MULTI-CRITERIA DESIGN OF AIRCRAFT CONTROL SYSTEMS USING A-TEAMS

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Abstract. *Modern aircraft companies are required to tackle the problem of finding high performance solutions for attitude control and navigation under extremely demanding constraints. Complex control problems are met with higher level of automation, optimization and integration of a variety of subsystems that compose a typical modern aircraft. The performance may require multiple objectives such as response-time, accuracy, realiability, safety, comfort and production cost, all of which must be considered simultaneously by the designer. In this work, asynchronous teams (A-Teams) are proposed to automate the problem of finding numerical solutions to multi-objective optimization problems, particularly in the field of aeronautical applications. More specifically, this work focuses a problem of tuning autopilot parameters using an A-Team. An A-Team is composed of several different algorithms that collaborate to search for a solution, sharing solutions among them without requiring a supervisor. The A-Team used in this work comprises tradicional multi-criteria algorithms such as weighted sum and goal programming methods. The main aim is to increase the probability of achieving global optimality.*

Keywords: *Multi-Objective Optimization, Asynchronous Teams, Aircraft Control*

1. Introduction

Flight control technology has changed the methods to design airplanes, with strong consequences on their flight characteristics. One of the most important subsystems of an aircraft is the *Flight Control System* (FCS), responsible for directing the aircraft in accordance with the pilot's command. Because of the complexity of this type of task, the FCS is required to interact with other subsystems, such as propulsion, control surfaces and sensors. Furthermore, FCS design engineer has to deal with many uncertainties and is faced to problems such as wind gusts, variations in the airplane weight, aerodynamic forces and noises in the sensors. In this context, aircraft manufacturing companies should attempt to diminish costs and production time, through the increase in the level of automation, use of optimization techniques, and integration of many subsystems that compose a typical modern aircraft.

In this paper, a fixed structure controller for an aircraft has been considered (more specifically, a proportional-integral controller with pre-filter). Then, the controller parameters are optimized to improve the aircraft performance considering, simultaneously, multiple objectives.

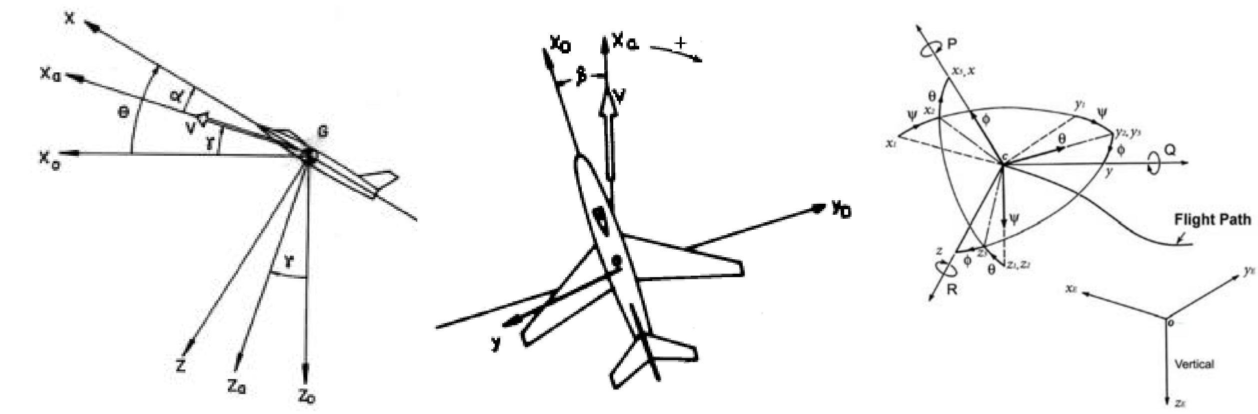
Some algorithms present nice properties such as high speed of convergence. However the average quadratic error in the output can still be relatively high. Other algorithms may achieve small average quadratic error, however they can present low convergence speed. Then, an interesting proposal is to construct a computational structure that uses many different types of algorithms working asynchronously, in parallel, to yield a better result than each algorithm working alone. The algorithms work as a team, called Asynchronous Team (A-Team), sharing the available informations in a common area. An A-Team constitutes a way to organize diverse softwares (agents) to solve a problem. The agents work in an asynchronous, interactive and cyclical form, on a data set deposited in shared memories (Souza and Talukdar, 1993) (Peixoto and Souza, 1994).

Combining some algorithms through an asynchronous teams structure, reliable values may be found in terms of global optimality. As an example for application of the proposed method, control of an F-16 aircraft is presented.

2. Aircraft Control and Simulation

2.1. Mathematical Model

Consider components of the displacements, speeds, forces, and other variables such as moments, inertia products and stability derivatives, described in a reference system with its origin in the aircraft's CG (Figure 1).



(a) (b) (c)

Figure 1 - Inertial, Reference and Body System of axes: (a) Lateral View and (b) for Top View. (c) Euler Angles.

The equations of motion for a rigid body can be expressed by the following vector equations (P is the momentum and H is the angular momentum, and considering m constant, that is, the mass doesn't vary with the time):

Translation: $$\sum \vec{F}_{ext} = \frac{d}{dt}\left\{ \vec{P}\Big|_E \right\} = \frac{d}{dt}\left\{ m.\vec{V}\Big|_E \right\} \quad (1)$$

Rotation: $$\sum \vec{\mathrm{M}}_{ext} = \frac{d}{dt}\left\{ \vec{H}\Big|_E \right\} \quad (2)$$

Furthermore, considering $\vec{\omega}$ the angular velocity of an aircraft in relation to the Earth and, adopting the body system as reference, one obtains that:

$$\frac{d}{dt}\left\{ \vec{V}\Big|_E \right\} = \frac{d}{dt}\left\{ \vec{V}\Big|_B \right\} + \left(\vec{\omega} \times \vec{V} \right) \quad (3)$$

In an analogous way, the time derivate of the angular momentum becomes:

$$\sum \vec{\mathrm{M}}_{ext} = \frac{d}{dt}\left\{ \vec{H}\Big|_E \right\} = \frac{d}{dt}\left\{ \vec{H}\Big|_B \right\} + \left(\vec{\omega} \times \vec{H} \right) \quad (4)$$

Using the motion equations and adding the kinematics relations given by the Euler angles (relative orientation between the terrestrial-inertial reference system and the aircraft body) represented by ϕ, θ and ψ, one gets the motion equations for the nonlinear aircraft model. In this paper, the aircraft model assumes six degrees of freedom as approximated by rigid body equations represented in coordinated system of the aircraft (Stevens and Lewis, 1992). The aircraft states vector is thus represented by (5), where u, v and w are the velocities in relation to X, Y and Z body-axis (forming the vector speed V); ϕ, θ and ψ are the Euler angles; P, Q and R are the angular velocities; N_{dis}, E_{dis} and h are the navigation variables (h = altitude).

$$x = [u \quad v \quad w \quad \phi \quad \theta \quad \psi \quad p \quad q \quad r \quad N_{dis} \quad E_{dis} \quad h]^T \quad (5)$$

2.2. Automatic Control Systems

Aircraft control systems can be designed to fulfill several types of requirements. Three examples of tasks that an aircraft control system can perform are: (1) *Stability Augmentation Systems* (SAS), a system that it modifies the aircraft dynamics through state feedback, modifying its stability derivatives and rendering the aircraft more robust to external disturbances; (2) *Control Augmentation Systems* (CAS), a system that allows to enhance the performance of control surfaces reducing the error between the reference signal and the output aircraft sensors, making possible a reduction of aircraft response time; (3) *Automatic Pilot* or *Autopilot*, a control system, usually in closed-loop, that makes possible a flight without pilot intervention, following commands issued *a priori*.

In this work, a CAS system was implemented (Figure 2), where x is the aircraft states vector, u is the control surface, v is the output compensator, y is the output internal loop SAS (C matrix), e is the error, r is the reference, z is the output properly said (H matrix) and, L and K are gains to be definitive in the project. For sake of simplicity in the presentation, a linearized model about a desired flight envelope is used in the example (Figure 2).

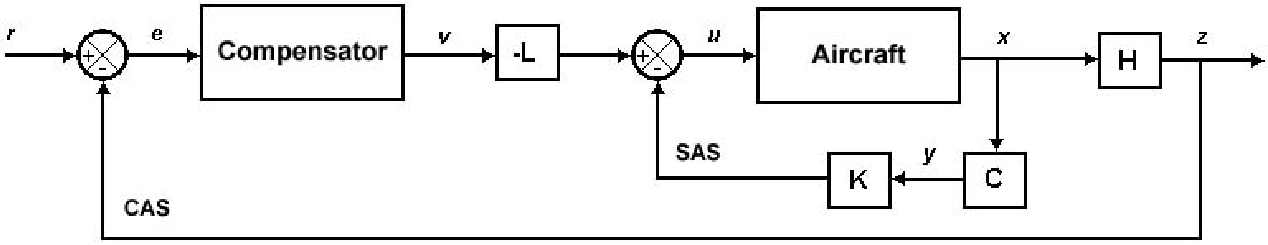


Figure 2 - Model of a CAS for aircraft.

3. Multi-Criteria Optimization

3.1. Definition

A problem of Multi-Criteria or Multi-Objective Optimization involves with more than one objective function that must be considered simultaneously. A general problem of multi-objective optimization can be represented as in (6) (Marler and Arora, 2004):

$$\underset{\boldsymbol{x}}{\text{Minimize}} \quad F(x) = [F_1(x), F_2(x), \dots, F_k(x)]^T \tag{6}$$

$$\text{subject to:} \quad g_j(x) \le 0, \qquad j = 1,2, \dots, m,$$
$$h_l(x) = 0, \qquad l = 1,2, \dots, e,$$

where k is the number of objective functions, m is the number of inequality constraints and, e is the number of equality constraints. Also, $x \in E^n$ is a vector of decision variables, where n is the number of independent variables x_i. $F(x) \in E^k$ is a vector of objective functions $F_i(x)$: $E^n \rightarrow E^1$. $F_i(x)$ are also called *objectives, criteria, cost functions, or value functions*. The gradient of $F_i(x)$ with respect to x is written as $\nabla_x F_i(x) \in E^n$. x_i^* denotes the point that minimizes the objective function $F_i(x)$.

A feasible solution x will be the one that satisfies $m+e$ constraint functions. Otherwise the solution will be not feasible. The set of all the feasible solutions forms the feasible region or search space S.

Each one of the objective functions $F_1(x)$, $F_2(x)$, ... , $F_k(x)$ can be maximized or minimized, however, it is convenient to convert all so that they are all to be maximized or minimized. The feasible decision space $\boldsymbol{X}$ (space of x) is defined as a set $\{x \mid g_j(x) \le 0,\ j = 1,2, \dots, m;$ and $h_l(x) = 0,\ l = 1,2, \dots, e\}$. The criterion space $\boldsymbol{Z}$ (space of objectives F) is defined as $\{F(x) \mid x \in X\}$. Then, for each solution x in the decision space, there is an $F(x)$ in the objective space.

3.2. Pareto Optimality

In contrast with simple objective optimization, in the multi-objective problems there may not be a simple global solution, but a set of points that can appear as good solutions for the problem in question, of which none is quantitatively better than another. The predominant concept in defining an optimal point is called Pareto optimality given by the following definition: a point $x^* \in X$, is Pareto optimal, iff there does not exist another point, $x \in X$, such that $F(x) \le F(x^*)$, and $F_i(x) \le F_i(x^*)$, for at least one function. In Figure 3, it is presented *Pareto Boundary* with the possible good solutions for a problem with two objectives. The solutions that belong to Pareto boundary are called Non-Dominated Solutions (points A and B).

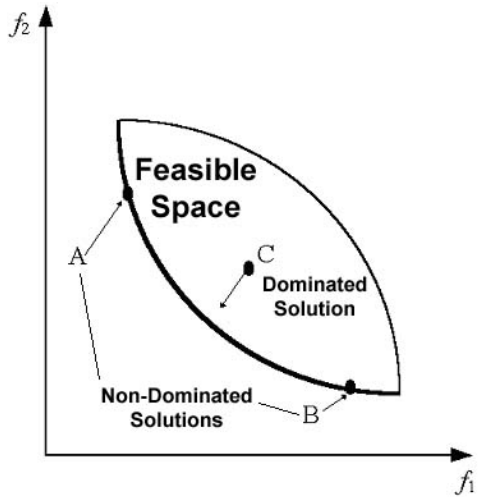


Figure 3 - Pareto optimal solution (in bold) in the objective space.

3.3. Traditional Techniques for Multi-Criteria Optimization

3.3.1. Weighted Sum

The weight sum strategy converts the multi-objective problem to one of minimizing a scalar objective function constructed by a weight sum of all the objectives, as shown in (7).

$$\text{Minimize} \quad f(x) = \sum_{i=1}^{m} w_i F_i(x) \qquad (7)$$

$$\boldsymbol{x} \in \boldsymbol{X}$$

The problem can be optimized using a simple optimization algorithm with or without constraints. The problem is to evaluate and find the best weight for each objective function. There are difficulties for cases of non-convex functions.

3.3.2. Goal Programming Method

This technique tries to find solutions that can reach a predetermined goal (target) for one or more objective functions. In case that there is not a feasible solution that reach the goals for all the objectives, this technique minimizes the deviations in relation to the goals. Considering $F^* = [F_1^*, F_2^*, ..., F_k^*]$, that it is the goals vector for $F(x)$, and w a weight vector associated to $F(x)$ function, the problem is re-written as (Matlab Help, 2005):

$$\text{Minimize} \quad \gamma \qquad (8)$$

$$\gamma \in \Re, \boldsymbol{x} \in \boldsymbol{X}$$

$$\text{subject to:} \quad F_i(x) - w_i\gamma \le F_i^*$$

4. Asynchronous Teams

4.1. Introduction

The task of tuning the gains of a controller can be cast as an optimization problem, where certain requirements for output of the dynamic system as response time, precision, cost, must be satisfied. Any multi-objective optimization algorithm can present some difficulties to converge to the minimum global point.

In this work the problem of multi-objective optimization is to be tackled with algorithms working in parallel and in an asynchronous way, each one cooperating with the other in order to get better result together that they would get separately. This structure is known as Asynchronous Teams (A-Teams) (Souza and Talukdar, 1993).

There are many different alternatives to develop an asynchronous team (Saito et al, 1999). A team can be formed with several different algorithms, but there may be copies (instances) of the same algorithm.

4.2. Asynchronous Team Components

The asynchronous teams are formed by independent elements and can be integrated through computer networks. Each net computer will be an element of asynchronous team. The project of implemented asynchronous team can be seen in Figure 4.

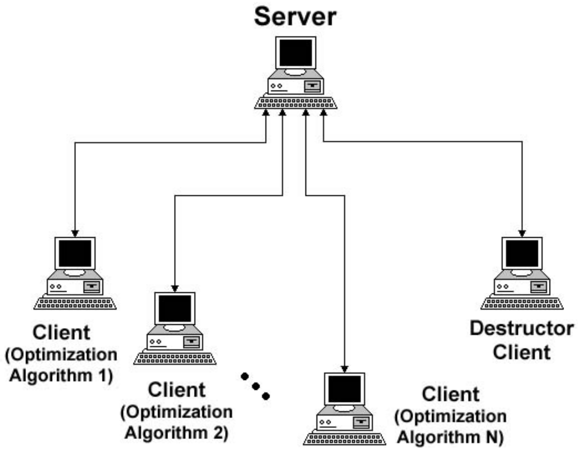


Figure 4 - Example of an Asynchronous Team.

The asynchronous team used in this work has a *server* computer. The other computers are considered *clients* (which can be optimizer clients and destructor clients).

The *server* coordinates all the A-Team information and its structure. It is responsible for creating the initial points to be used by optimizer clients. It can also control the team, creating new clients or destroying already existing one, in case of necessity. It also has the decision on when the team must stop. This occurs, in general, after applying a criterion to verify if the minimum has been found.

The *optimizer clients* have the function to execute the multi-objective optimization algorithms. An initial condition is retrieved from the server and the algorithm is executed up to a pre-determined number of iterations. At the end of the execution, the client sends the final solution to the server that places it in a solutions list for general access, called *Blackboard*. In this case, the following situations can occur: the algorithm converges to the minimum point, the algorithm doesn't converge of satisfactory form, or the algorithm diverges. These informations are supplied to the server that re-initiates the client if necessary.

The *destructor clients* have the function to prevent that the solutions list stored in the black picture grows in an uncontrolled form, obeying some criterion of decision. Different methods can be adopted, as simply to eliminate the *M* worst solutions or to calculate the probability to remove the solution in the blackboard by taking into account the distance to the best solution found until the moment. In cases where the asynchronous team has high complexity, agents can be used to inform to the server which the situation or state of each client, also being able to modify the parameters of each optimizer client.

5. Implementation and Aplication of the A-Team

For the A-Team functions to operate in a satisfactory way, it must use a communication protocol between the team components, defining the form the clients will communicate themselves with the server, and the tasks to be done. Protocol TCP/IP was used for the communication, which guaranteed the exchange of information between client and server without data loss.

The server creates a blackboard of initial conditions to provide different initial conditions created by an algorithm using *Tabu Zone* (Nascimento and Yoneyama, 2000). All the information exchanged between the client and the server are stored in the blackboard. The best found solutions, up to a certain instant, are stored and explored by the tabu zone algorithm. Moreover, other regions are explored, with lower probability, by Metropolis moves.

In the problem of CAS for the F-16 aircraft, given in (Stevens and Lewis, 1992), two cases have been analyzed: (1) the first case mentions a SISO system (longitudinal mode, short period) for the pitch-rate control system (i.e., state q); (2) the second case treats a MIMO system (lateral-directional mode) for a wing-leveler lateral control system (i.e., states ϕ and r).

For the considered problems, the value of overshoot M_p and the settling time t_s were used as objective function $F(x)$, and vector x was represented by the gains of control systems. The weighted sum and the goal programming algorithms, supplied in the MATLAB®, were used. For the problems, the A- Team consisted of two clients, each one running the cited algorithm, and a computer that had the role of server and destructor.

First, consider the SISO system with classical pitch-rate control as shown in Figure 5 (Stevens and Lewis, 1992), where r represents the reference (for q state), where its value was adjusted for 1°/s.

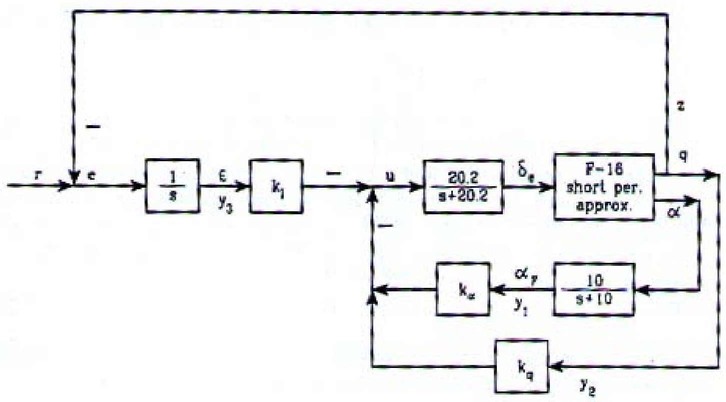
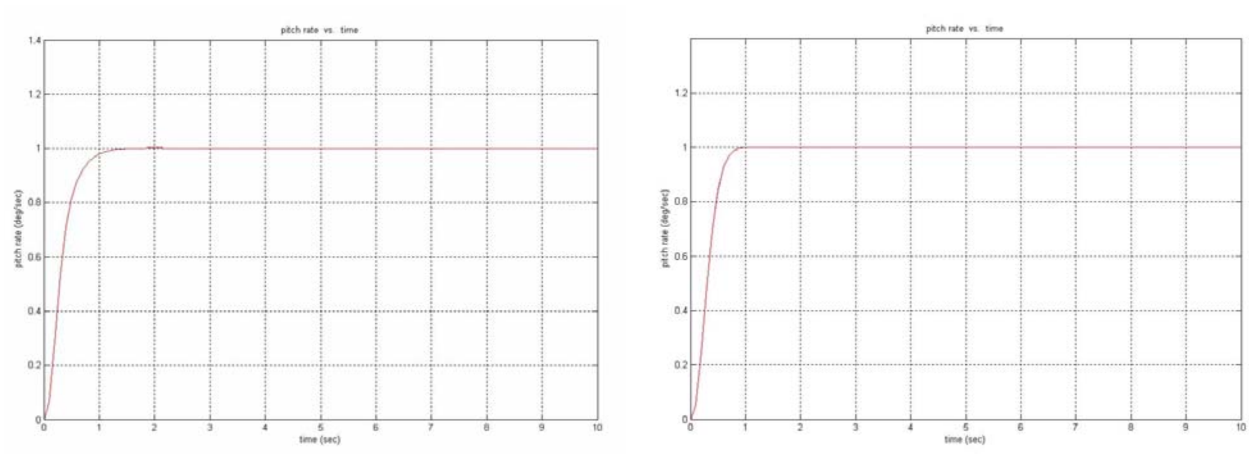


Figure 5 - Pitch-rate control system.

A comparison between the results found using LQR techniques given in (Stevens and Lewis, 1992) and the one found by the asynchronous team can be seen in Figure 6. In the graphs, the linear and nonlinear simulations of q state are presented.



(a) (b)

Figure 6 - Responses of q state, using (a) LQR and (b) Asynchronous Team.

For this simple case, a small improvement was obtained using the asynchronous team, i.e., a smaller settling time and overshoot for the system were observed.

In the second case, a MIMO system (wing-leveler lateral control) was considered as shown in Figure 7 (Stevens and Lewis, 1992), where r_ϕ and r_r represent, respectively, the references for states ϕ and r. In this case, reference were considered $r_\phi = 1$ rad and $r_r = 0$ rad/s.

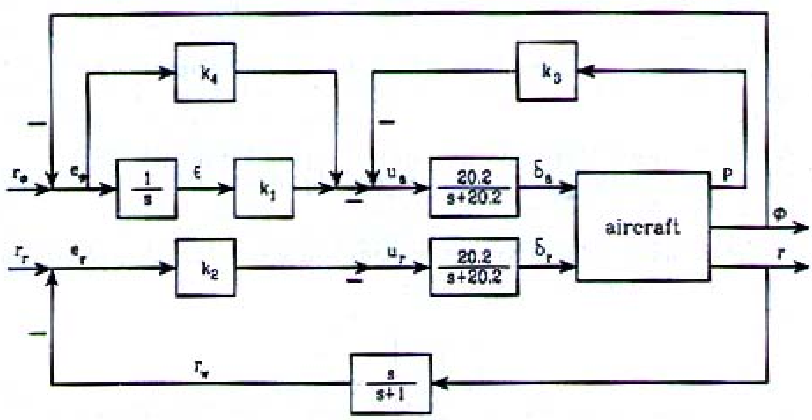
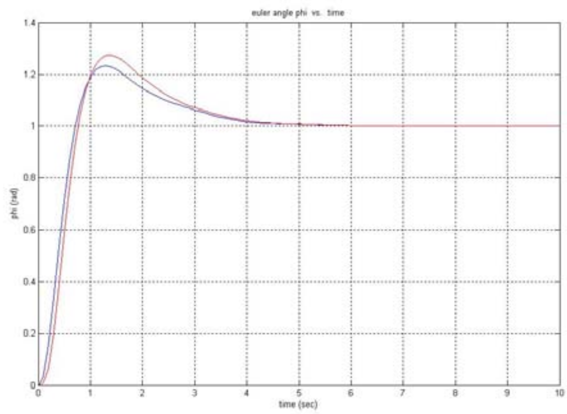
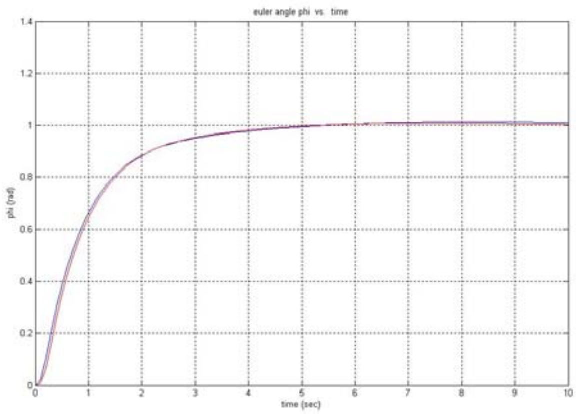


Figure 7 - Wing-leveler lateral control system.

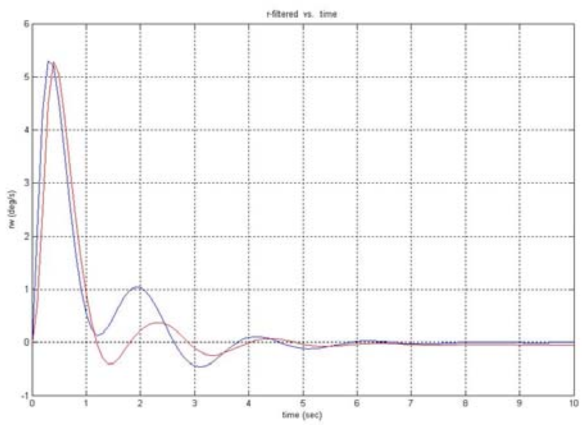
As before, a comparison between the results found using LQR techniques and the one determined by the asynchronous team, can be seen in Figure 8 (linear and nonlinear simulations).



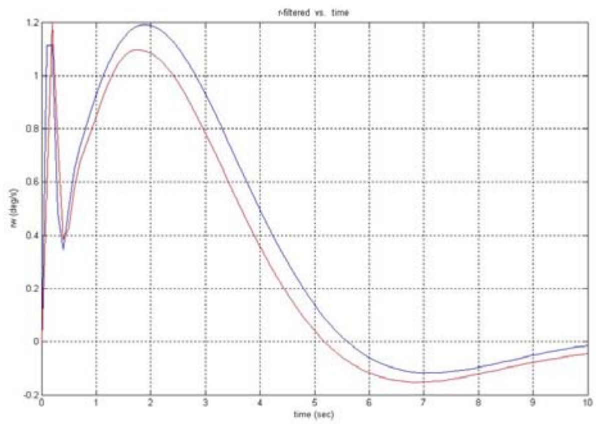
(a)



(b)



(c)



(d)

Figure 8 - Responses ϕ and r_W using (a) (c) LQR e (b) (d) Asynchronous Team, respectively.

One can note in the figure 8 that the results determined by using asynchronous team was quite adequate for this case of a MIMO system, where a fast response and a small overshoot were observed (in the case of ϕ), different in the case of LQR. Despite the good behavior of the ϕ state, the r state turned out to be somewhat slow to reach the equilibrium. On the other hand, the maximum variation of r_W is smaller than in the LQR optimization.

6. Conclusion

The problem of tuning the gains of a fixed structure controller can be solved through optimization algorithms, and in the case, multiple objectives were considered. A difficulty with some of the optimization algorithms is that only a local minimum of the cost function may be found or slow speed of convergence is achieved.

The A-Team structure tries to reduce the probability of encountering those problems by combining several multi-criteria algorithms, so as to exploit the best features of each one member of the team. It is then possible to get better results as in the example of aircraft controllers, presented in this paper.

By a careful choice of the cost functions, one can get excellent results in terms of Pareto solutions, as observed in the examples, where the comparison was made with respect to the results of LQR method.

The problem of developing more powerful clients is currently under investigation. In particular, one can examine the use of other algorithms as an Evolutionary Algorithm (as Multi-Objective Genetic Algorithm - MOGA, for example) and alternative multi-criteria algorithms.

7. References

Marler, R.T., Arora, J.S., 2004, "Survey of multi-objective optimization methods for engineering", Engineering Optimization.

Matlab Help, 2005, "Optimization Toolbox", www.mathworks.com/access/helpdesk/help/toolbox/optim/optim.html.

Nascimento Jr., C.L., Yoneyama, T., 2000, "Inteligência Artificial em Automação e Controle", Edgard Blücher.

Paglione, P., Zanardi, M.C., 1990, "Estabilidade e Controle de Aeronaves", Apostila curso MVO-03.

Peixoto, H.P., Souza, P.S. de, 1994, "Uma metodologia de Especificação de Times Assíncronos", Technical Report DCC-94-12, Unicamp, Campinas.

Saito Jr, P.A., Nascimento Jr, C.L. e Yoneyama, T., 1999, "Treinamento de Redes Neurais Artificiais utilizando Time Assíncrono", IV Congresso Brasileiro de Redes Neurais, pp. 78-83.

Souza, P.S. de, Talukdar, S.N., 1993, "Asynchronous Organizations for Multi-Algorithm Problems", SAC 1993, pp. 286-293.

Stevens, B.L., Lewis, F.L., 1992, "Aircraft Control and Simulation", John Wiley & Sons, Inc., Second Edition, 680 p.