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ROBUST OPTIMIZATION OF MULTIVARIABLE CONTROL SYSTEM OF UAV LATERAL MOTION VIA GENETIC ALGORITHMS

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The design of flight robust control law is always a challenge to the engineer. This difficulty is more actual in the area of the unmanned aerial vehicles (UAVs), which are vulnerable to the internal and external disturbances. This paper is devoted to the design of flight robust control law for the lateral channel of UAV based on H_2/H_∞-robust optimization. The task is divided into two stages, in the first stage a linear quadratic Gaussian (LQG) is synthesized based on the separation theorem. The second stage is consecrated to the robust optimization of the aforementioned regulator. It is known that the genetic algorithm optimization is more robust than traditional optimization procedures, also it has the propriety to converge to the global minimum and well suited to seek a compromise between multi-objectives function. The simulation results prove the efficiency of the proposed procedure.

Introduction. During the recent years, the unmanned aerial vehicles (UAVs) have proved to hold a significant role in the world of the aviation. Since, it accomplishes a variety of tasks, starting from military investigation to civilian and scientific researches. Consequently, this area brought a great interest to the scientific community, in order to develop the field and make it more flexible and accurate.

The most expanded area is the flight dynamic control, which makes the UAVs full autonomous or semi-autonomous. The design of such systems is a challenge and requires engineering skills. As it is known, the UAVs during the flight are subjects to the disturbances, which could be external produced from the change in atmospheric conditions and internal ones caused from the change of the parameters of the UAVs during the flight. Therefore, the control law designed for the nominal flight parameters may not perform in the same way when disturbances occur. Hence, to overcome these difficulties and ensure the handling qualities the control law should be robust.

The flight robust control, is widely developed due to its characteristics [1 – 4] allowing the rejection of exogenous and endogenous perturbation. The technique used in this paper is based on H_2/H_∞-robust optimization. This technique is divided into two stages; in the first a linear quadratic Gaussian is designed based in the separation theorem, the second level of this method is to “robustify” the control law, this is given by the aforementioned optimization method. The cost function used in this optimization, is computed using H_2-norm of the sensitivity function to estimate the performances of the closed loop system and H_∞-norm of the complementatrity sensitivity function to quantify the degree of robustness. The mixed H_2/H_∞-optimization is used to find a trade-off between the multi-objectives of the performance and the robustness to satisfy the handling qualities of the aircraft flight.

To prove the effectiveness of this method, the lateral channel Aerosonde UAV in coordinate turn is used as a case study. It is necessary to notice, that robust optimization of the longitudinal motion of UAV was considered in [5]. In this paper the approach developed in [6] is expanded at the control of lateral motion.

The first stage: LQG regulator synthesis. Let the following state space model describe the lateral channel of the UAV,

$$\begin{aligned} X &= A_i X + B_i U + G_i w \\ Y &= C_i X + D_i U + \eta \end{aligned} \tag{1}$$

where $\boldsymbol{i}$ is the number of mathematical models used for description of the UAV dynamics ($i = 1, 2, 3$). To prove the effectiveness of the method used in this paper, three models are generated form the linearization of the Aerosonde nonlinear model [5]. These models correspond to $\boldsymbol{3}$ values of the true airspeed $\boldsymbol{V}$, due to the dependency of the UAV dynamics on this variable. The first model matrices (2) constitute the nominal plant and correspond to $V = 30\,\mathrm{m/sec}$, the matrices (3) and (4) correspond to the parametrically disturbed plants with $V_2 = 25\,\mathrm{m/sec}$, $V_2 = 35\,\mathrm{m/sec}$, respectively.

$$\boldsymbol{A_{nom}} = \begin{bmatrix} -0.83 & 0.57 & -30 & 9.78 & 0 \\ -5.48 & -27 & -13 & 0 & 0 \\ 0.89 & -3.5 & -1.36 & 0 & 0 \\ 0 & 1 & 0.02 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}; \quad \boldsymbol{B_{nom}} = \begin{bmatrix} -2.13 & 5.44 \\ -187.35 & 3.37 \\ -7.39 & -34.41 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}; \tag{2}$$

$$\boldsymbol{A_{p1}} = \begin{bmatrix} -0.69 & 1.21 & -25 & 9.80 & 0 \\ -4.55 & -22.4 & 10.8 & 0 & 0 \\ 0.73 & -2.9 & -1.13 & 0 & 0 \\ 0 & 1 & 0.05 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}; \quad \boldsymbol{B_{p1}} = \begin{bmatrix} -1.48 & 3.78 \\ -129.8 & 2.36 \\ -5.12 & -2.36 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}; \tag{3}$$

$$\boldsymbol{A_{p2}} = \begin{bmatrix} -0.97 & 0.06 & -35 & 9.81 & 0 \\ -6.38 & -31.44 & 15.13 & 0 & 0 \\ 1.04 & -4.078 & -1.58 & 0 & 0 \\ 0 & 1 & 0.001 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}; \quad \boldsymbol{B_{p2}} = \begin{bmatrix} -2.9 & 7.4 \\ -254.7 & 4.58 \\ -10.04 & -46.8 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}. \tag{4}$$

The state vector is $X = [\mathrm{v} \quad p \quad r \quad \varphi \quad \psi]$, where v is the lateral velocity component, $\boldsymbol{r}$ is the yaw rate, $\boldsymbol{p}$ is the roll rate, φ is the bank angle and ψ is the heading angle. The control inputs $U = [\delta_a \quad \delta_r]$ are ailerons and rudder, respectively. The vector $\boldsymbol{w}$ in (1) stands for the processes disturbances, η represents the measurements noises. The matrix $\boldsymbol{G_i}$ is defined by the model of the atmospheric conditions and the mathematical model of the UAV [2; 6]. The model of the atmospheric conditions used here is a Dryden filter defined by the following quadruple of matrices $[\boldsymbol{A_{dr}}, \boldsymbol{B_{dr}}, \boldsymbol{C_{dr}}, \boldsymbol{D_{dr}}]$, the numerical values of this model can be computed as follows [7]:

$$A_{dr} = \begin{bmatrix} -\frac{1}{\tau_p} & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & \frac{-1}{\tau_v^2} & \frac{-2}{\tau_v} & 0 \\ 0 & \frac{k_v}{\tau_r} & \frac{k_v\lambda_v}{\tau_r} & \frac{-1}{\tau_r} \end{bmatrix}; \quad B_{dr} = \begin{bmatrix} \frac{k_p}{\tau_p} & 0 \\ 0 & 0 \\ 0 & \frac{1}{\tau_r} \\ 0 & 0 \end{bmatrix}; \quad C_{dr} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & k_v & k_v\lambda_v & 0 \\ 0 & \frac{k_v}{\tau_r} & \frac{k_v\lambda_v}{\tau_r} & \frac{-k_r}{\tau_r} \end{bmatrix}. \tag{5}$$

where $\tau_p = 4b/\pi V$, $k_p = \left(\sigma_w\sqrt{0.8/V}\,(\pi/4b)^{1/6}\right)/L_w^{1/3}$, $\tau_v = L_v/V$, $\lambda_v = \sqrt{3}/V$, $k_v = \sigma_v\sqrt{L_v/\pi V}$, $k_r = 1/V$ and $\tau_r = L_v/V$.

$\boldsymbol{L_v}$ and $\boldsymbol{L_w}$ represent the turbulence scale lengths; σ_v, σ_w are the r.m.s values of turbulent wind lateral and vertical velocities.

The computation of these values depend on the altitude at which the aircraft is flying, in our case the models represented in (2), (3) and (4) are obtained for the altitude $h = 200$ m. The inputs to the filter (5) are white Gaussian noises corresponding to the lateral wind gust component and vertical one; the outputs are the lateral turbulent speed component $\boldsymbol{v}_g$, the turbulent yaw rate $\boldsymbol{r}_g$ and turbulent roll rate $\boldsymbol{p}_g$.

So far we have three values of $\boldsymbol{V}$ ($25, 30, 35$ m/sec), three filters would be taken in account. The models of the actuators are approximated by the first order model given by the transfer function:

$$G_{act} = \frac{1}{1 + \tau_{act} s}.$$

In this work we suppose that we have three sensors to measure r, p, ψ, which are affected by noises, the remaining states are estimated by Kalman filter.

After connecting Dryden filter and the actuators to the model of the UAV, the extended model is formed and is given by the following matrices:

$$\left[\begin{array}{c|c} \boldsymbol{A}_{ex} & \boldsymbol{B}_{ex} \\ \hline \boldsymbol{C}_{ex} & \boldsymbol{D}_{ex} \end{array}\right] = \left[\begin{array}{cc|cc} \boldsymbol{A}_{nom} & \boldsymbol{G}_{nom}\boldsymbol{C}_{dr} & \boldsymbol{B}_{nom} & \boldsymbol{G}_{nom}\boldsymbol{B}_{dr} \\ \boldsymbol{0}_{r\times n} & \boldsymbol{A}_{dr} & \boldsymbol{0}_{r\times q} & \boldsymbol{B}_{dr} \\ \hline \boldsymbol{C}_{nom} & \boldsymbol{0}_{p\times r} & \boldsymbol{D}_{nom} & \boldsymbol{0}_{p\times 2} \end{array}\right]. \quad (6)$$

It can be seen, that the extended model given in (6) has 11 states and it known that, in the area of unmanned vehicle the designer should minimize the number of airborne sensors used to measure the controlled states, but some variables should be known to ensure a good control. Therefore, Kalman filter is used to restore the full states vector using three measurements corresponding to yaw rate $\boldsymbol{r}$, roll rate $\boldsymbol{p}$ and heading angle ψ. After the filtering estimation of the full state vector, the linear quadratic regulator (LQR) is used to control the aircraft, this theory is known as separation theorem [9 – 11].

The optimal Kalman filter is defined as:

$$\dot{\tilde{X}} = A_{ex}\tilde{X}_{ex} + B_{ex}U + L\left(Y - C_{ex}\tilde{X}_{ex} - D_{ex}U\right),$$

$$\begin{bmatrix} \tilde{Y} \\ \tilde{X} \end{bmatrix} = \begin{bmatrix} C_{ex} \\ I \end{bmatrix}\tilde{X}_{ex} + \begin{bmatrix} D_{ex} \\ 0 \end{bmatrix}U.$$

L is the Kalman gain matrix given by the following expression:

$$\boldsymbol{L} = \boldsymbol{P}\boldsymbol{C}_{ex}^{T}\boldsymbol{R}_{N}^{-1} \quad (7)$$

where $\boldsymbol{P}$ is the unique positive-definite solution to the following *Algebraic Riccati Equation (ARE):*

$$\boldsymbol{A}_{ex}\boldsymbol{P} + \boldsymbol{P}\boldsymbol{A}_{ex}^{T} + \boldsymbol{B}_{ex}\boldsymbol{Q}_{N}\boldsymbol{B}_{ex}^{T} - \boldsymbol{P}\boldsymbol{C}_{ex}^{T}\boldsymbol{R}_{N}^{-1}\boldsymbol{C}_{ex}\boldsymbol{P} = \boldsymbol{0}$$

$\boldsymbol{Q}_N$ and $\boldsymbol{R}_N$ are the covariance matrices associated with the measurement and process noises, respectively. The state feedback $\boldsymbol{K}$ is given in the following expression:

$$\boldsymbol{K} = \boldsymbol{R}^{-1}\boldsymbol{B}_{ex}^{T}\boldsymbol{S} \quad (8)$$

where $\boldsymbol{S}$ is the unique positive definite matrix of *(ARE)* associated with the optimal feedback problem:

$$\boldsymbol{A}_{ex}^{T}\boldsymbol{S} + \boldsymbol{S}\boldsymbol{A}_{ex} - \boldsymbol{S}\boldsymbol{B}_{ex}\boldsymbol{R}^{-1}\boldsymbol{B}_{ex}^{T}\boldsymbol{S} + \boldsymbol{Q} = \boldsymbol{0}$$

and the optimal control law minimizing the performance index, is as follows:

$$\boldsymbol{U} = -\boldsymbol{K}\tilde{\boldsymbol{X}}_{ex}.$$

The state space model of the closed loop system shown in fig.1 is given by the following equations:

$$\begin{bmatrix} X \\ \tilde{X} \end{bmatrix} = \begin{bmatrix} A_{ex} & -B_{ex}K \\ LC_{ex} & A_{ex} - LC_{ex} - B_{ex}K \end{bmatrix} \begin{bmatrix} X \\ \tilde{X} \end{bmatrix}.$$

Stage two: robust optimization. As stated before, the most wanted and valuable property in flight control system is the robustness without loosing performances. Many methods were proposed in the literature to recover the robustness of the closed loop system [4]. In this section, we will discuss this property and propose a solution to this crucial problem in flight dynamic. The method used is based on H_2/H_∞-robust optimization [7; 12]. During flight various uncertainties occur due to the parameters change. These uncertainties could be external and/or internal, structural and/or unstructured, which produce certain deviation from the nominal behavior to perturbed one. The idea is to find a compromise between the robustness and the performances for any perturbed model of the closed loop system with a single controller designed for the nominal plant. The design algorithm, is to estimate the performance and robustness of the closed loop system using H_2-norm of the sensitivity function and H_∞-norm of the complementary sensitivity function, then try to find the compromise between this two properties. For this reason, the solution to this problem to this problem is to insert several objectives in one cost function and try to satisfy them at the same time, it is known as multi-objectives optimization problem [13 – 15].

The optimization variables are the Kalman gain matrix L and the regulator gain matrix K, their initial values are computed in equations (7) and (8), respectively. The optimization procedure adopted in this paper is based on genetic algorithm, this technique is known as a suited method for multi-objectives optimization problems [14]. The block diagram shown in fig. 1, gives an overview of the scheme used in this study:

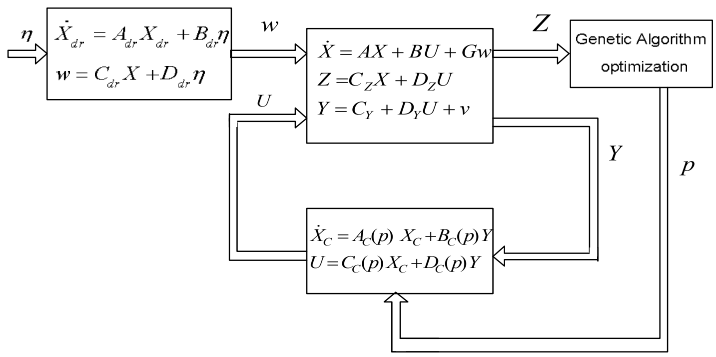

Fig. 1. Closed loop system (p is a vector of adjustable parameters of controller)

The performances and robustness are estimated for the three models, defined in the last section, by computing the H_2/H_∞-norms for the closed loop system depicted in fig. 1, for different scenario (In stochastic case and deterministic case). The composite performance index is given in the following [2; 3; 6]:

$$J = \lambda_{dn}\|H_{UZ}\|_2^{dn} + \lambda_{sn}\|H_{UZ}\|_2^{sn} + \lambda_{\infty n}\|T_{wZ}\|_\infty^{n} + \sum_{k=1}^{2}\lambda_{dpk}\left(\|H_{UZ}\|_2^{dpk}\right) + \sum_{k=1}^{2}\lambda_{spk}\left(\|H_{UZ}\|_2^{spk}\right) + \sum_{k=1}^{2}\lambda_{\infty pk}\left(\|T_{wZ}\|_\infty^{pk}\right) \quad (9)$$

where $\|H_{UZ}\|_2^{dn}$ defines the H_2-norm of the nominal model in deterministic case, $\sum_{k=1}^{2}\|H_{UZ}\|_2^{dpk}$ stands for summation of the H_2-norms of the two perturbed models. $\|T_{wZ}\|_\infty^{n}$ is the H_∞ – norm and gives the estimation of the robustness of the nominal controlled plant, $\sum_{k=1}^{2}\|T_{wZ}\|_\infty^{pk}$ computes the summation of the H_∞-norm for two parametrically disturbed plants. $\|H_{UZ}\|_2^{sn}$ defines the performances of the nominal stochastic model, the same summation of the H_2 – norm being defined for the two perturbed models with the expression $\sum_{k=1}^{2}\|\boldsymbol{H}_{UZ}\|_{2}^{spk}$. The computation of these quantities is given in [2; 3; 6; 13]. The LaGrange factors λ_{dn}, λ_{sn}, λ_{dpk}, λ_{spk}, $\lambda_{\infty n}$, $\lambda_{\infty pk}$ weight the contribution of each term in the cost function.

So far as the computation of $\boldsymbol{H}_2$ is based on the controllability Gramian the closed loop system should be stable and fully controllable over the whole optimization procedure, therefore the total cost function should include another term called penalty function (PF), restricting location's area of the closed loop system poles in the predefined region in the complex plan, the references [2 – 4] gives a mathematical model of this penalty function.

$$\boldsymbol{J}_{\Sigma} = \boldsymbol{J} + \boldsymbol{PF}_i \tag{10}$$

As it was mentioned before, complicated cost function (10) in practical cases is not convex, that is why local minima could take place in the optimization. As it is shown in [14 – 16], genetic algorithms optimization procedure is the most adequate and suited procedure to solve such problems.

Genetic algorithms. Genetic algorithms are a type of trial-and-error search technique that are guided by principles of Darwinian evolution [14 – 16]. Just as the genetic material of two living organisms can intermix to produce offspring that are better adapted to their environment, GAs expose genetic material, frequently strings of 1s and 0s, to the forces of artificial evolution: selection, mutation, recombination, etc. Genetic algorithms start with a pool of randomly-generated candidate solutions which are then tested and scored with respect to their utility. Solutions are then bred by probabilistically selecting high quality parents and recombining their genetic representations to produce offspring solutions. Offspring are typically subjected to a small amount of random mutation. After a pool of offspring is produced, this process iterates until a satisfactory solution is found or an iteration limit is reached. Genetic algorithms have been applied to a wide variety of problems in many fields, including chemistry, biology, and many engineering disciplines. GAs are applied to solve difficult problems where the fitness function to be optimized does not guarantee the existence of the derivative and satisfies multi-objectives, which can be contradictory. In this work the initial population is generated for the Kalman gain matrix $\mathbf{L}$ and static gain matrix $\mathbf{K}$, the fitness function given in the equation (9). Several selection methods were developed, in our case the normalized geometric distribution [14] is used. In this study the arithmetic crossover was adopted as a crossover function. The multi-non uniform mutation distribution is used to mutate the individual.

Simulation results and conclusions. In the computations of the initial Kalman gain matrix the following covariance matrices of the process and measurement noises are used $R_n = diag([0{,}05 \quad 0{,}05])$, $Q_n = diag([0{,}2 \quad 0{,}01 \quad 1])$, and are defined by the corresponding accuracy of the sensors. The weighting matrices Q_r, R_r for the optimal deterministic performance are given as: $Q_r = diag([0{,}1\ 0{,}1\ 0{,}01\ 0{,}04\ 0{,}02\ 0{,}1\ 0{,}1\ 1\ 0{,}1\ 0{,}01\ 0{,}1])$ $R_r = diag([0{,}031 \quad 0{,}1])$, as stated before Kalman filter uses 3 measurements to restore 11 states. Using the above covariance matrices the initial Kalman gain matrix in (7) is given as follows:

$$\mathbf{L} = \begin{bmatrix} 0.048 & 0.2108 & 0.0366 & 0.0086 & 0.0005 & 0 & -0.0009 & -0.006 & -0.0149 & 0 & 0 \\ 0.2961 & 0.7463 & 0.1905 & 0.0715 & 0.0209 & 0.0001 & -0.0033 & -0.0252 & -0.0501 & 0 & 0 \\ 0.0003 & 0 & 0.0002 & 0.0006 & 0.002 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}^T$$

After the optimization procedure $\mathbf{L}_{opt}$ is found as follows:

$$\mathbf{L}_{opt} = \begin{bmatrix} 0.0672 & 0.5561 & 0.0334 & 0.194 & 0.0003 & 0 & -0.0005 & -0.0002 & -0.0095 & 0 & 0 \\ 0.1686 & 1.3105 & 0.1361 & 0.0065 & 0.0053 & 0.0002 & -0.0012 & -0.0014 & -0.0185 & 0 & 0 \\ 0.0005 & 0.0001 & 0.0002 & 0.0025 & 0.0128 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}^T.$$

As well as the state feedback gain matrix before the optimization is given in the following:

$$\mathbf{K}=\begin{bmatrix} 0.0378 & -0.3984 & -0.2562 & -1.2077 & -0.5958 & 0.1568 & 242.02 & -9.6414 & 0.6951 & 6.0842 & -0.0341 \\ 1.6237 & 0.4357 & -4.8161 & 1.4632 & -0.1887 & -0.3289 & -99.77 & -21.3978 & 10.94 & -0.6936 & 8.4828 \end{bmatrix}.$$

The feedback gain matrix after the optimization procedure $\mathbf{K}_{opt}$ is found as follows:

$$\mathbf{K}_{opt}=\begin{bmatrix} -0.0833 & -0.1345 & -0.2114 & -0.6525 & -1.3823 & -0.0621 & -1.87 & -11.87 & 0.51 & 0.3326 & -0.01 \\ 0.6023 & 0.058 & -2.0817 & 3.1566 & -0.3706 & -0.4378 & -30.44 & 7.2748 & 3.8429 & -2.2514 & 18.62 \end{bmatrix}.$$

The simulation results are shown in figures 2 and table:

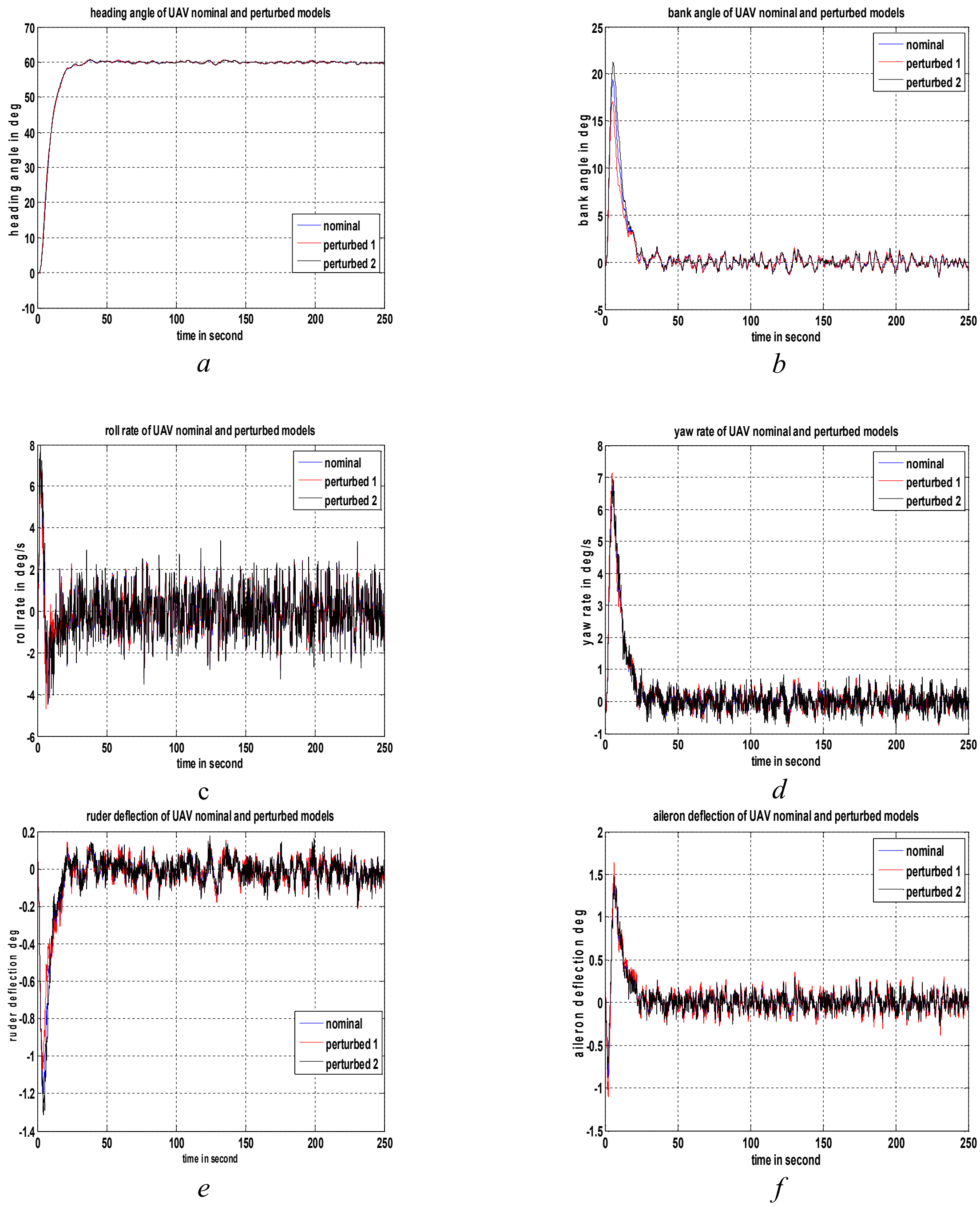

Fig. 2. Simulation results of UAV lateral motion: *a* – heading angle in deg; *b* – ruder deflection in deg; *d* – yaw rate in deg/sec; *e* – bank angle in deg; *c* – aileron deflection in deg; *f* – roll rate in deg/sec

H_2 and H_∞ norms of sensitivity function and complementary sensitivity function

Plant		H_2 Deterministic	H_2 Stochastic	H_∞
Vn = 30 [m/s]	nominal	0,8377	0,8315	3,0084
Vp_1 = 25 [m/s]	Perturbed 1	0,6167	0,6096	3,0082
Vp_2 = 35 [m/s]	Perturbed 2	1,2149	1,2091	3,0473

Conclusion. The simulation results of the lateral channel of the UAV prove the effectiveness of the proposed control method. The required flight performances are respected as well as the robustness of the control law. It can be seen that the handling quality of the nominal and the perturbed models are satisfied. The heading of the UAV is held at the reference signal ($60\deg$) as shown in the fig. 2, *a*, the maximum angles deflection of the ruder and aileron are $-1{,}3\deg < \delta_r < 0{,}2\deg$ and $-1{,}1\deg < \delta_a < 1{,}7\deg$, respectively. The other angle deflections for such UAV are respected as it can be seen in the latter figures. The compromise between the performances and the robustness is assured as it is shown in the figure.

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М. А. Туат

Робастная оптимизация многомерной системы управления боковым движением беспилотного летательного аппарата на основе генетических алгоримов

Рассмотрена процедура синтеза робастного закона управления для бокового движения беспилотного летательного аппарата с использованием процедуры H_2/H_∞ – робастной оптимизации на основании генетических алгоритмов. Качество и робастность системы управления оценены с помощью H_2-нормы для функции чувствительности и H_∞-нормы для комплементарной функции чувствительности. Комплексный показатель “робастность-качество” оптимизирован с помощью генетического алгоритма для нахождения компромисса между качеством и робастностью системы управления. Результаты моделирования замкнутой системы свидетельствуют об эффективности предложенной процедуры.

М. А. Туат

Робастна оптимізація багатомірної системи керування бічним рухом безпілотного літального апарата на основі генетичних алгоритмів

Розглянуто процедуру синтезу робастного закону керування для бічного руху безпілотного літального апарата з використанням процедури H_2/H_∞-робастної оптимізації на основі генетичних алгоритмів. Якість та робастність системи керування оцінено за допомогою H_2-норми для функції чутливості та H_∞-норми для комплементарної функції чутливості. Комплексний показник “робастність-якість” оптимізовано за допомогою генетичного алгоритму з метою відшукання компромісу між якістю та робастністю системи керування. Результати моделювання замкненої системи свідчать про ефективність запропонованої процедури.