Expert Supervision of Conventional Control Systems

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Abstract

The objective of this paper is to outline a general concept for the design of supervising fuzzy controllers to back up or monitor a conventional control system. The use of fuzzy logic in an external, hierarchical control structure provides a systematic approach to integrate heuristics in a conventional control loop. Supervising techniques become especially interesting, when the system to be controlled is highly non-linear (parameter variation, saturation of the control surfaces etc.). By the means of two application examples it will be shown, how this method can effectively be used to improve the performance of a conventional control system. Both examples are part of an extended research project that is being carried out at Aérospatiale and E.N.S.I.C.A. in France to study the role of fuzzy control for potential applications in aircraft control systems.

1. Introduction

Fuzzy logic and rule-based techniques have proven to be an useful tool in control engineering. In direct control applications rule-based approaches can be used to define complex non-linear control laws by modeling human control strategies in form of linguistic, fuzzy rules. In contrast to conventional design methods the definition of a "fuzzy control law" can be carried out independently of a mathematical model of the system to be controlled. In several application examples it could be shown that fuzzy controllers perform more robust than their analytic counterparts. However, the design procedure of a fuzzy controller, namely the calibration of its parameters, often turns out to be quite difficult, especially when systems with multiple input and output are concerned [3]. Furthermore there is no direct methodology that allows to predefine and to validate a desired dynamic performance of a fuzzy logic control system. Rule-based and analytical methods are sometimes viewed as competitive technologies. However, it seems rather reasonable to use these methodologies in tandem combining human experience or "engineer intelligence" with conventional control algorithms. Such a combination could eventually allow to exploit the advantages of both approaches.

This paper explores the conception and the application of fuzzy systems to back-up a conventional control system. This approach is often referred to as hierarchical or supervisory control. The objective is to introduce human expert knowledge on a supervisory level in order to adjust the control system, when either an insufficient performance (overshoot, saturation etc.) is detected or a change of the system and its environment occurs. In addition to that, a supervisor can be thought of as security backup which "overwrites" the command of the conventional controller in extreme operating conditions.

Although the concept of expert supervision has some common elements with adaptive control, both approaches should be well distinguished: In adaptive control the adjusting mechanism of the controller is a part of the control system. In contrast to this, a supervising controller is considered as an *external controller* which is added to an already existing control system. In addition to that, adaptive control is limited to the adjustment of the controller parameters, whereas supervisory control may comprise any modification of the control system including the input and the output of the controller.

This paper is organized as follows: In the first part a general overview of fuzzy supervising techniques will be presented. Various types of adaptive control mechanisms will be considered, whereas the term "adaptive" will be interpreted as stated above. To demonstrate the potential of these techniques and to show the vari-

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ety of problems that can be treated, the following two examples will be presented in the second part of the paper:

(a) An adaptive fuzzy controller for an Anti-Skid braking system of a commercial aircraft is proposed. The function of the supervisor is to control the set point value of the braking system in order to adapt it to different runway conditions.

(b) A security supervising system for the longitudinal control of a cargo aircraft is discussed to avoid a saturation of the elevator in the case of an emergency break-off of the landing approach with maximum thrust.

2. Design of a Fuzzy Supervising System

2.1. General Aspects

The general configuration of a fuzzy supervisor is shown in Figure 1. The Supervisor can be divided in two subsystems: the Data Processing Unit (DPU) and the Information Processing or Decision Making Unit (IPU). The task of the DPU is to generate from the input data an information about the dynamic behavior and/or the actual configuration of the overall system and its environment. This information, which can be both numeric or linguistic, is processed by the IPU to determine the adaptation commands to be applied to the closed loop system. As input data of the supervisor any measured or calculated variable of the closed loop system and its environment may be choosen.

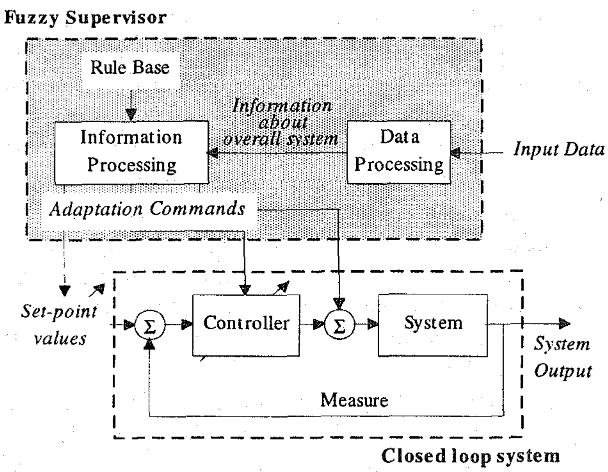


Figure 1. Concept of Fuzzy Supervising

The adaptation commands, i.e. the output of the supervisor, are connected to the closed loop. They are chosen according to the desired task of the fuzzy supervisor. Typical tasks that may be performed are listed below [9], [1]:

- Selecting the most appropriate controller and control structure
- Tuning the controller parameters (gain scheduling, changing the sample time, etc.).
- Changing the set-point values
- Define an additional or corrective control command to be added to the controller output.
- Limit the control command.

In the following paragraphs the data and information processing parts will be described.

2.2. Information about the Overall System

The purpose of introducing a fuzzy supervisor is to monitor the overall performance and the configuration of the closed loop system by the means of expert knowledge. The supervisor will adapt the closed loop system, when either a significant change of the system properties or an undesired performance of the control loop is detected. In order to design the supervisor, it is first necessary to define the desired performance of the closed loop system and to analyze the interdependence between parameter changes and system performance. Before the expert rules of the supervisor can be formulated, the expert has to decide which information is needed to define the appropriate adaptation commands to be applied to the closed loop system. This information is evaluated by the DPU using the measured in- and output signals of the process and eventually additional external parameters. The output of the DPU may be of both numerical or linguistic (fuzzy) type.

Generally speaking, the DPU can be considered as an estimator of the system properties the latter referring to both the time response performance and the actual configuration of the system and its environment. As estimation algorithm classical analytic techniques as well as neural network or rule based approaches may be considered. In the following an overview of different estimation structures will be given.

Performance Indices. In classical control theory the performance of a system is generally characterized by its time response behavior and its steady-state accuracy. Typical performance indices, which describe the dynamic behavior of a system are the damping rate, the oscillation rate, the offset overshoot and the rise time.

All of these parameters apply to any dynamic system. If it is possible to determine or to estimate them from the measured input variables, these performance indices can be used by the expert as information about the system performance. Possible approaches to evaluate the above parameters can be found in [10].

For expert supervision it is often useful to describe the performance of a system by referring directly to those parameters and variables, which are directly related to the particular physics of the system. Such performance indices would be for example the fuel consumption, the nervousness of a control or state variable, the braking efficiency of a braking control system, etc..

Model Reference. The concept of a model reference scheme is shown in Figure 2. The basic idea is to compare the dynamic behavior of the closed loop system with that of a reference model, the latter representing the desired system dynamics. Thus, the information obtained by using a reference model is an error between the system output and the model output. The model reference scheme is widely used in classical adaptive control. The adaptation algorithm consists of changing the controller parameters such that the error between model and system output is minimized. In expert control, this minimization criterion is not explicitly defined. It is rather assumed that the expert rules intuitively contain a minimization criterion thus ensuring a correct functioning of the supervising system. Thus, analytical optimality cannot be expected. The optimality obtained with a fuzzy supervising system must rather be considered as a fuzzy or qualitative optimality.

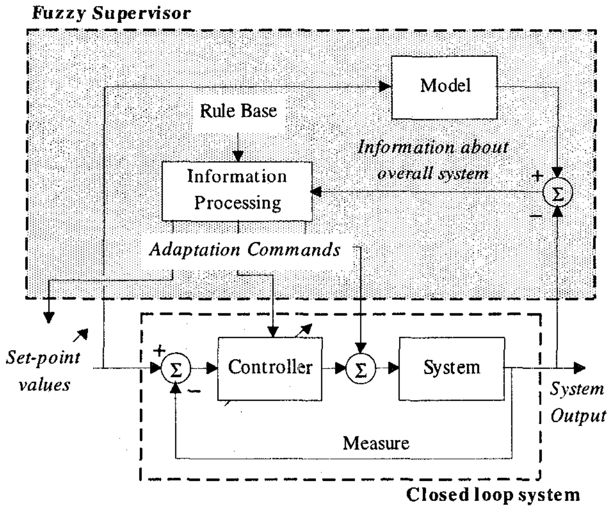


Figure 2. Model Reference Scheme

Estimation of the System Properties. In classical adaptive control a parameter estimation is applied to determine a process model by using system identification methods such as a recursive least square method for instance. From the estimated model the controller parameters can be recalculated according to a control design method which has been defined in advance. These type of adaptive controllers are referred to in literature as self-tuning regulators.

In expert supervision the purpose of a parameter estimation is to obtain a rather qualitative knowledge about the physical configuration of the process and its environment. It is noted, that this qualitative knowledge might include analytical system identification as well as a rough estimation of particular system parameters (Figure 3). On the other hand, it is possible to identify external parameters as information about the system environment. For example, for the supervision of a flight control system it might be useful to "identify" the actual weather conditions (temperatur, humidity, wind, etc.). The precision of the information obtained from parameter estimation must be determined by the expert who formulates the supervising fuzzy rules.

Implicit Estimation of the System Properties. In some cases the measured input data of the supervisor already contain sufficient information about the system, so that no explicit estimation of the system properties is necessary. Thus the DPU can be omitted and the adaptation commands are directly evaluated in the decision making unit (IPU). In fact, the estimation of the system properties is implicitly included in the expert rules of the IPU. Implicit estimation can be illustrated by the following example: Given the identification rule "If the apple is red, it is ripe" followed by the decision rule "If the apple is ripe, I pick it", it seems likely to replace these two rules by a single one that says "If the apple is red, I pick it" combining the identification and the decision making rule.

2.3. Decision Taking Process

In order to determine the appropriate adaptation commands the IPU performs a symbolic decision taking process using fuzzy logic theory. The IPU can be considered as a fuzzy system which is defined by a number of expert rules, a set of linguistic variables, an inference algorithm and a module to transform the result of the inference process into a numerical output (defuzzy-

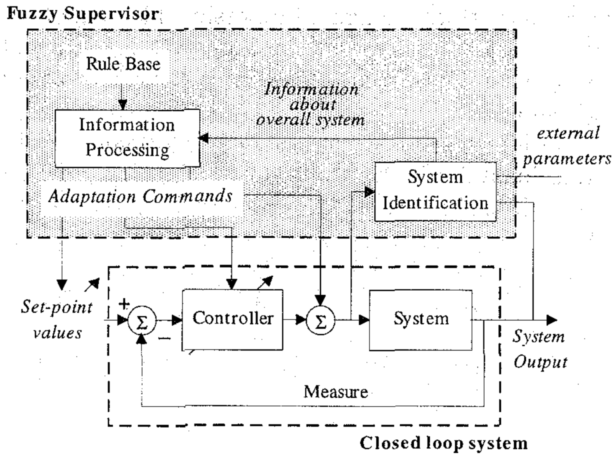


Figure 3. Explicit Estimation

fier). The input information can be both a numerical or a fuzzy value. In the first case a singleton fuzzyfication must be applied. The case of a fuzzy input is of great interest, because it allows to deal with imprecise and vague input information. However, it must be emphasized, that the decision making process is not restricted to the use of fuzzy logic. In general, it can be thought of using fuzzy and non-fuzzy rules in the IPU, combining both symbolic and analytic representation of expert knowledge. Since non-fuzzy rules can be seen as special cases of fuzzy rules, it is justified to consider the IPU in general as a fuzzy system.

Several methods are available for the definition of a fuzzy logic system. Complete treatments of fuzzy systems can be found for example in [8], [2] or [11]. The general steps, which are necessary to define the IPU are listed below:

1. Determine the task to be carried out by the supervisor (gain scheduling, controller choice, command limiting, etc.) and choose the parameters or variables of the closed loop system to be adapted.

2. Determine which input information about the system necessary to define the expert adaptation rules.

3. Define the fuzzy expert rules and the associated fuzzy "vocabulary" to be used in the rule base. For a Multi Input Single Output fuzzy system a single expert rule will take the following general form:

   $Rule^{(j)}$: IF (P_1^j and P_2^j ... and P_n^j) THEN Y^j

   where the premisses P_i^j and the consequence Y^j are linguistic expressions of the form: "x_i is a_i" and "y is b" respectively. The x_i are the input variables, y is the output variable, a_i and b are linguistic values.

4. Define the fuzzyfier, the inference algorithm and the defuzzyfier. The method which has been employed in the following application examples uses a *singleton* fuzzyfication, *max-min* composition, *minimum* inference and *center of gravity* defuzzyfication (see [8] for example).

3. Application Examples

3.1. Supervision of an Anti-Skid Control System of a Commercial Aircraft

The braking system of the Airbus A320/A321 is controlled by a digital anti-skid system (ABS). Its role is to prevent the wheels from locking up and to assure a maximum braking force. A maximum braking force is of major importance when the runway is slippery and/or very short. On dry runways wheel skidding must be avoided in order to minimize the wear of the tyres and to prevent them from bursting. The principal problem of anti-skid control design is the complex, non-linear relation between the braking force and the braking torque of the wheels [6][4].

The friction force between a tyre and the runway surface is proportional to the normal force acting on the wheel. The force conversion factor, known as the adhesion coefficient μ, largely influences the braking performance of the wheel. It can be expressed as a function of the wheel slip s, which is defined as the relative difference between the aircraft speed and the translational wheel speed. Experimental data show that the friction characteristic $\mu(s)$ depends on the condition of the runway surface (e.g. dry, wet, icy etc.). Typical adhesion characteristics for different runway surfaces are shown on Figure 4. It can be observed that all curves $\mu(s)$ start at μ=0 for zero slip, which corresponds to the non-braked wheel. With increasing slip the adhesion coefficient increases up to a maximum value which is located between a slip ratio of about 5% and 20%. Beyond this maximum value the slope of the adhesion characteristic is negative. At a slip ratio of 100% the wheel is completely sliding, which corresponds to a complete lockup. From the equations of motion of the braked wheel it can be shown, that the system tyre/runway is stable when the slope of the curve $\mu(s)$ is positive and it is instable when its slope is negative. If the brake torque level is small enough, the wheel speed will attain an equilibrium state in the front side of the adhesion characteristic $\mu(s)$. However, either forcing the brake torque higher, or encountering a sudden change in friction force, would cause the wheel slip to slide beyond the stable region, and the wheel will immediately lockup.

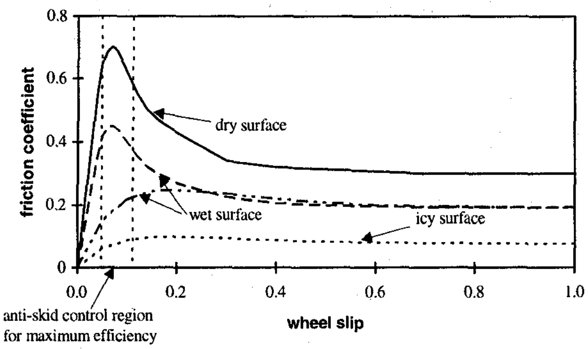


Figure 4. Adhesion Coefficient vs Slip

The conventional ABS controller is based upon a wheel speed control. The output of the controller is computed by a system of digital low-pass filters as a function of the error between the measured wheel speed and a reference wheel speed, which is determined from the desired wheel slip s_c. Assuming the case of full braking, the functioning of the ABS can be outlined as follows: At the moment, when the pilot pushes the brake pedal the brake torque starts to increase. The wheel slip still being on the front side of the adhesion characteristic, the ABS will control the wheel speed to its reference value. If the wheel slip should slide beyond the stable side of the adhesion characteristic and the wheel starts to lockup, the ABS rapidly releases the brake pressure to force the wheel speed back to the stable side of the adhesion curve. In fact, this situation occurs, when either the desired slip s_c has been chosen on the instable side of the friction characteristic, or when a sudden change in ground force is encountered (e.g. a transition from a dry to a wet runway surface). Thus, for an optimal braking performance the value of s_c has to be chosen in the front part of the adhesion characteristic near the maximum friction coefficient. The conventional ABS uses a fix reference slip value of 12%. For runways with low friction this value is supposed to be located on the stable side near the optimum of the $\mu(s)$ curve (see Figure 4). On a runways with high friction, however, this reference slip lies on the unstable side, which provokes a cyclic lockup of the wheel. As a result of this, the braking distance augments considerably, whereas the wear of the tyres increases (with the danger of a possible blow up of the tyre). A simulation of the braking system on a wet runway with a maximum friction coefficient of about 0,4 is shown on Figure 5.

In order to improve the braking performance of the conventional ABS, an expert supervising system, that adapts the reference slip to the actual runway conditions, is proposed (A more detailed presentation can be found in [4]). The IPU of the supervisor is a fuzzy system with 3 inputs and 1 output. The inputs of the fuzzy system are the measure of the brake pressure p, the wheel speed error Δv ant its variation $\Delta \dot{v}$. The output is the variation $\Delta \dot{s}_c$ of the reference slip.

The definition of the expert rules is based upon the following general strategies, which are obtained from the overall knowledge about the physical behavior of the braking system:

1. Reduce the value of the reference slip rapidly, when a wheel lockup has been detected. As explained previously this situation occurs when the reference slip lies on the instable part of the friction characteristic.

2. Increase s_c slowly when the system is stabilized. If this is the case, s_c is certainly on the stable side of the friction characteristic. By carefully increasing s_c the friction coefficient is moved towards its optimum.

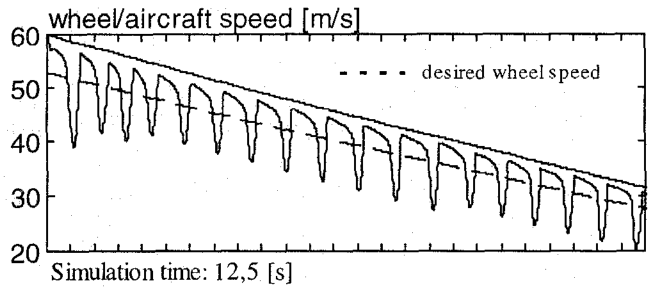
3. Increase s_c rapidly when low friction is detected and the system is stabilized. This rule makes sure that s_c does not become too small on an icy or wet runway characteristic.

4. Take no action if none of the above conditions holds.

These strategies can now be expressed in form of fuzzy rules using linguistic values for the input and the output variables. Two representative rules which correspond to the strategies 1 and 2 respectively would be:

Rule 1: **If** p is big **and** $\Delta \dot{v}$ is negative big
then $\Delta \dot{s}_c$ is negative big.
Rule 2: **If** Δv is zero **and** $\Delta \dot{v}$ is zero
then $\Delta \dot{s}_c$ is positive small.

Figure 5 shows the results obtained with the supervised ABS on a wet runway surface. This simulation demonstrates very clearly the adaptation strategy outlined in the previous section: After detecting a lockup of the wheel, the reference slip is rapidly increased to a reference slip ration of 5%. Since this new value of s_c



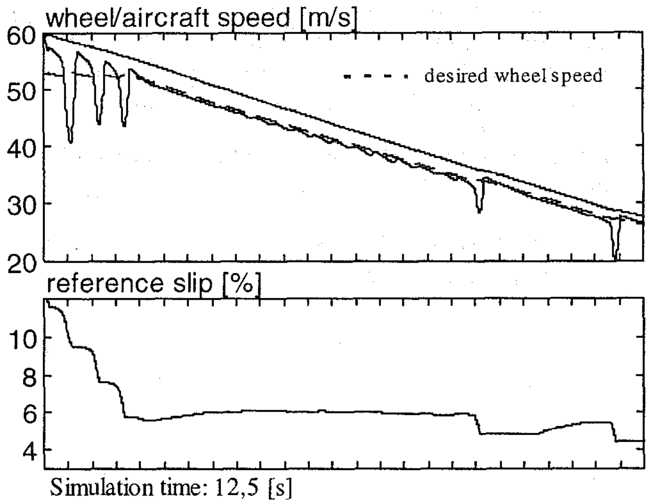


Figure 5. Braking on a Wet Runway Surface: Actual ABS (left), Supervised ABS (right)

is located on the front side of the adhesion characteristic the braking is now stable. This in turn causes the supervisor to very slowly increase the value of s_c, in order to brake as close as possible at the maximum adhesion coefficient. Good results could also be achieved for runways with changing surface conditions.

3.2. Supervision of the Thrust during Break-off of the Landing Approach

The following example concerns the design of a security supervising system as additional backup of the longitudinal flight control system of a commercial cargo aircraft of type AIRBUS. The task of the security system is to monitor the maximum admissable thrust of the aircraft during an emergency break off of the landing approach. During this extreme flight manoeuvre, the pilot has to apply the maximum available thrust, whereas the speed of the aircraft is controlled via the elevator by the flight control system. Since the thrust is fix, the flight path angle and the pitch attitude of the aircraft can no longer be controlled independently. The problem which occurs in the particular case of the considered cargo aircraft is the high vertical position of the center of gravity (c.g.) of the aircraft with full load. The extreme position of the c.g. in combination with full thrust in climb configuration might lead to the following extreme situations [3]:

- The elevator command necessary to maintain the speed reaches its point of saturation (at about 15 deg). To control the aircraft in this case, the elevator has to be "liberated" by reducing the maximum thrust. However, to avoid an abrupt manoeuvre, this reduction has to be applied before the elevator becomes saturated, i.e. the controller has to "know" in advance, when a saturation occurs. On the other hand, the reduction of the thrust should be minimal to guarantee a maximum of thrust available for the take off manoeuvre.
- The pitch attitude θ of the aircraft exceeds its maximum admissible value. (For maximum thrust in combination with a high vertical position of the c.g. the aircraft becomes unstable, when θ is bigger than about 20 deg). In this case, the maximum thrust must be reduced.

To ensure a safe, though optimal performance of the aircraft during an emergency take-off manoeuvre, a fuzzy supervisor has been designed to automatically reduce the maximum thrust when necessary. To identify the aforementioned extreme situations a model reference scheme (Figure 2) is applied. The DPU performs a comparison between the closed loop system and a model aircraft, defining a limit for the pitch attitude and the elevator command (Figure 6). As numerical inputs of the IPU the following three variables have been chosen: the difference between measured and model pitch angle: $e_\theta = \theta - \theta_m$, the difference of pitch rate: $e_{\dot{\theta}} = \dot{\theta} - \dot{\theta}_m$ and the difference of the elevator command: $e_\delta = \delta - \delta_m$. The output variable is the variation of the thrust $\Delta\pi$.

The control strategy of the supervisor is based upon the following principles:

1. Reduce the thrust if the elevator command exceeds the prescribed limit defined by the model aircraft.
2. Reduce the thrust if the pitch attitude exceeds the prescribed limit and the elevator command is near the prescribed limit.
3. Take no action if both pitch attitude and elevator command are below the prescribed limit.
4. Take no action if the error in pitch attitude between aircraft and model rests constant.

These principles can now be expressed in form of fuzzy rules using linguistic values for the input and output variables. In total, 25 rules have been used in the supervisor. A representative rule would be:

If e_θ is pos. big **and** $e_{\dot\theta}$ is pos. big **and** e_δ is zero **then** $\Delta\pi$ is neg. big.

Figure 6 shows the results of a computer simulation comparing the original with the fuzzy supervised system. For this simulation the c.g. was set to its maximum vertical position, whereas the horizontal position is located at its maximum rear position. It can be observed that for this aircraft configuration the elevator becomes saturated the aircraft being unstable. By the use of the supervisor this situation could be avoided.

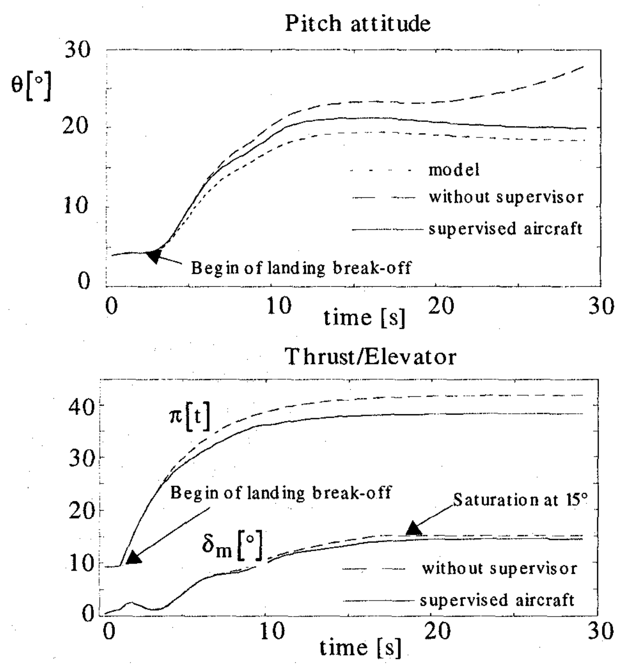


Figure 6. Take-off with Maximum Thrust

4. Conclusions

In this paper a general outline of rule-based supervising techniques was proposed. The objective was to give a definition of a supervising system and to classify different possible architectures of adjustment mechanisms. To show potential applications of expert supervision, two examples have been briefly presented. These examples show that the use of heuristics in an external, hierarchical control loop allows to improve the overall performance of a conventional control system with respect to changes of the system and its environment.

Future work will concentrate on the problem of validation of such control structures. Classical, analytic approaches seem to be possible (see [11] for example). However, these approaches limit the freedom in defining the heuristics, because they impose a very rigid representation of the expert knowledge. In addition to this, for an analytic validation a precise model of the system and its environment is needed. A second approach could be to limit the supervising actions to a certain bandwidth, inside of which the control system can be validated.

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