DESIGN ASPECTS OF INTELLIGENT FLIGHT CONTROL SYSTEMS

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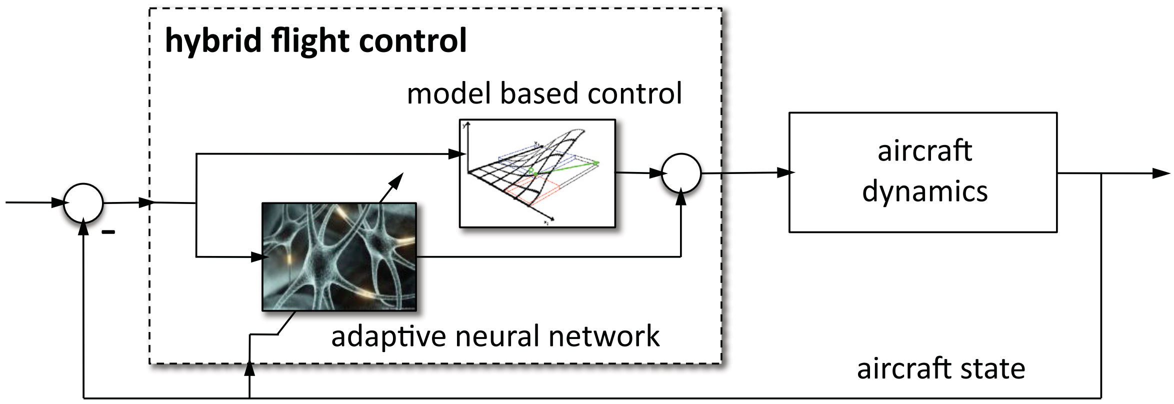
Abstract

Within the scope of the recently initiated joint project "Bürgernahes Flugzeug," the Institute of Aerospace Systems (ILR) of the TU Braunschweig conducts research in the field of intelligent flight control systems (IFCS). While previous research efforts focused mainly on neural network based control of unmanned aerial vehicles (UAVs), this project extends this focus to conventional aircraft and strives to develop new solutions that enable a secure flight in both nominal and faulty conditions.

This paper will first outline the overall purpose and the goals of the joint project "Bürgernahes Flugzeug" in order explicate the role of and the need for rigorous research in the field of IFCS. The institute's current state of UAV control based on artificial neural networks forms the foundation for ongoing research and will thus be briefly depicted. So far, the investigation of learning algorithms and their stability were emphasized as they embody a crucial aspect of machine learning. Subsequently, some relevant literature on hybrid, fault tolerant, and intelligent flight control will be briefly surveyed. Lastly, the key concepts are summarized and links to future work will be pointed out.

The general structure of a hybrid flight controller which forms the inner loop of an IFCS is displayed in the figure below. It is the main idea to combine modern control design methodologies, such as dynamic inversion, with a neural network as an adaptive element. Since inversion based approaches often suffer from inversion errors due to structural system uncertainties or are sensitive to parameter errors, an adaptation to changing operating conditions is beneficial even for nominal flight. The highly valuable aspect of this hybrid combination is the capability to accommodate to drastically changing flight regimes due to structural failures or severe atmospheric turbulence.



Schematic block diagram of a hybrid flight controller

Since the early 1980s the research on advanced flight control systems has brought up a vast variety of methodologies. Intelligent flight control is associated to the field of hybrid, fault tolerant, and reconfigurable control. The authors try to categorize these approaches in order to clarify the possible routes taken in future work. In general, the following requirements are to be satisfied:

- Adaptation must be done under real-time conditions and quick enough to provide good transient performance and stability.
- Human interaction should be minimal meaning that some automatic decision making mechanism must be available for controller reconfiguration
- Independent of the actual situation, the selected method must provide a solution even if it is not optimal.

The main part of this paper will consist of a review and a description of the relevant design aspects with respect to the applicability to a commercial aircraft IFCS . These aspects are among others: redundancy, control re-allocation, on-line model identification, actuator constraints, reliability, and stability of both the entire system and the utilized learning algorithms. This preliminary investigation shall serve as a baseline for the design of a hybrid system architecture that strives to bring flight safety and performance to a new level.

NOMENCLATURE

a ... spline coefficent for x-coordinate
b ... spline coefficent for y-coordinate
b_j ... bias value of neuron j
d ... measured deviation from the spline
$\hat{d}$ ... predicted deviation from the spline
E_j ... squared error of the network output
f ... transfer function of a neuron
$\mathbf{J}$ ... Jacobian matrix of the network weights
n ... argument of the transfer function
s ... parameter for the position on the spline
t_j ... target of neuron j
u_j ... output signal of neuron j
w_{ij} ... weight from neuron i to j
x ... x-coordinate in the geodetic system
y ... y-coordinate in the geodetic system
δ_j ... error signal of a neuron
μ ... learning rate
λ ... sliding function parameter
ξ_c ... control signal of the ailerons

1. INTRODUCTION

The joint project "Bürgernahes Flugzeug[1]" has the vision to meet the citizens' demand for a next generation aircraft with a short start and landing capability[1]. Connecting Europe's metropolises, these new aircraft shall increase mobility while reducing noise pollution, energy consumption, and thus total cost of operation. The technologies that will be developed together at the DLR, TU Braunschweig, TU Clausthal, and Leibniz-Universität Hannover combine

- multifunctional, hybrid leightweight structural design
- high performance jet engines with enhanced operating space
- advanced aerodynamical and aeroacustical design methodologies
- integration and automation of onboard and ground-based air traffic control
- technological foundations for a one-man-cockpit in commercial aircraft by new approaches of intelligent flight control and reconfiguration of degraded systems.

Despite being one of the safest means of transportation, aircraft accidents happen on rare occasions with catastrophic consequences. This motivates the research on intelligent flight control systems that not only lower pilot work load in nominal flight but also handle a wide range of faulty and off-nominal flight regimes. Much research has been conducted on this topic in the last two decades[2, 3, 4, 5, 6, 7, 8, 9]. Thus, this paper tries to provide a categorization of the proposed designs and summarizes the critical design aspects that need to be taken into account when designing an IFCS.

The next section of this paper surveys the basics of intelligent flight controller designs. Starting from a rather abstract description of IFCS, the necessary components and design options will be briefly described. Subsequently, approaches of hybrid neural control as adaptive inner loops are discussed. Within this scope, a modular, purely neural flight controller that was successfully applied to a simulated UAV[10] will be reviewed. This projects strives to transfer the gained experiences and discusses the applicability of the presented concepts to commercial aircraft such as the Airbus A320. Finally, conclusions will be drawn and links to future work will be pointed out.

2. INTELLIGENT FLIGHT CONTROL

With the increasing density and automation of air traffic, classical flight controllers have become an integral part of almost any commercial aircraft system[11]. Today, these control systems are designed to handle basic functions and different flight regimes, such as cruise, start and landing. Even though in principle an entire flight could be conducted automatically, off-nominal flight conditions due to fault, damage or severe atmospheric conditions can overburden such a classical flight control system.

In 1989, for example, a disintegrating turbine disk destroyed the hydraulic lines of a DC-10 aircraft leading to complete malfunction of all control surfaces[12]. Using just differential thrust, the captain was able to stabilize and land the aircraft saving the lifes of the majority of the passengers and crew members. Another, more recent case happened in 2009 when US Airways Flight 1549 landed in the Hudson River of Ney York City. Just after departure, the plane had suffered a "double bird strike" causing both engines to fail. Again, it was the incredible skill of the pilot that prevented a catastrophy.

Clearly, the main reason for the integration of "intelligence" into the onboard flight controller is to incorporate features that enable a self-repairing flight control that maximizes controllability and prevents the mission from failing. The control system must be able to correct for unanticipated system failures using current technology flight sensors and computer algorithms. However, the design engineer faces a complex problem for many levels of a flight control system are involved in this ambitious endeavor (see Figure 1). The planning of trajectories does not only have to meet the requirements of the designed control law, it further has to take degraded dynamics and sensed obstacles into account. Optimization of energy consumption or flight duration again constrains the planning. Another important aspect is the proper allocation of manipulated inputs to functioning control surfaces and is closely interlinked to controller design. Before the IFCS

[1]literal translation: "citizen-friendly aircraft"

can react on any fault, an appropriate algorithm is to be implemented that diagnoses the subsystems, detects abnormal properties, and isolates the fault in a way such that its influence is both known and minimized. All these technologies have been subject to extensive research and, for obvious reasons, cannot be detailed here.

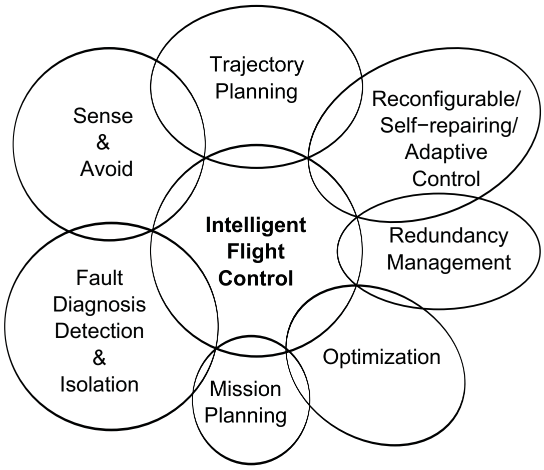
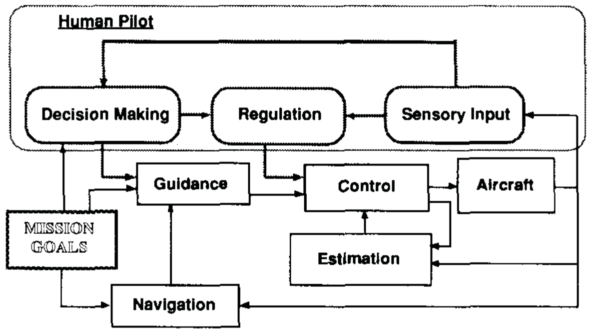


Figure 1: Adjacent technologies that are combined to an intelligent flight control system

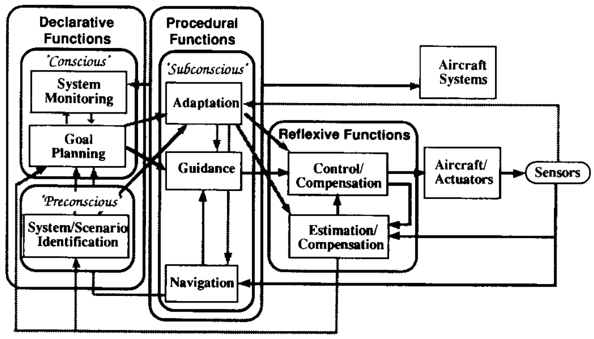
In 1993, Robert F. Stengel proposed an IFCS that mimics the cognitive processing of the human brain (see Figure 2(a)). Following his paper[13], the components of intelligent flight control systems can be categorized into *declarative actions* that involve decision making, mission planning, and system/health monitoring and diagnosis, *procedural actions* that enable the aircraft to perform skilled behavior such as guidance and control, and lastly *reflexive actions* that enable fast adaptation, estimation and spontaneous reactions. Figure 2(b) displays a block diagram of this concept. This categorization matches the traditional control design principle of having a cascaded structure with low-bandwidth outer loops with large amplitude and high-bandwidth inner loop functions with small amplitude.

The project described in this paper strives to combine analytical, model-based control with artificial neural networks to hybrid neural systems that perform the reflexive part of an IFCS. This approach has been put into the context of *expert control*[14] that embodies a paradigm for controllers that yield higher degrees of automation by performing tasks and making decisions that normally expert human operators would do.

At this stage, possible hybrid control architectures were surveyed and will be described in the next subsection. The training algorithm of a neural network has to be selected carefully as it has implications not only on stability but also on adaptation performance. In this context, a



(a)



(b)

Figure 2: (a) Human pilot in the flight control loop (b) Intelligent flight control architecture (taken from[13])

recently developed training algorithm based on sliding modes will be briefly reviewed.

2.1. Hybrid Flight Control

The investigation of hybrid systems[2] that integrate not only sequential, symbolic algorithms but also artificial neural networks is a relatively new research domain. In 2000, Stefan Wermter and Ron Sun[15] gave a generalized overview on hybrid neural systems both in terms of classification and taxonomy. The main motivation for usage of both symbolic processing (i.e. analytical equations and models) and neural networks is based on different viewpoints: From the point of view of the recently more and more popular approach of bio-inspired control, a purely neural processing architecture may be the most desirable. In simple words, both human and insect brains work by means of massively parallel neural networks that fulfill a formidable task in coping with unstructured and uncertain environments and rich sensory data. Still, the design engineer still faces a significant gap in complexity between natural neural networks and the bio-mimical

[2]It should be noted that in a different context *hybrid systems* can also mean the combination of discrete and continuous time systems.

digital counterpart: even the brain of one of the simplest insects, the fruit fly (*drosophila*) with its 10^5 neurons, contains orders of magnitudes more neurons than the largest nets that can be effectively implemented on dedicated signal processors.

Artificial Neural Networks (ANNs) are a computational model that tries to simulate the functioning of biological neural networks. On the lowest level, they consist of neurons that are connected to other neural cells by weighted interlinks. Having just one output but possibly many input signals, the sum of all inputs of a single neuron is passed to the transfer (or activation) function which is often realized as a sigmoid function. Layers of neurons are connected in a sequential fashion in order to construct a complex network with a high-dimensional space of synaptic weights. To achieve the goal of mapping inputs to outputs in a desired way, these weights have to be adjusted by applying an appropriate training algorithm such as the gradient descent method, the Levenberg-Marquardt algorithm, or more advanced approaches[16]. Even simple neural networks have been proven to yield excellent results in various technological fields. The integral part of their application is comprised of rigorous training based on carefully chosen data where the net learns the knowledge of how to perform a certain task. This knowledge, however, is stored implicitly in terms of numerical values that represent the synaptic weights. In most cases, this representation lacks an obvious, natural interpretation.

Despite their remarkable performance, it is still difficult for scientists to provide a comprehensible, unified explanation why a certain configuration of a neural network succeeds to fulfill a technological task - the mapping between input and output is hidden in the multidimensional space of weights. Especially for security critical applications this fact has so far obviated the certification of systems that employ neural networks. This "black box" character has lead not only to criticism in the past but has also driven the effort to "open" this box by using modular and hybrid architectures. For the same reason, purely neural flight control aggravates the incorporation of human expertise to simplify algorithm complexity and improve closed loop performance and robustness - a neural network always has to learn from scratch. For neural networks to be widely applied to flight control systems, an explanation capability should be an integral part of the functionality of a trained neural network. This aspect will be in the center of research for this project.

In principle, adaptive flight control can be divided into three categories:

1. *indirect adaptive control*

   Aircraft parameters are estimated in real-time and serve as knowledge base for gain scheduling, reconfiguration and variable structure control[17]. Numerous estimation techniques exist with different properties and real-time suitability[18], including neural network approaches[19].

2. *hybrid/direct adaptive control*

   A common case of direct adaptive control is to extend a model-based nonlinear dynamic inversion control law with an estimator of the inversion error. Artificial Neural Networks (ANN) are well suited for this task since by learning in real-time they acquire implicit knowledge of parameters, unmodelled system dynamics and faults at the same time[20, 21, 22, 23].

3. *model-free neural control*

   Model-free neural control forms the highest degree of adaptation and does not explicitly involve any modelling of system/plant dynamics. Instead, (possibly modular) neural networks function as observer or controller.

The next section will review such a model-free neural control design as proposed by T. Krüger et al.[25].

2.2. Modular Neural UAV Control

An important elemtent of this neural control strategy is the implementation of the commanded flight path as cubic Bézier-splines. These splines are interlinked with each other to generate a desired flight path. This allows a continuous determination of the deviation from the desired path[26] which is critical information for the neural control approach. A simple example of a single, planar spline is shown in Figure 3.

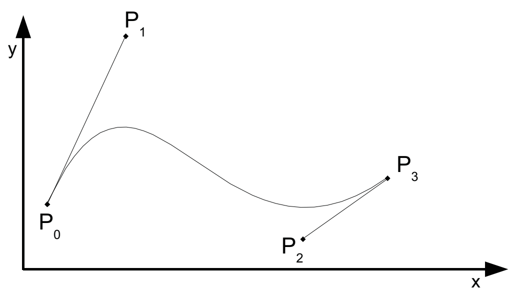


Figure 3: Example of a single cubic spline used to define the flight path by interlinking several spline segments

The Bézier-splines

(1) $$x(s) = a_3 \cdot s^3 + a_2 \cdot s^2 + a_1 \cdot s + x_0$$

(2) $$y(s) = b_3 \cdot s^3 + b_2 \cdot s^2 + b_1 \cdot s + y_0$$

are each defined by four points $\{P_0, \ldots, P_3\}$ given in the geodetic coordinate system, where s is the parameter defining the position on the spline ($s \in [0,1)$)

while $a_1 = 3(x_1 - x_0)$, $a_2 = 3(x_0 - 2x_1 + x_2)$ and $a_3 = -x_0 + 3x_1 - 3x_2 + x_3$. The coefficents b_1 to b_3 from (2) are calculated likewise simply using y_0 to y_3. The two main advantages of this method are: Firstly, the desired flight attitude can be determined beforehand for every point on the trajectory, since the desired roll-angle is a function of the curvature of the spline and secondly, the deviation from the spline as a direct measure of lateral trajectory following can be measured at every control step. This information is used as an additional input signal for the neural controller and is used as target value for the neural observer.

One main element of the control strategy[10] is depicted in Fig. 4. The neural observer (or predictor) is trained to map the deviation from the target trajectory of the next discrete time step. The permanent measurement of the spline-deviation d compared with $\hat{d}$ provides the direct quality signal $\Delta\hat{d}$ for predictor training. Since there is no direct quality signal for the controller, the inverse dynamic of the predictor is used to backpropagate the spline deviation, so that the error signal $\Delta\xi_c$ for online-training can be generated. Below, a possible procedure to calculate this error signal is presented.

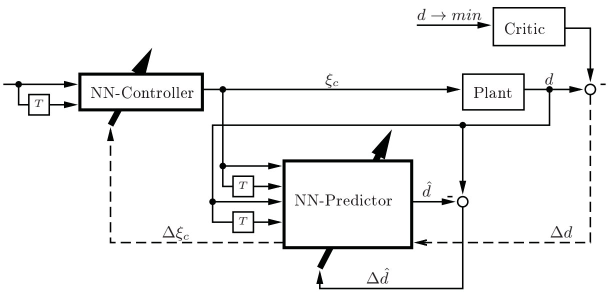


Figure 4: Principal design of the neural control architecture. The time-delayed inputs ensure the learning of the dynamic behaviour.

As depicted in Fig. 4 there is no possibility to directly measure the error of the control signal $\Delta\xi_c$. If the aileron signal ξ_c is the input j of the predictor network it is possible to calculate a corresponding backpropagated error for this input neuron δ_j^1 in correspondance to a measured spline deviation Δd. This backpropagated error signal characterizes the change of the error function E_j with regard to an altered input signal ξ_c. Thus, if $\hat{d}$ is equal or nearly equal to d, Δd can be used to calculate the direct training signal $\Delta\xi$ for the controller training. It becomes apparent that the stable functioning of the neural predictor is a prerequsite for a usable controller training signal. Furthermore, a proof of stable network behaviour is imperative for any control application. Therefore a training algorithm derived from sliding mode control (SMC) principles which limits the learning rate $\mu > 0$ is applied.

2.3. Sliding Mode Training Algorithm

The idea of SMC is to identify a region within the state space of a dynamic system where the system is stable and returns to the equilibrium within finite time after activation[28]. If such a region exists, also called *sliding surface*, a control law has to be found, which ensures that the system reaches this sliding surface within finite time and does not leave it again. The training process of a neural network has parallels to a control process as seen in Fig. 5. The procedure is given in general vector notation for networks with more than one output signal.

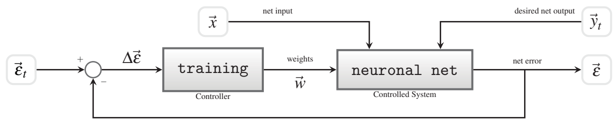


Figure 5: Training of a neural network as a control process.

The difference between the target network error $\vec{\varepsilon}_t$, which can be derived from a desired flight attitude, and the actual network error $\vec{\varepsilon}$ is fed into the training block which changes the connection weights of the neural network. The network calculates an output signal $\vec{y}$ from the inputs $\vec{x}$. The actual network error $\vec{\varepsilon}$ is the difference between the desired network output $\vec{y}_t$ and the actual output $\vec{y}$. There are different approaches regarding the combination of neural network training and SMC[29, 30, 31]. To realize a network training with SMC, the change of the connection weights is defined as follows:

$$(3) \qquad \Delta\vec{w} = \left(\frac{\partial\vec{y}(\vec{w},\vec{x},\vec{y}_d)}{\partial\vec{w}(t)}\right)^T \cdot \mu \cdot \mathrm{diag}\left(\mathrm{sign}(\vec{S})\right) \cdot |\vec{\varepsilon}|.$$

This is an expansion of the standard gradient descent method adding the sign sliding surface function $\vec{S}$ with

$$(4) \qquad \vec{S} = \dot{\vec{\varepsilon}} + \lambda \cdot \vec{\varepsilon} \quad .$$

For $S = 0$ the sytem is directly on the sliding surface, where the network error converges towards 0, if the factor λ is positive:

$$(5) \qquad \vec{S} = \dot{\vec{\varepsilon}} + \lambda \cdot \vec{\varepsilon} = 0 \quad \Rightarrow \quad \vec{\varepsilon} = \vec{\varepsilon}(t_0) \cdot \mathrm{e}^{-\lambda(t-t_0)}.$$

A proof of learning stability can be found in[25].

The simulations in Figure 6 show that with this training algorithm stable and fast adaptation can be achieved. The neural predictor is capable to adapt to the unsymmetric wind conditions without a severe loss of performance. Yet, the question remains whether the error signal from the predictor is still adequate to allow a sustainable controller training. Apart from a few slight degradations, it can be observed that the neural controller is still able to reduce the errors in a significant way. The standard deviation of d decreases from 0.858 m for the conventional controller to 0.718 m for the ANN controller, whereas the maximum error is reduced from -5.67 m to -3.18 m.

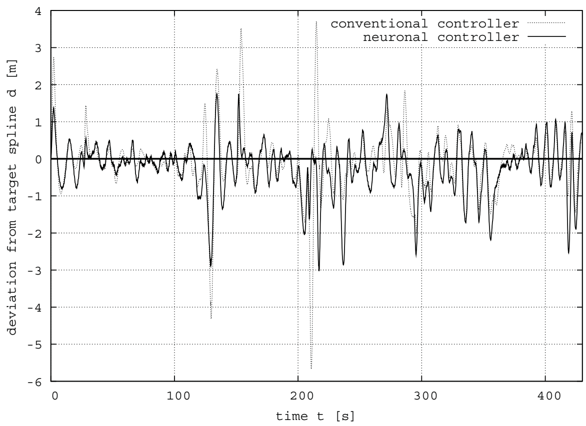


Figure 6: Deviation from the desired flight path with asymmetric wind conditions and online optimization of the neural controller.

3. CONCLUSIONS

The authors' research has so far focused mainly on unmanned aerial vehicle (UAV) flight control[10, 32]. However, when dealing with large-scale, commercial aircraft, the designer faces a much higher degree of complexity:

- The flight control of commercial aircraft is a sophisticated system of state machines and complex logical functions. Therefore, much care has to taken to integrate new designs appropriately into the remaining software architecture.

- As seen in Figure 7, a large scale aircraft has a significant number of (partially) redundant control surfaces. Examples of flight control algorithms that take this redundancy into account were, for example, developed by de Almeida and Lei"sling[33]

- Clearance of flight control laws is a lengthy, multidisciplinary, and also costly process. Any new algorithm that is applied to real aircraft have to be rigorously verified and validated[34]. In an intermediate stage, high-fidelity flight simulation could get a central role in this process.

The previous research results have proven that hybrid neural control is a very promising candidate for a high-performance flight controller. Thus, as a next major step, the experiences gained with UAV control will be transferred to meet the requirements and the increased complexity of a commercial aircraft. Then, a solution for control signal allocation has to be found that deals with the redundant control surfaces. One possible route could be the combination of parameter estimation and

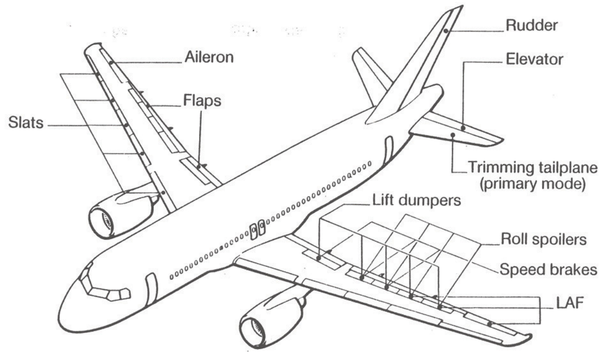


Figure 7: Aerodynamical control surfaces of an Airbus A320 (taken from Pélégrin[35]).

hybrid control with neural networks. Also, banks of neural networks could be a solution where each network is configured in a different way. As the processing speed of onboard hardware increases, it will become more and more feasible to have multiple, complex neural networks being executed at the same time enabling optimization and topology adaptation. A "mediator" algorithm can then decide which neural network is trusted most and gets control authority.

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