Classical and fuzzy-genetic autopilot design for unmanned aerial vehicles

A.R. Babaeia,*, M. Mortazavib, M.H. Moradici

a Aerospace Engineering Department, Amirkabir University of Technology (Tehran Polytechnic), Tehran, Iran
b Aerospace Engineering Department, member of Center of Excellence in Computational Aerospace, Amirkabir University of Technology (Tehran Polytechnic), Tehran, Iran
c Medical Engineering Department, Amirkabir University of Technology (Tehran Polytechnic), Tehran, Iran

ARTICLE INFO

Article history:
Received 15 February 2008
Received in revised form 19 October 2009
Accepted 17 November 2009
Available online 22 November 2009

Keywords:
Autopilot
UAV
Genetic algorithm
Fuzzy logic control
Nonlinear dynamic
Robustness
Non-minimum phase
Uncertainty

ABSTRACT

In this paper, an efficient strategy is proposed to design the altitude hold mode autopilot for a UAV which is non-minimum phase, and its model includes both parametric uncertainties and unmodeled nonlinear dynamics. This work has been motivated by the challenge of developing and implementing an autopilot that is robust with respect to these uncertainties. By combination of classic controller as the principal section of the autopilot and the fuzzy logic controller to increase the robustness in a single loop scheme, it is tried to exploit both methods advantages. The multi-objective genetic algorithm is used to mechanize the optimal determination of fuzzy logic controller parameters based on an efficient cost function that comprises undershoot, overshoot, rise time, settling time, steady state error and stability. Simulation results show that the proposed strategy performances are desirable in terms of the time response characteristics for both phugoid mode and short period mode, the robustness, and the adaptation of itself with respect to the large commands.

© 2009 Elsevier B.V. All rights reserved.

1. Introduction

The main difficulties in the aerospace vehicles autopilot design are due to the aerodynamic parameters uncertainties. Since the knowledge of aerodynamic coefficients as well as their dependencies on some parameters (e.g. angle of attack, side slip angle) is very imprecise, a designed controller must not be sensitive to the variations of these coefficients. Also, aerospace vehicles are controlled by assuming that the inertial cross-couplings among roll, pitch, and yaw dynamics are negligible. In practice, the dynamics of aerospace vehicles is nonlinear, time varying, and uncertain, and these may lead to performance degradation. To design a high performance autopilot, it is desirable to use a more general model containing the nonlinear terms. Therefore, one of the major problems in designing flight control systems is to regard the uncertainties such as parameters variations and unknown nonlinear dynamics. Here, controller design methods are applied to the altitude hold mode autopilot for an UAV (unmanned aerial vehicle) which is aerodynamically controlled by the elevator control surface so that the considered uncertainties are due to both parametric uncertainties and unmodeled nonlinear terms.

In order to get rid of the exact model restrictions, several adaptive schemes have been introduced to solve the problem of linearly parameterized uncertainties which are referred to as structured uncertainties [2,10]. Unfortunately, in some applications, there are some controlled systems which are characterized by an unmodeled or/and unknown dynamics which are referred to the unstructured uncertainties. The feedback linearization[18] is a popular method used in nonlinear control applications, and there have been several flight control demonstrations [1,6,13,19]. This technique has taken much of the attention and shows great promise. The main drawback of the nonlinear control approach such as feedback linearization is that, as a model-based control method, they require accurate knowledge of the plant dynamics. This is significant in flight control because at least, the aerodynamic parameters contain some degree of uncertainties. In fact, the I/O feedback linearization technique which has been regard as the powerful design method for nonlinear systems cannot be directly applied to altitude control of UAVs because the altitude to the elevator relation is inherently non-minimum phase. This fact makes it difficult to design high performance autopilot. FLC method [21] has been used for various cases [5,7,9,23], and it can be used as a robust method for our case. Further, the optimal determination of fuzzy systems properties by using evolutionary algorithms [8] has been widely used in different applications [4,12,14,17,20,22]. In [2,7], the altitude hold mode autopilot is designed based on the linear model. The authors of these references have tried to improve only the parametric robustness. In [2], UAV altitude is controlled by combination of classic controller and a simple adaptive controller to improve the robustness with respect to only parametric uncertainties. In [7], the UAV...
altitude is controlled by the expert knowledge-based FLC so that the robustness with respect to parametric uncertainty is achieved. In [4,20], the missile acceleration that is non-minimum phase is indirectly controlled (lateral velocities are controlled) by the FLC and a multi-objective GA. In [12], the fuzzy PID controller based on GA is presented to eliminate the undershoot of non-minimum phase linear systems. In [14], a GA-based fuzzy logic controller has been designed to stabilize a satellite attitude.

In this paper, it is tried to achieve some properties: suitable time response characteristics, robustness with respect to parametric uncertainty, robustness with respect to unmodeled dynamics and desirable tracking of commands in the wide range. For these reasons, it is proposed a strategy based on the combination of classic controller and fuzzy logic controller. The classic controller is considered as a principal section of autopilot, and the fuzzy logic controller that is independent of a system model is used to increase the robustness. In this paper, unlike the conventional architecture, a single loop scheme is used to design the altitude hold mode autopilot that leads to decrease the required measurable variables. Only in [2,7], the single loop scheme has been seen to design the altitude hold mode autopilot. The multi-objective genetic algorithm is used to mechanize the optimal determination of the fuzzy logic controller parameters as well. These objectives comprise undershoot, overshoot, rise time, settling time, steady state error and stability.

The rest of the paper is organized as follows: Section 2 presents the nonlinear and linear model of UAV. The proposed strategy will be discussed in Section 3. After the implementation of the proposed strategy, several results are presented in Section 4. Finally, conclusions are drawn in Section 5.

2. UAV model

Our purpose in this section is to derive the equations of motion of a UAV. UAV model could be built from a set of simultaneous ODEs. The equations of motion of UAV as a rigid body can be separated into rotational equations and translational equations. The rotational motion of UAV will then be equivalent to yawing, pitching, and rolling motions about the center of mass. The remaining components of the motion will be translation of center of mass in 3D space. Therefore, the state model derived here will be a six-degree-of-freedom model.

We have derived the dynamics equations of UAV as follows.

Translational dynamics equations:

\[
\dot{U} = -9.8 \sin \theta - QW + RV - 0.0125U - 16.63\alpha + 16.63\delta_E + 4.5 \tag{1-a}
\]

\[
\dot{V} = 9.8 \sin \phi \cos \theta + PW - RU - 263.7\beta - 0.0053P + 1.64R - 0.0032\delta_A - 58.2\delta_R \tag{1-b}
\]

\[
\dot{W} = 9.8 \cos \phi \cos \theta + QU - PV - 0.068U - 259\alpha - 1.3Q + 57.5\delta_E + 21 \tag{1-c}
\]

Rotational dynamics equations:

\[
\dot{\phi} = -1.51QR + 0.04PQ + 76.7\beta - 1.9P - 0.68R + 149\delta_A + 105\delta_R \tag{1-d}
\]

\[
\dot{\psi} = 1.03PR - 0.017(P^2 - R^2) - 988\alpha - 8.9Q + 1362\delta_E - 0.284 \tag{1-e}
\]

\[
\dot{\theta} = -0.038QR - 0.85PQ + 306\beta - 0.044P - 2.82R + 2.27\delta_A + 4345R \tag{1-f}
\]

In these equations, the constants are function of mass properties and stability and control derivatives. We have computed these derivatives by using procedures presented in [16], Besides, the kinematics equations are presented as follows [15]:

\[
\dot{\alpha} = \frac{W \cos \alpha - \dot{U} \sin \alpha}{V_t \cos \beta} \tag{1-g}
\]

\[
\dot{\beta} = \frac{1}{V_t} \left[ -\dot{U} \cos \alpha \sin \beta + \dot{V} \cos \beta - W \sin \alpha \sin \beta \right] \tag{1-h}
\]

\[
\dot{\phi} = P + Q \sin \phi \tan \theta + R \cos \phi \tan \theta \tag{1-i}
\]

\[
\dot{\theta} = Q \cos \phi - R \sin \phi \tag{1-j}
\]

\[
\dot{\psi} = (Q \sin \phi + R \cos \phi) \sec \theta \tag{1-k}
\]

\[
\dot{h} = V_t \sin \gamma \tag{1-l}
\]

\[
V_t = \sqrt{U^2 + V^2 + W^2} \tag{1-m}
\]

\[
\gamma = \theta - \alpha \tag{1-n}
\]

These equations are nonlinear and highly coupled.

We are aimed to design the altitude hold mode autopilot for this UAV. An altitude hold mode is an autopilot mode which is able to maintain the altitude by the elevator input. This mode has practical
importance for unmanned aerial vehicles due to flying in vicinity of terrain to implement missions by terrain following maneuver. This work has been motivated by the challenge of developing and implementing an autopilot that is robust with respect to parametric uncertainties and unmodeled dynamics to implement efficiently a terrain following maneuver in wide range of altitude.

The nominal linear model for altitude is derived by linearization of Eq. (1) about the cruise flight trim conditions (terrain following maneuver in wide range of altitude. 

\[ \text{The nominal linear model is considered as the available mathematical model that the autopilot is designed based on it.} \]

(2) The classic methods have advantages to design an autopilot such as the capability of stability analysis and simplicity of implementation. These methods have special place in automatic flight control systems. For these reasons, the autopilot is initially designed by using classic methods based on nominal linear model.

(3) Fuzzy systems are knowledge-based or rule-based systems that were initiated by Zadeh [24]. The heart of a fuzzy system is a fuzzy IF–THEN rule. A fuzzy IF–THEN rule is an IF–THEN statement in which some words are characterized by continuous membership functions. A block diagram of a fuzzy logic system is shown in Fig. 1. It is known that the stability analysis of FLC is difficult and insecure while this can be accomplished for model-based procedures such as classic methods. As it was discussed in the previous section, the classic autopilot that is designed based on the available mathematical model (here, nominal linear model) has probably unsuitable performances in presence of parametric uncertainties, unmodeled dynamics, and a wide range of altitude in the actual model. From these reasons, fuzzy logic control that is independent of the plant model is proposed to improve the basic autopilot performances (the classic controller) in terms of these criteria. Consequently, the efficient strategy is proposed to design the altitude hold mode autopilot by combination of classic control and fuzzy logic control. In this strategy, in addition to improve the time response characteristics of the UAV accompanied with the classic controller, the robustness with respect to uncertainties is the fundamental contribution of FLC. In Fig. 2, this strategy is illustrated while \( u \) is the contribution of FLC in control of the UAV.

3. Proposed strategy to design the altitude autopilot

In this section, the proposed strategy to design the altitude autopilot of the UAV is discussed as follows:

(1) Conventionally, the altitude autopilot is designed with three loops so that altitude, pitch rate, and pitch angle variables are measured (pitch angle autopilot is inner loop of altitude autopilot, and pitch rate controller is inner loop of pitch angle autopilot). This architecture leads to a suitable robustness, but complex and expensive controller because three controllers should be designed and three variables should be measured. In this paper, pitch rate and pitch angle loops are left so that

\[ \text{the single loop architecture is used. In this simple architecture, it is sufficient to measure the altitude by the altimeter.} \]

\[ \text{(2) The classic methods have advantages to design an autopilot such as the capability of stability analysis and simplicity of implementation. These methods have special place in automatic flight control systems. For these reasons, the autopilot is initially designed by using classic methods based on nominal linear model.} \]

\[ \text{(3) Fuzzy systems are knowledge-based or rule-based systems that were initiated by Zadeh [24]. The heart of a fuzzy system is a fuzzy IF–THEN rule. A fuzzy IF–THEN rule is an IF–THEN statement in which some words are characterized by continuous membership functions. A block diagram of a fuzzy logic system is shown in Fig. 1. It is known that the stability analysis of FLC is difficult and insecure while this can be accomplished for model-based procedures such as classic methods. As it was discussed in the previous section, the classic autopilot that is designed based on the available mathematical model (here, nominal linear model) has probably unsuitable performances in presence of parametric uncertainties, unmodeled dynamics, and a wide range of altitude in the actual model. Due to these reasons, fuzzy logic control that is independent of the plant model is proposed to improve the basic autopilot performances (the classic controller) in terms of these criteria. Consequently, the efficient strategy is proposed to design the altitude hold mode autopilot by combination of classic control and fuzzy logic control. In this strategy, in addition to improve the time response characteristics of the UAV accompanied with the classic controller, the robustness with respect to uncertainties is the fundamental contribution of FLC. In Fig. 2, this strategy is illustrated while \( u \) is the contribution of FLC in control of the UAV.} \]

\[ \text{Fig. 2. The proposed strategy scheme based on the combination of FLC and classic controller.} \]

Table 1

<table>
<thead>
<tr>
<th>Stability derivative</th>
<th>Quantity most affected</th>
<th>How affected</th>
</tr>
</thead>
<tbody>
<tr>
<td>( C_{m\alpha} )</td>
<td>Damping of the short period, ( \xi_s )</td>
<td>Increase ( C_{m\alpha} ) to increase the damping</td>
</tr>
<tr>
<td>( C_{m\delta} )</td>
<td>Natural frequency of the short period, ( \omega_{ns} )</td>
<td>Increase ( C_{m\delta} ) to increase the frequency</td>
</tr>
<tr>
<td>( C_{d\alpha} )</td>
<td>Damping of the phugoid, ( \xi_p )</td>
<td>Increase ( C_{d\alpha} ) to increase the damping</td>
</tr>
<tr>
<td>( C_{d\delta} )</td>
<td>Natural frequency of the phugoid, ( \omega_{np} )</td>
<td>Increase ( C_{d\delta} ) to increase the frequency</td>
</tr>
</tbody>
</table>
3.1. Fuzzy logic control

Here in, the fuzzy logic controller is implemented as a 17-rule Mamdani fuzzy system with two inputs and one output. The two inputs are error and error rate, and the output is the contribution of FLC in UAV control. Seven membership functions are used to describe each of inputs and output; namely, NEGATIVE BIG, NEGATIVE MEDIUM, NEGATIVE SMALL, ZERO, POSITIVE SMALL, POSITIVE MEDIUM and POSITIVE BIG (see Fig. 3). The rules base is presented in Table 2 (11) (the rules 16 and 17 are used to decrease the undershoot that is created due to non-minimum phase behavior of UAV). For example, the first rule implies that,

IF \( e \) IS PB and \( \dot{e} \) IS ZE, \ THEN \( u \) IS PE \ (4)

3.2. Genetic algorithm

Conventionally, FLC is designed by the expert’s knowledge and experience. It is difficult to decide about control rules as the system gets complex, a non-minimum phase system for instance. To solve this problem, the determination of FLC parameters is mechanized by GA to comport time response characteristics and robustness. GA is a general-purpose search algorithm that is theoretically and empirically proven to provide a robust search in complex spaces.

Here, the continuous or real-valued GA is used. First, a chromosome population (\( N_{pop} \)) is randomly generated. Each chromosome specifies a candidate solution of the optimization problem. The fitness of all individuals with respect to the optimization task is then evaluated by a scalar cost function (fitness function). A cost function generates an output from a set of input variables (a chromosome). The object is to modify the output in some desirable fashions by finding the appropriate values for the input variables. If the chromosome has \( N_{var} \) variables given by \( p_1, p_2, \ldots, p_{N_{var}} \), then the chromosome is written as an \( N_{var} \) element row vector. Then is the time to decide which chromosomes in the initial population are fit enough to survive and possibly reproduce offspring in the next generation. The \( N_{pop} \) costs and associated chromosomes are ranked from lowest cost to highest cost. From the \( N_{pop} \) chromosomes in a given generation, only the top \( N_{keep} \) are kept for mating (process of natural selection) and the rest are discarded to make room for the new offspring. Subsequently, one mother and one father in some random fashions are selected. Each pair produces two offspring that contain traits from each parent. A single offspring variable value, \( p_{new} \), comes from a combination of the two corresponding offspring variable values:

\[
p_{new} = b_0 p_{mn} + (1 - b_0) p_{dn} \tag{5}
\]

If care is not taken, GA can converge too quickly into one region of the cost surface. If this area is in the region of the global minimum, that is good. However, some functions have many local minima. If this tendency to converge quickly is not solved, the local minimum rather than the global minimum is attained. To avoid this problem, it is forced to explore other areas of the cost surface by randomly introducing changes, or mutations, in some of the variables. Most users of the continuous GA add a normally distributed random number to the variable selected for mutation:

\[
p'_{n} = p_{n} + \sigma N_{n}(0, 1) \tag{6}
\]

3.3. Cost function

In desirable design of FLC by GA, presentation of an efficient cost function is of great importance. Here, the cost function is presented so that undershoot, overshoot, settling time, steady state error, and unstable behavior are decreased. Thus, this is a multi-objective problem. Multi-objective cost function is proposed as follows:

\[
J = W_1 S_1 + W_2 S_2 + W_3 S_3 \tag{7}
\]

where \( W_i \) is the corresponding weight (see Fig. 4. The parameters in Fig. 4 are defined as follows: \( t_1 \) is the time of first intersection between the altitude time response and the altitude command, \( t_2 \) is the time of second intersection between the altitude time response and the altitude command, and \( T \) is the final time of simulation. If the intersections are not created, the \( t_i \) parameter is considered zero value) and:

\[
W_1 = \frac{1}{t_1} \frac{1}{t_2} \frac{1}{T} \]

\[
W_2 = \frac{1}{\text{overshoot}} \frac{1}{\text{undershoot}} \frac{1}{\text{settling time}} \]

\[
W_3 = \frac{1}{\text{steady state error}} \frac{1}{\text{unstable behavior}} \]

Table 2

<table>
<thead>
<tr>
<th>Rule no.</th>
<th>( e )</th>
<th>( \dot{e} )</th>
<th>( u )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>PB</td>
<td>ZE</td>
<td>PB</td>
</tr>
<tr>
<td>2</td>
<td>ZE</td>
<td>NB</td>
<td>NB</td>
</tr>
<tr>
<td>3</td>
<td>NB</td>
<td>ZE</td>
<td>NB</td>
</tr>
<tr>
<td>4</td>
<td>ZE</td>
<td>PB</td>
<td>PB</td>
</tr>
<tr>
<td>5</td>
<td>PM</td>
<td>ZE</td>
<td>PM</td>
</tr>
<tr>
<td>6</td>
<td>ZE</td>
<td>NM</td>
<td>NM</td>
</tr>
<tr>
<td>7</td>
<td>NM</td>
<td>ZE</td>
<td>NM</td>
</tr>
<tr>
<td>8</td>
<td>ZE</td>
<td>PM</td>
<td>PM</td>
</tr>
<tr>
<td>9</td>
<td>PS</td>
<td>ZE</td>
<td>PS</td>
</tr>
<tr>
<td>10</td>
<td>ZE</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td>11</td>
<td>NS</td>
<td>ZE</td>
<td>NS</td>
</tr>
<tr>
<td>12</td>
<td>ZE</td>
<td>PS</td>
<td>PS</td>
</tr>
<tr>
<td>13</td>
<td>ZE</td>
<td>ZE</td>
<td>ZE</td>
</tr>
<tr>
<td>14</td>
<td>PB</td>
<td>NS</td>
<td>PM</td>
</tr>
<tr>
<td>15</td>
<td>PS</td>
<td>NB</td>
<td>NM</td>
</tr>
<tr>
<td>16</td>
<td>NB</td>
<td>PS</td>
<td>NM</td>
</tr>
<tr>
<td>17</td>
<td>NS</td>
<td>PB</td>
<td>PM</td>
</tr>
</tbody>
</table>

Fig. 3. Membership functions for inputs and output.
S_1 = \int_{0}^{T_1} |h - h_c| dt, \text{ this parameter covers the rise time and the undershoot,}
S_2 = \int_{T_1}^{T_2} |h - h_c| dt, \text{ this parameter includes the overshoot value,}
S_3 = \int_{T_2}^{T_3} |h - h_c| dt, \text{ this parameter includes the settling time, the steady stat error, and unstable effects.}

In this alternative form of the cost function, the computation of all objectives is not individually required, and we can easily consider several important objectives in the simple cost function.

Due to the computational requirements, the FLC is generally evolved off-line (using GA and a model of the controlled process). For this reason, the nominal linear model, as an available mathematical model of UAV, is utilized to achieve FLC parameters. Then, using the degraded linear model and the nonlinear model in the simulation procedure, the robustness of controller with respect to uncertainties that are not considered in GA is investigated.

4. Results

In this section, the proposed strategy is implemented for the UAV model presented in Section 2. This work is done in three steps: (1) design and evaluation of classic autopilot, (2) design and evaluation of fuzzy logic autopilot, and (3) combination of the result derived in step 1 and step 2 (of course, the result derived in step 2 needs some modifications to match with classic autopilot).

4.1. Classic autopilot design

The classic autopilot is designed for \( \psi \) and \( h \) variables using nominal linear model (the linear dynamic is considered for the actuator). However, the \( \psi \)-autopilot has desirable performances, it is not presented here, but it is assumed that there are not uncertainties in the directional-lateral channel. By considering a trade-off procedure between the time response characteristics and the robustness, the following compensator is designed through the root locus techniques:

\[
G_C = \frac{0.0068(S + 0.1)(S^2 + 2.12S + 98.4)}{(S + 20)(S^2 + 6.94S + 13.1)}
\] (8)

For closed loop system, dominant desirable characteristics are attained by applying this autopilot to the nominal linear model (2) as \( \xi = 0.79, \omega = 1.36 \). To evaluate this autopilot, it is applied to nominal linear model, degraded linear model and nonlinear model (it should be noted that the elevator trim angle (here, \( \delta_{\text{trim}} = -1.92^\circ \) must be added to the control input in the nonlinear simulation procedure because the controllers have been designed based on the nominal linear model) and the simulation results are investigated. The commands are considered as \( \psi = 0 \) and 10 degree and \( h = 10 \) m. The simulation results are illustrated in Fig. 5. According to Fig. 5a, the desirable response is seen for the nominal linear model, but low parametric robustness is known for the degraded linear model. By inspection of Fig. 5b, the time response of the classic autopilot has been degraded for the UAV nonlinear model because the nonlinear terms have been appeared. Clearly, increasing the \( \psi \)-command value leads to increase the degraded coupling nonlinear effects. Therefore, the compensators cannot meet the wanted requirements in terms of the parametric uncertainties and the unmodeled dynamics. Now, elimination of the nonlinear terms effects is required to achieve the desirable tracking. In addition, autopilot should not be very sensitive to the variation of system parameters. Due to these reasons, it is tried to exploit the knowledge-based FLC.

4.2. Fuzzy logic autopilot design

Subsequently, the FLC is designed by the GA. The input variables boundaries are considered as \( u_{\text{up}} = 50 \) m, \( e_{\text{low}} = -50 \) m, \( \dot{e}_{\text{up}} = 50 \) m s\(^{-1}\), and \( \dot{e}_{\text{low}} = -50 \) m s\(^{-1}\) and for the output variable, these are \( u_{\text{up}} = 12 \) and \( u_{\text{low}} = -12 \). These parameters are selected by concerning to UAVs flight characteristics and try and error based on the nominal linear model to achieve the requirements. Also, the centers of output membership functions (\( \mu_i \)) and variances (\( \sigma_i \)) for inputs membership functions are considered as a chromosome. The GA with the following properties is used to determine FLC parameters (these properties are determined by try and error based on nominal linear model):

- Chromosome population, \( N_{\text{pop}} = 50 \)
- The number of generation = 50
- Mutation rate = 2%
- \( N_{\text{keep}} = 50\% \)

Also, by considering a trade-off procedure between time response characteristics and robustness, the weights are chosen.
Table 3
Optimal properties of fuzzy logic autopilot.

<table>
<thead>
<tr>
<th>(\sigma_{\text{PB}})</th>
<th>(\sigma_{\text{NM}})</th>
<th>(\sigma_{\text{NS}})</th>
<th>(\sigma_{\text{ZE}})</th>
<th>(\sigma_{\text{PS}})</th>
<th>(\sigma_{\text{PM}})</th>
<th>(\sigma_{\text{PB}})</th>
</tr>
</thead>
<tbody>
<tr>
<td>13.27</td>
<td>19.22</td>
<td>11.68</td>
<td>8.09</td>
<td>11.73</td>
<td>16.25</td>
<td>16.05</td>
</tr>
</tbody>
</table>

Simulations results are illustrated in Fig. 7 for nominal linear model, degraded linear model and nonlinear model. Concerning Fig. 7a, this autopilot gives the desirable time response characteristics (dotted line) and almost good parametric robustness (solid line). The desirable time response is shown in Fig. 7b by eliminating the nonlinear effects. Therefore, the robustness with respect to unmodeled dynamics can be achieved for the fuzzy logic autopilot.

4.3. Classical and fuzzy logic autopilot design

Now, it is tried to implement the proposed strategy by combination of the above autopilots. The control variable boundaries are chosen \(u_{\text{up}} = 40, u_{\text{low}} = -40\) and these are \(e_{\text{up}} = 15\) m, \(e_{\text{low}} = 15\) m, \(\dot{e}_{\text{up}} = 30\) m s\(^{-1}\) and \(\dot{e}_{\text{low}} = -30\) m s\(^{-1}\) for the inputs. The weights are considered as \(W_1 = W_2 = W_3 = 1\), the population size is considered 30, and the other properties of the GA are selected similar to the above FLC. For this case, to improve the autopilot performance in the presence of nonlinear effects, rules 9 and 11 are modified as the following procedure:

Rule 9 : IF \(e\) IS PS and \(\dot{e}\) IS ZE, THEN \(L \cdot u\) IS PB, ...

In fact, the FLC output contribution is multiplied by \(L\) (here, it is chosen 3.5) to improve the FLC performance in presence of the nonlinear coupling effects in the vicinity of command (zero error rate and small error). The GA results based on the UAV nominal linear model are presented in Table 4, and the mean fitness value in each generation is shown in Fig. 8. The simulation results, for the linear and nonlinear model, are illustrated in Fig. 9. This figure displays that the time response characteristics (such as overshoot, rise time, and settling time) and parametric robustness have been highly improved (Fig. 9a). Besides, this strategy leads to the acceptable elimination of nonlinear effects (see Fig. 9b).

Table 4
Optimal properties of FLC in the proposed strategy.

<table>
<thead>
<tr>
<th>(\sigma_{\text{PB}})</th>
<th>(\sigma_{\text{NM}})</th>
<th>(\sigma_{\text{NS}})</th>
<th>(\sigma_{\text{ZE}})</th>
<th>(\sigma_{\text{PS}})</th>
<th>(\sigma_{\text{PM}})</th>
<th>(\sigma_{\text{PB}})</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.94</td>
<td>3.59</td>
<td>4.75</td>
<td>3.7</td>
<td>4.56</td>
<td>4.55</td>
<td>5.42</td>
</tr>
<tr>
<td>12.48</td>
<td>10.82</td>
<td>8.94</td>
<td>9.05</td>
<td>9.66</td>
<td>10.34</td>
<td>11.3</td>
</tr>
</tbody>
</table>

Simulations results are illustrated in Fig. 7 for nominal linear model, degraded linear model and nonlinear model. Concerning Fig. 7a, this autopilot gives the desirable time response characteristics (dotted line) and almost good parametric robustness (solid line). The desirable time response is shown in Fig. 7b by eliminating the nonlinear effects. Therefore, the robustness with respect to unmodeled dynamics can be achieved for the fuzzy logic autopilot.
4.4. More investigation of autopilots

Subsequently, it is tried to investigate these autopilots in terms of other practical criteria:

(A) In the altitude autopilot design procedure, it is required to concentrate on the other longitudinal variables such as pitch angle, pitch rate, and elevator angle (altitude variable is important in phugoid mode, and pitch angle and pitch rate are dominant in short period mode). Due to this reason, these variables are illustrated in Fig. 10 for three designed autopilots. As it is clear, the time response of these variables for the classic autopilot is better than the others. The classic autopilot has been designed so that both short period mode and phugoid mode are improved. Fuzzy logic autopilot has been led to improve only the phugoid mode through the altitude hold mode autopilot. Proposed strategy not only leads to improving phugoid mode, but also leads to sufficiently improving short period mode.

(B) For large commands, applying a filter or a dynamic model is necessary to avoid the large input and the large load factor because it leads to construct a smooth command with sufficiently high time constant. By proper selection of the lower and upper bounds of the fuzzy logic controller inputs and output, the acceptable load factor can be applied to UAV without saturation of the control input. According to Fig. 11, the elevator is saturated (the maximum elevator angle is considered 25°) and applied load factor is high for classic autopilot due to the large commands. But, FLC causes the time response to adapt itself with large commands so that the elevator may not be saturated and the applied load factor is acceptable. Fortunately, the proposed strategy is better than the fuzzy logic autopilot in terms of this advantage.

4.5. Comparison of the autopilots

Summarily, the three autopilots are compared as follows:

(1) Excellently, the proposed strategy performances are better than the others in terms of the time response characteristics.

(2) The parametric robustness of the proposed strategy is high. This capability depends on the classic controller quality and FLC.
tracking of commands in the wide range. For these reasons, we have proposed a strategy based on the combination of classic controller as the principal section of the autopilot and a fuzzy logic controller to increase robustness. To fulfil this paper’s goals, several considerable points have been used as follows: (1) unlike the conventional architecture in the altitude autopilot design, a single loop scheme has been used so that it leads to decrease the required measurable variables; (2) the proposed strategy exploits both the classic method advantages such as the simplicity and capability of stability analysis and FLC that is independent from the system model; (3) the multi-objective genetic algorithm has been used to mechanize the optimal determination of fuzzy logic controller parameters based on an efficient cost function; (4) autopilot has been designed based on nominal linear model as an available mathematical model, and robustness has been investigated based on degraded linear model and nonlinear model; (5) the proposed strategy has been investigated at different criteria that are important in practice; (6) at final, this simple strategy is proposed for other applications that include uncertainties.

References