
\n(36)

Invoking [\(35\)](#page-6-2) and [\(36\)](#page-6-3), \dot{E}_h is given by

$$
\dot{E}_h = \xi_3 + 3\mu_h \xi_2 + 3\mu_h^2 \xi_1 + \mu_h^3 e_h
$$

= $F_h(x, \delta_e) - \ddot{V}_d + 3\mu_h \xi_2 + 3\mu_h^2 \xi_1 + \mu_h^3 e_h$ (37)

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We design the following hybrid pseudocontrol υ*h*:

$$
\nu_h = \hat{F}_h(\mathbf{x}, \delta_e) \tag{38}
$$

where $F_h(x, \delta_e)$ represents the estimate of $F_h(x, \delta_e)$ and the estimation error is formulated as δ_h = $F_h(\mathbf{x}, \delta_e) - F_h(\mathbf{x}, \delta_e)$. Then Eq. [\(37\)](#page-6-4) is rewritten as

$$
\dot{E}_h = \delta_h + \hat{F}_h(\mathbf{x}, \delta_e) - \ddot{v}_d + 3\mu_h \xi_2 + 3\mu_h^2 \xi_1 + \mu_h^3 e_h \tag{39}
$$

Assumption 4 Based on Assumption [3,](#page-6-5) we have that $\partial F_h(\mathbf{x}, \delta_e)/\partial \delta_e$ is continuous and positive.

We design the hybrid controller υ*h* as

$$
\nu_h = \nu_{h1} + \nu_{h2} - \nu_{h3} + \nu_{h4} \tag{40}
$$

where $v_{h1} = \ddot{v}_d$ and $v_{h2} = -K_h E_h - (3\mu_h \xi_2 + \dots)$ $3\mu_h^2 \xi_1 + \mu_h^3 e_h$; $K_h \in \mathbb{R}^+$ is a chosen parameter and v_{h3} will be developed to handle δ_h ; v_{h4} is a robust term to be designed.

From [\(38\)](#page-7-0), we can directly achieve the following altitude control effort:

$$
\delta_{\rm e} = \hat{F}_h^{-1}(\mathbf{x}, \nu_h) \tag{41}
$$

Using (38) and (40) , it is derived from (39) that

$$
\dot{E}_h = \delta_h + \nu_{h1} + \nu_{h2} - \nu_{h3} + \nu_{h4} - \ddot{\nu}_d \n+3\mu_h \xi_2 + 3\mu_h^2 \xi_1 + \mu_h^3 e_h \n= -K_h E_h + \delta_h - \nu_{h3} + \nu_{h4}
$$
\n(42)

with

$$
\delta_h - \upsilon_{h3} = F_h(\mathbf{x}, \hat{F}_h^{-1}(\mathbf{x}, \upsilon_{h1} + \upsilon_{h2} - \upsilon_{h3} + \upsilon_{h4}))
$$

\n
$$
- \hat{F}_h(\mathbf{x}, \hat{F}_h^{-1}(\mathbf{x}, \upsilon_{h1} + \upsilon_{h2} - \upsilon_{h3} + \upsilon_{h4})) - \upsilon_{h3}
$$

\n
$$
= F_h(\mathbf{x}, \hat{F}_h^{-1}(\mathbf{x}, \upsilon_{h1} + \upsilon_{h2} - \upsilon_{h3} + \upsilon_{h4}))
$$

\n
$$
- \upsilon_{h1} - \upsilon_{h2} - \upsilon_{h4}
$$
\n(43)

Define $v_{hl} \triangleq v_{h1} + v_{h2}$ and v_h^* $\stackrel{\Delta}{=}$ $\hat{F}_h(x, F_h^{-1})$ (\mathbf{x}, ν_h)). Then, we obtain $\nu_h = F_h(\mathbf{x}, \hat{F}_h^{-1}(\mathbf{x}, \nu_h^*))$. Thus, Eq. [\(43\)](#page-7-3) becomes

$$
\delta_h - \upsilon_{h3} = F_h(\mathbf{x}, \hat{F}_h^{-1}(\mathbf{x}, \upsilon_h)) - \upsilon_{h1} - \upsilon_{h4}
$$

= $F_h(\mathbf{x}, \hat{F}_h^{-1}(\mathbf{x}, \upsilon_h)) - F_h(\mathbf{x}, \hat{F}_h^{-1}(\mathbf{x}, \upsilon_h^*)) - \upsilon_{h4}$ (44)

Employing Mean Value Theorem, we further get

$$
\delta_h - \upsilon_{h3} = F_h(\mathbf{x}, \hat{F}_h^{-1}(\mathbf{x}, \upsilon_h))
$$

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$$
-F_h(\mathbf{x}, \hat{F}_h^{-1}(\mathbf{x}, \upsilon_h^*)) - \upsilon_{h4}
$$

= $F_h(\bar{\upsilon}_h)(\upsilon_h - \upsilon_h^*) - \upsilon_{h4}$
= $F_h(\bar{\upsilon}_h)(\upsilon_{hl} - \upsilon_{h3} + \upsilon_{h4}$
 $-\hat{F}_h(\mathbf{x}, F_h^{-1}(\mathbf{x}, \upsilon_{hl}))) - \upsilon_{h4}$
= $F_h(\bar{\upsilon}_h)(\bar{\upsilon}_{hl} - \upsilon_{h3} + \upsilon_{h4}) - \upsilon_{h4}$ (45)

where $\bar{v}_{hl} = v_{hl} - \hat{F}_h(\mathbf{x}, F_h^{-1}(\mathbf{x}, v_{hl})) = F_h(\mathbf{x}, \hat{F}_h^{-1})$ $(v, v_h^*))$ – v_h^* is an unknown term; $F_h(\bar{v}_h)$ $=\frac{\partial F_h}{\partial \delta_e} \frac{\partial \delta_e}{\partial v_h}\Big|_{v_h=\bar{v}_h} = \frac{\partial F_h}{\partial \delta_e}$ $\frac{\partial \hat{F}_h}{\partial \delta_e} \bigg|_{\delta_e = \hat{F}_h^{-1}(\boldsymbol{x}, \nu_h)}$ > 0 and $\bar{\nu}_h = \theta_h \nu_h + (1 - \theta_h) \nu_h^*$ with $\theta_h \in [0, 1].$ Substituting [\(45\)](#page-7-4) into [\(42\)](#page-7-5) yields

$$
\dot{E}_h = -K_h E_h + F_h(\bar{\upsilon}_h)(\bar{\upsilon}_{hl} - \upsilon_{h3}) + F_h(\bar{\upsilon}_h)\upsilon_{h4}
$$
\n(46)

To cancel \bar{v}_{hl} , we define $v_{h3} = \bar{v}_{hl}$. Owing to the fact that \bar{v}_{hl} cannot be calculated since it is unknown, we also introduce one FWNN to approximate it.

$$
\bar{v}_{hl} = \boldsymbol{W}_h^{*T} \boldsymbol{\psi}_h(\boldsymbol{\ell}_h) + \varepsilon_h \tag{47}
$$

where $\ell_h = x$ is the input vector of FWNN and $W_h^* \in$ \mathfrak{R}^N is an ideal weight vector; the formulation of $\psi_h(\ell_h)$ is the same as (11) ; ε_h is the approximation error and there exists a constant $\varepsilon_{hM} \in \mathbb{R}^+$ such that $|\varepsilon_h| \leq \varepsilon_{hM}$.

We select the following υ*h*3:

$$
\nu_{h3} = \frac{1}{2} E_h \hat{\varphi}_h \boldsymbol{\psi}_h^{\mathrm{T}}(\boldsymbol{\ell}_h) \boldsymbol{\psi}_h(\boldsymbol{\ell}_h)
$$
(48)

where $\hat{\varphi}_h$ denotes the estimation of $\varphi_h = ||\boldsymbol{W}_h^*||^2 \in \mathbb{R}$ and its adaptive law is designed as

$$
\dot{\hat{\varphi}}_h = \frac{\eta_h}{2} E_h^2 \boldsymbol{\psi}_h^{\mathrm{T}}(\boldsymbol{\ell}_h) \boldsymbol{\psi}_h(\boldsymbol{\ell}_h) - 2\hat{\varphi}_h \tag{49}
$$

with $\eta_h \in \mathfrak{R}^+$.

Then Eq. [\(46\)](#page-7-8) leads to

Based on [\(47\)](#page-7-6) and [\(48\)](#page-7-7), $\delta_h - v_{h3}$ is described as

$$
\bar{v}_{hl} - v_{h3} = W_h^{*T} \boldsymbol{\psi}_h(\boldsymbol{\ell}_h) + \varepsilon_h - \frac{1}{2} E_h \hat{\varphi}_h \boldsymbol{\psi}_h^T(\boldsymbol{\ell}_h) \boldsymbol{\psi}_h(\boldsymbol{\ell}_h)
$$
\n(50)

 $\dot{E}_h = -K_h E_h + F_h(\bar{v}_h) W_h^{*T} \psi_h(\ell_h) + F_h(\bar{v}_h) \varepsilon_h$ $-\frac{1}{2}F_h(\bar{v}_h)E_h\hat{\varphi}_h\mathbf{\psi}_h^{\mathrm{T}}(\boldsymbol{\ell}_h)\mathbf{\psi}_h(\boldsymbol{\ell}_h) + F_h(\bar{v}_h)v_{h4}$ (51) The robust term v_{h4} is chosen as

$$
\upsilon_{h4} = -\frac{E_h}{2\rho_h^2} \tag{52}
$$

where $\rho_h \in \mathfrak{R}^+$ is a constant to be designed. Substituting (52) into (51) , we obtain

$$
\dot{E}_h = -K_h E_h + F_h(\bar{v}_h) W_h^* \Psi_h(\ell_h) + F_h(\bar{v}_h) \varepsilon_h
$$

$$
- \frac{1}{2} F_h(\bar{v}_h) E_h \hat{\varphi}_h \Psi_h^T(\ell_h) \Psi_h(\ell_h) - F_h(\bar{v}_h) \frac{E_h}{2\rho_h^2}
$$

(53)

Theorem 2 *Consider the closed-loop system consisting of plant* [\(3\)](#page-2-1) *under Assumptions* [3](#page-6-5) *and* [4](#page-7-10) *with controller* [\(40\)](#page-7-1) *and adaptive law* [\(49\)](#page-7-11)*. Then, all the signals involved are semi-globally uniformly ultimately bounded.*

Proof Define estimate error $\tilde{\varphi}_h = \hat{\varphi}_h - \varphi_h$.

Define the following Lyapunov function:

$$
V_h = \frac{E_h^2}{2} + \frac{\bar{F}_h \tilde{\varphi}_h^2}{2\eta_h} \tag{54}
$$

where $F_h \in \mathbb{R}^+$ is a constant to be ingeniously chosen such that $F_h \leq F_h(\bar{v}_h)$ when $\tilde{\varphi}_h \tilde{\varphi}_h \geq 0$ or else $F_h >$ $F_h(\bar{v}_h)$. Then, we get $F_h\tilde{\varphi}_h\tilde{\varphi}_h/\eta_h \leq F_h(\bar{v}_h)\tilde{\varphi}_h\tilde{\varphi}_h/\eta_h$.

Taking time derivative along (54) , V_h is given by

$$
\dot{V}_h = E_h \dot{E}_h + \frac{\bar{F}_h}{\eta_h} \tilde{\varphi}_h \dot{\tilde{\varphi}}_h \le E_h \dot{E}_h + \frac{F_h(\bar{\upsilon}_h)}{\eta_h} \tilde{\varphi}_h \dot{\tilde{\varphi}}_h \tag{55}
$$

By utilizing (49) and (53) , V_h further becomes

$$
\dot{V}_h \le -K_h E_h^2 + F_h(\bar{\upsilon}_h) E_h W_h^{*T} \psi_h(\ell_h) \n+ F_h(\bar{\upsilon}_h) E_h \varepsilon_h - \frac{1}{2} F_h(\bar{\upsilon}_h) E_h^2 \hat{\varphi}_h \psi_h^T(\ell_h) \psi_h(\ell_h) \n- F_h(\bar{\upsilon}_h) \frac{E_h^2}{2\rho_h^2} + \frac{1}{2} F_h(\bar{\upsilon}_h) E_h^2 \tilde{\varphi}_h \psi_h^T(\ell_h) \psi_h(\ell_h) \n- \frac{2F_h(\bar{\upsilon}_h) \tilde{\varphi}_h \hat{\varphi}_h}{\eta_h} \n= -K_h E_h^2 + F_h(\bar{\upsilon}_h) E_h W_h^{*T} \psi_h(\ell_h) + F_h(\bar{\upsilon}_h) E_h \varepsilon_h \n- \frac{1}{2} F_h(\bar{\upsilon}_h) E_h^2 \varphi_h \psi_h^T(\ell_h) \psi_h(\ell_h) \n- F_h(\bar{\upsilon}_h) \frac{E_h^2}{2\rho_h^2} - \frac{2F_h(\bar{\upsilon}_h) \tilde{\varphi}_h \hat{\varphi}_h}{\eta_h}
$$
\n(56)

Because $E_h W_h^{*T} \psi_h(\ell_h) \leq \frac{E_h^2}{2} \left\| W_h^{*T} \psi_h(\ell_h) \right\|^2 +$ **2**_{*h*} *w*_{*h*} *ψ*_{*h*} (*e_n*) $\frac{1}{2}$ = $\frac{2}{2}$ ||*v*_{*h*} *w*_{*h*} (*e_n*)||
 $\frac{1}{2} = \frac{E_h^2}{2}$ ||*W*_{*h*}||² ||ψ_{*h*}(*e_n*)||² + $\frac{1}{2} = \frac{E_h^2}{2}$ φ_{*h*} ψ_{*h*} (*e_n*) ψ_{*h*} $2^{2} + \frac{1}{2} = \frac{E_{h}^{2}}{2} \varphi_{h} \psi_{h}^{T}(\ell_{h}) \psi_{h}(\ell_{h})$ $+\frac{1}{2}$, $2\tilde{\varphi}_h \hat{\varphi}_h \geq \tilde{\varphi}_h^2 - \varphi_h^2$ and $E_h \varepsilon_h \leq |E_h| \varepsilon_{hM} =$ $\frac{2}{2}$ $\frac{E_h}{2} \left| \varepsilon_{hM} \leq \frac{E_h^2}{4} + \varepsilon_{hM}^2$, Eq. [\(56\)](#page-8-3) is further calculated as

$$
\dot{V}_h \le -K_h E_h^2 + F_h(\bar{v}_h)
$$
\n
$$
\times \left[\frac{E_h^2}{2} \varphi_h \psi_h^T(\ell_h) \psi_h(\ell_h) + \frac{1}{2} \right]
$$
\n
$$
+ F_h(\bar{v}_h) \left(\frac{E_h^2}{4} + \varepsilon_{hM}^2 \right)
$$
\n
$$
- \frac{1}{2} F_h(\bar{v}_h) E_h^2 \varphi_h \psi_h^T(\ell_h) \psi_h(\ell_h)
$$
\n
$$
- F_h(\bar{v}_h) \frac{E_h^2}{2\rho_h^2} - \frac{F_h(\bar{v}_h)}{\eta_h} \left(\tilde{\varphi}_h^2 - \varphi_h^2 \right)
$$
\n
$$
= -K_h E_h^2 - \frac{F_h(\bar{v}_h)}{\eta_h} \tilde{\varphi}_h^2 + \frac{F_h(\bar{v}_h) E_h^2}{4}
$$
\n
$$
- F_h(\bar{v}_h) \frac{E_h^2}{2\rho_h^2} + F_h(\bar{v}_h) \varepsilon_{hM}^2
$$
\n
$$
+ \frac{F_h(\bar{v}_h)}{\eta_h} \varphi_h^2 + \frac{F_h(\bar{v}_h)}{2} \qquad (57)
$$

Let $\rho_h = \sqrt{2}$ and then we conclude from [\(57\)](#page-8-4) that

$$
\dot{V}_h \le -K_h E_h^2 - \frac{F_h(\bar{v}_h)}{\eta_h} \tilde{\varphi}_h^2 + F_h(\bar{v}_h) \varepsilon_h^2
$$
\n
$$
+ \frac{F_h(\bar{v}_h)}{\eta_h} \varphi_h^2 + \frac{F_h(\bar{v}_h)}{2} \tag{58}
$$

Define the following compact sets:

$$
\Omega_{E_h} = \left\{ E_h \left| |E_h| \le \sqrt{\left(F_h(\bar{\upsilon}_h) \varepsilon_{hM}^2 + \frac{F_h(\bar{\upsilon}_h)}{\eta_h} \varphi_h^2 + \frac{F_h(\bar{\upsilon}_h)}{2} \right) / K_h} \right\}
$$
\n
$$
\Omega_{\tilde{\varphi}_h} = \left\{ \tilde{\varphi}_h \left| |\tilde{\varphi}_h| \le \sqrt{\left(\varepsilon_{hM}^2 + \frac{\varphi_h^2}{\eta_h} + \frac{1}{2} \right) / \left(\frac{1}{\eta_h} \right)} \right\} \right\}
$$
\n(59)

If $E_h \notin \Omega_{E_h}$ or $\tilde{\varphi}_h \notin \Omega_{\tilde{\varphi}_h}$, then $V_h < 0$. Hence, E_h and $\tilde{\varphi}_h$ are semi-globally uniformly ultimately bounded. Furthermore, when we design infinitely large K_h , the velocity tracking error can converge to an arbitrarily small value. This is the end of the proof. \Box

Remark 2 For each subsystem, only one FWNN is applied to approximate the unknown term. Hence, disturbance rejection performance is guaranteed for the addressed controller and meanwhile the computational costs are low.

Remark 3 The existing studies [\[10](#page-11-16),[20](#page-11-10)[–23\]](#page-11-13) require that all the control design parameters K_{V1} and K_h must be greater than unknown positive constants. In this paper, novel roust terms v_{V4} and v_{h4} are developed such that $K_{V1} \in \mathbb{R}^+$ and $K_h \in \mathbb{R}^+$ can ensure the stability of closed-loop control system, which infers that larger stable regions than the previous methodologies [\[10,](#page-11-16)[20–](#page-11-10) [23](#page-11-13)] are achieved in this study.

4 Simulation results

This section presents the simulation test of the proposed hybrid controller (HB) in comparison with a traditional back-stepping control (TBC) approach [\[26\]](#page-11-17) to show its superiority in velocity and altitude tracking performance. The input vectors of FWNNs are $\ell_V = V$ and $\ell_h = x = [\gamma, \theta, Q]^T$ with $V \in [7700 \text{ ft/s},$ 8700 ft/s], $\gamma \in [-5^{\circ}, 5^{\circ}], \theta \in [-10^{\circ}, 10^{\circ}], Q \in$ [−10◦/s, 10◦/s]. Other design parameters are chosen as: $K_{V1} = 0.5$, $K_{V2} = 0.8$, $\eta_V = 0.1$, $\kappa_h = 12$, $\mu_h = 7$, $K_h = 50$, $\eta_h = 25$, $N=10$. To test the robustness performance, we suppose that all the aerodynamic coefficients (i.e., C_T^0 , $C_T^{\alpha^i}$, $C_D^{\delta^i_e}$, $C_D^{\alpha^i}$, C_D^0 , $C_L^{\delta_e}$, C_L^{α} , C_L^0 , $C_{M,\alpha}^{0}$, $C_{M,\alpha}^{\alpha^{i}}$, *c*_e, N_1^0 , $N_1^{\alpha^{i}}$, $N_2^{\alpha^{i}}$, N_2^0 , $N_2^{\delta_e}$ and β_j (*h*, \bar{q}), where $i=1,2, j=1,2, ..., 8$.) are uncertain. A maximum uniform variation within 40% of the nominal value is considered by defining

$$
C = \begin{cases} C_0, & 0 \le t \le 50 \text{ s} \\ C_0 \left[1 + 0.4 \sin(0.1 \pi t) \right], \text{ else} \end{cases} \tag{60}
$$

where *C* represents the value of uncertain coefficient mentioned above and C_0 means the nominal value of C.

The obtained simulation results, presented in Figs. [3,](#page-9-1) [4,](#page-9-2) [5,](#page-10-1) [6,](#page-10-2) [7](#page-10-3) [8,](#page-10-4) show that the proposed control strategy can provide better tracking of reference commends in contrast to TBC in the presence of seriously parametric uncertainties. Figures [3](#page-9-1) and [4](#page-9-2) reveal that velocity tracking error and altitude tracking error obtained by HB are smaller than the ones provided by TBC, and this superiority is more obvious when parameters are uncertain (50 s $\lt t \leq 80$ s). Hence, the exploit controller exhibits better robustness performance than TBC. For both controllers, Figs. 5 and 6 show that the responses of Φ and δ_e , γ , θ and Q are smooth and there is no high frequency chattering. It is noticed from Fig. [7](#page-10-3) that the flexible states of applying HC are smoother than utilizing TBC. The estimations of $||W^*_{V}||$ and $||W^*_{h}||$,

Fig. 3 Velocity tracking performance

Fig. 4 Altitude tracking performance

presented in Fig. [8,](#page-10-4) indicate that $||\hat{W}_V||$ and $||\hat{W}_h||$ can turn themselves along with the variations of uncertain parameters, which means that desired FWNN approximations are achieved and robustness performance can be guaranteed for the studied controllers.

Fig. 5 Control inputs

Fig. 6 Attitude angles

5 Conclusions

This study investigates a direct nonaffine hybrid controller for HFVs. For velocity subsystem and altitude subsystem, direct nonaffine controllers are addressed without model simplifications, extending the previous indirect nonaffine control approaches. By a fusion of FWNN approximation and pseudocontrol strategy,

Fig. 7 The flexible states

Fig. 8 Estimations of $||W^*_{V}||$ and $||W^*_{h}||$

both the nonaffine dynamics and parametric uncertainties are well handled. Further, advanced regulation laws are exploited for online learning parameters to reduce computational load and guarantee real-time performance. In addition, the stable regions of closedloop control system are broadened via exploiting robust terms. Finally, numerical simulation results are presented to validate the effectiveness and superiority of the developed control scheme.

Compliance with ethical standards

Conflicts of interest The author(s) declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

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