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Expert Supervision of an Anti-Skid Control System of a Commercial Aircraft

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Abstract

A rule-based supervising system that incorporates fuzzy logic has been designed to back-up a conventional anti-skid braking system (ABS). Expressing the expert knowledge about the ABS in terms of linguistic rules, the supervising fuzzy system adapts the reference wheel slip of the ABS with respect to the actual runway condition. Two approaches are presented: The first uses a simple rule-based decision logic, which evaluates a new reference slip directly from the measured system variables. The second approach employes an explicit identification of the runway condition, which is used as input information of a fuzzy system to evaluate a new reference slip. This application example demonstrates the capabilities of a parallel use of conventional control techniques and fuzzy logic.

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 addition to this, the concept of fussyness allows to deal with imprecise and vague information. In several application examples it could be shown that fuzzy logic is a viable technique in process control, and it could be observed that fuzzy controllers often perform more robustly 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, its seems rather logical to use these methodologies in tandem combining human experience or "engineer intelligence" with conventional control algorithms [1],[9]. Such a combination could eventually allow to exploit the advantages of both approaches.

This paper explores the conception and the use of a fuzzy expert system as a back-up of a conventional anti-skid controller of a commercial aircraft. The objective is to introduce human expert knowledge on a supervisory level in order to observe the closed loop braking system and to adjust the anti-skid controller when an insufficient braking performance is detected. This approach is often referred to as hierarchical fuzzy control.

In the first part of this paper a description of the braking system and the anti-skid controller of a commercial aircraft is given. The second part focuses on the design of a supervising system for the anti-skid controller. After a general introduction to the concept of fuzzy systems and their application to supervising control, two different versions of an anti-skid supervising system will be proposed.

2. Braking System

In this section the braking system of a commercial aircraft shall be considered. A simplified representation of the braking circuit using a one wheel model is shown in figure 1.

When the pilot pushes the brake pedal a current is established which commands the brake pressure via an electro-hydraulic actuator. The pressure is transformed by the brakes into a brake torque, which causes the wheel to decelerate provoking a ground force between tire and runway. The role of the anti-skid controller is to prevent the wheels from locking 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 tires and to prevent them from bursting.

Physical Model

The braking performance of the aircraft (neglecting aerodynamic and thrust braking forces) is determined by the forces acting on the braked wheels. These forces are:

- the normal force F_z, which is derived from the equations of motion of the aircraft.
- the friction force F_r between the tyre and the runway surface.

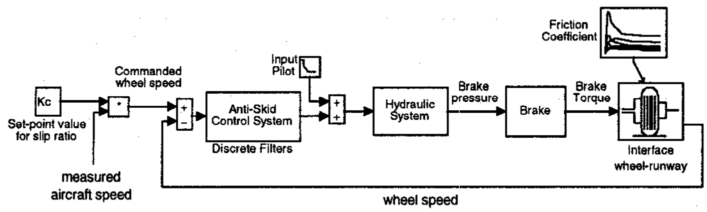


Figure 1: Braking System for a Single Wheel

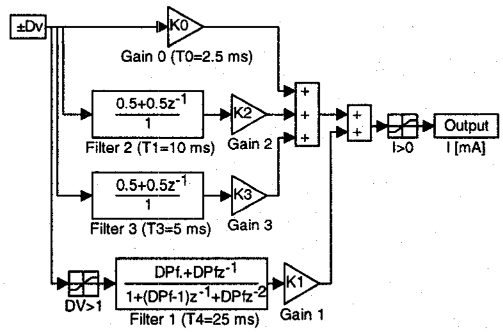


Figure 2: Anti-Skid Controller

By introducing the adhesion coefficient μ the friction force is calculated as:

$$F_r = \mu \cdot F_z \tag{1}$$

The adhesion coefficient μ is a function of the wheel slip s, which is defined as the relative difference between the aircraft speed and the translational wheel speed $\omega \cdot R$:

$$s = \frac{v - \omega \cdot R}{v} \tag{2}$$

where R is the radius of the wheel and ω its rotational 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 in figure 3. 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 lock up.

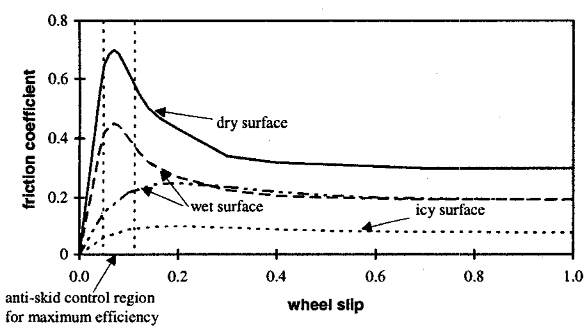


Figure 3: Adhesion Coefficient vs. Slip

A physical model of the system tire/runway is obtained from the equations of motion applied to a rotating wheel. From figure 4 it follows that:

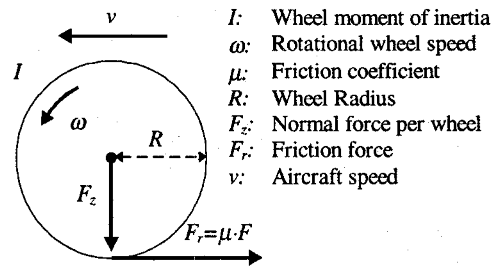


Figure 4: Forces Acting on a Braked Wheel

$$\dot{\omega}\, I = F_r \cdot R - T \tag{3}$$

where T is the brake torque. Assuming that brake pressure and brake torque are proportional T can be calculated as:

$$T = K_f \cdot p \tag{4}$$

with K_f being the torque conversion constant. The aircraft speed and the normal force F_z on the wheel are calculated from the nonlinear equations of motion of the aircraft.

The brake pressure is controlled by an electro-hydraulic actuator. The input current is inversely proportional to the pressure. The actuator dynamics can be represented by a second order model with the transfer function:

$$G(s) = \frac{-6,875}{1 + \frac{2\xi}{\omega_n} s + \frac{1}{\omega_n^2} s} \tag{5}$$

The parameters used for simulation are: $\omega_n = 56,6$ $[rad]$ et $\xi = 0,5$ $[rad]$.

Digital Anti-Skid Controller (ABS)

From equation 3 it can easily be deduced that the system tire/runway is stable when the slope of the curve $\mu(s)$ is positive, and it is instable when its slope is negative. If the 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 lock up.

The role of the anti-skid controller is to prevent the wheel from lock up and to achieve a maximum braking performance, i.e. to keep the wheel speed near the maximum of the friction characteristic. A block diagram of the controller is shown in figure 2. The output of the controller is computed by a system of three parallel digital low-pass filters and a constant gain. The input of the controller is the wheel speed error Δv defined as:

$$\Delta v = K_c \cdot v_{ref} - \omega R \tag{6}$$

where ω is the measured rotational wheel speed and $K_c \cdot v_{ref}$ is the reference wheel speed. The constant K_c fixes the value of the desired slip $s_c = 1 - K_c$.

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 pressure 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. During this phase only Filter 1 is active. Its time constant is about 4s. If the wheel slip should slide beyond the stable side of the adhesion characteristic and the wheel starts to lock up, the ABS rapidly releases the brake pressure to force the wheel speed back to the stable side of the adhesion curve. In this case all filters of the ABS are active. 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). The actual ABS uses a fix reference wheel slip of 12%. For adhesion characteristics with a smooth front side this value is located near the optimum of the $\mu(s)$ curve (see figure 3). These type of adhesion characteristics can be found on runways with low friction. However, on runways with a very low optimum slip (about 5%), the reference slip lies on the unstable side of the adhesion characteristic provoking a cyclic look up of the wheels. As a result of this, both the braking distance and the wear of the tires augment considerably. On dry runways, this might even lead to a blow-up of the tire. In Figure 5 a numerical simulation of a full braking at the speed of 70 [m/s] is shown. The aircraft is supposed to brake on a runway surface with different low friction adhesion characteristics (wet-icy) and a varying optimum slip (between 5 and 20 %). It can be observed that the wheel speed starts to oscillate when the optimum slip becomes very small. On the other hand, the braking becomes stable as the optimum slip increases. Thus, an improvement of the braking performance can be expected from adapting the reference slip to the actual runway condition.

3. Anti-Skid Supervising System

The use of rule-based techniques and fuzzy logic in anti-skid control has been studied by several researchers and recently a number of publications have appeared in this domain [10],[6]. An adaptation of the reference slip has been proposed by Matsumoto et al. [5] for an automobile application. In this paper two approaches of a supervising system to adapt the reference slip are proposed. The first approach uses a fuzzy logic system to calculate a variation of the reference slip which is added to the constant used in the ABS. This approach is similar to that presented by Matsumoto. However, as the supervising system considered here is particularly related to aircraft braking, there are some basic differences in the design strategy of the supervisor. The second approach which will be discussed in this paper uses an explicit estimation of the runway surface condition to directly evaluate the reference slip value.

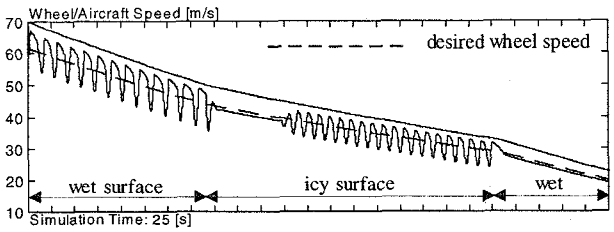


Figure 5: Braking on a Wet and Icy Runway Surface with the Actual ABS

Rule-based Supervising Systems

A general configuration of a fuzzy supervisor is shown in figure 6. 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 numeric input data an information about the dynamic behavior and/or the actual configuration of the overall system and its environment. This information is processed by the IPU to determine the adaptation commands to be applied to the closed loop system. The input data of the supervisor may be any measured or calculated variable of the closed loop system and its environment. For the application presented in this paper a fuzzy logic system is used as IPU. Supervising systems may used for various control problems such as [4],[9]:

- 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.

Fuzzy Logic Systems

The following description of fuzzy logic systems (FLS) is necessarily general and brief. More complete treatments can be found in references [8], [2]. An FLS can be viewed as an expert system which is based upon

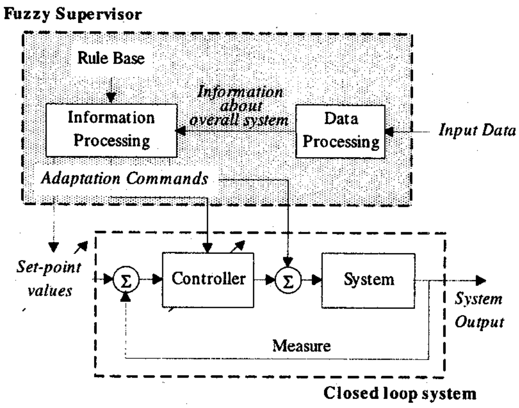


Figure 6: Supervising System

the concept of fuzzy reasoning. The knowledge base is represented by a number of IF-THEN rules. In most control applications the FLS has net, i.e. numerical, inputs and outputs. In order to evaluate a fuzzy rule base, the numerical inputs have first to be translated into a symbolic or linguistic information, which is processed via some decision logic in the inference module. Finally the result of this inference process has to be transformed again into a numerical output. These steps are respectively called *Fuzzyfication*, *Inference* and *Defuzzyfication*. This is the classical procedure used for fuzzy controllers.

The first step in developing a FLS is to chose the in- and output variables and to define a vocabulary, i.e. linguistic labels, for each of these variables. The linguistic values are typically labelled as *positive big (PB)*, *negative small (NS)*, etc. The supervisor which is described in the following section for example uses the three input variables pressure, wheel speed error and its variation. The linguistic labels are *fuzzy sets* defined by their membership functions. The latter determines the degree of membership of a numeric value to the corresponding fuzzy set. The linguistic values defined for the in- and output variables can now be employed to formulate the rule base of the FLS. A typical rule would be:

IF *pressure* is big AND *variation of error* is negative big THEN *variation of output* is negative big.

In general, for a Multi Input Single Output FLS a fuzzy rule with n premisses P_i^j takes the form:

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

The IF part of the rule is called the antecedent, and the THEN part is called the consequence. 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. The rules of the FLS thus relate the inputs to the output. The mapping from the fuzzy sets $A = [a_1, a_2, \ldots, a_n]$ into the fuzzy set $B = b$ is called a fuzzy relation. Several methods are available for evaluating a fuzzy rule. These methods are based upon the translation of the fuzzy condition $A \rightarrow B$ into a fuzzy relation. The method which has been employed for the supervisor uses *singleton* fuzzyfication, *max-min* composition, *minimum* inference and *center of gravity* defuzzyfication (for details see [8] for example).

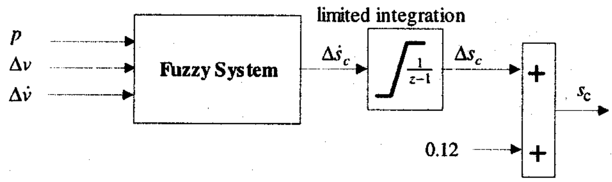


Figure 7: Supervisor with Implicit Runway Condition Estimation

Reference Slip Supervisor

A block scheme of the supervisor is shown in figure 7. The supervisor can be represented as a FLS with 3 inputs and 1 output. In this configuration the data processing unit (DPU) is omitted, i.e. the output of the FLS is directly evaluated from the inputs of the supervisor. Since the system properties, notably the condition of the runway, are not explicitly estimated, this approach is referred to as implicit estimation supervisor [4].

The inputs of the FLS at the instant n are the brake pressure $p(n)$, the wheel speed error $\Delta v(n)$ ant its variation $\Delta \dot{v}(n) = \Delta v(n) - \Delta v(n-1)$. The output is the variation $\Delta \dot{s}_c(n)$ of the reference slip. The new value of the constant K_c is calculated from the following equation:

$$K_c(n) = 1 - (0{,}12 + \Delta s_c(n)) = 1 - s_c(n) \qquad (7)$$

The additional factor $\Delta s_c(n)$ is obtained by a limited numerical integration of $\Delta \dot{s}_c(n)$. The upper and lower limits of K_c are fixed, such that $0{,}85 \leq K_c \leq 0{,}97$. The value of K_c is updated every 25ms.

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 lock up is detected. As explained previously this situation occurs when the reference slip lies on the instable part of the friction characteristic. To identify a wheel lock up, the wheel speed error ("$\Delta v(n)$ is negative") and its derivative ("$\Delta \dot{v}(n)$ is negative big") are used. This rule is graduated according to the pressure, i.e. the smaller the pressure the smaller the reduction of s_c.

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 increasing s_c carefully the friction coefficient is moved towards its optimum. The system can be considered as stabilized, when "$\Delta v(n)$ and $\Delta \dot{v}(n)$ are close to zero".

3) Increase s_c rapidly when low friction is detected and when the system is stabilized. This rule ensures that s_c

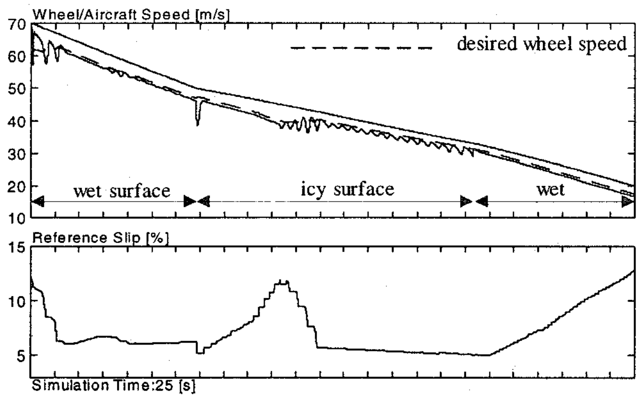


Figure 8: Braking on a Wet and Icy Runway Surface with the Supervised ABS

does not become too small on icy or wet runways with a smooth front side of the adhesion characteristic. Low friction can be identified via the brake pressure ("$p(n)$ is small").

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

These strategies have been expressed in form of fuzzy rules using linguistic values for the input and the output variables. In total 10 fuzzy rules have been used. Two representative rules which correspond to the strategies 1 and 2 respectively would be:

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

In figure 8 a numerical simulation of the supervised ABS is shown. To compare its performance with that of the original ABS the simulation has been carried out with the same runway surface conditions as for the simulation with the ABS alone (figure 5). The results clearly illustrate the adaptation strategies outlined above. After detecting a lock up of the wheel the supervisor decreases the reference slip to a value of 5%. The braking now being stable, the reference slip is slowly increased to brake as close as possible to the maximum adhesion coefficient. On the icy part of the runway, the system first detects low friction and stable braking causing a rapid increase of s_c. The reference slip is augmented again, when the wheel starts to lock up again. The simulation shows the ability of the supervising system to adapt the reference slip value to different runway conditions with changing friction and varying optimum slip. The average adhesion coefficient could be augmented by approximately 10% as compared to the original ABS. Good results could also be achieved on runways with high friction.

Reference Slip Supervisor with Explicit Estimation of the Runway Condition

This second supervisor is composed of an identification or classification part (DPU) and a decision taking part (IPU) as shown in figure 9. The task of the DPU is to assign to a set of numerical input data a degree of membership with respect to the categories *dry*, *wet* and *icy*. The aggregation of high level linguistic information from a set of basic single measurements is referred to as fuzzy sensoring [7]. The reference slip is evaluated in the IPU according to the following basic rules:

If surface is dry **then** reference slip is 5%
If surface is wet **then** reference slip is 10%
If surface is icy **then** reference slip is 15%

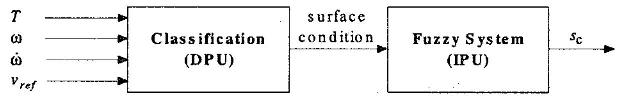


Figure 9: Supervisor with Explicit Runway Condition Estimation

These rules can be completed by additional rules taking into account further information about wheel lock up and stable braking as described in the previous paragraph. In the context of this paper only a brief outline of the classification algorithm can be given. A more detailed treatment of this topic will be the subject of a forthcoming publication.

The numerical inputs of the supervisor are the wheel speed ω, its derivative $\dot{\omega}$, the brake torque T and the reference speed v_{ref}. In a first step the wheel slip s and the friction coefficient μ are calculated as intermediate variables using equations 2 and 3.

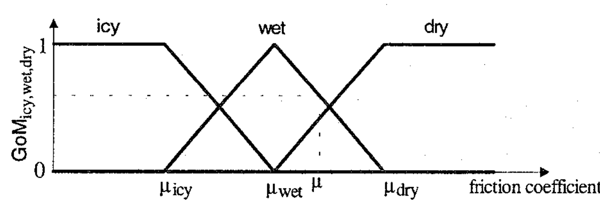
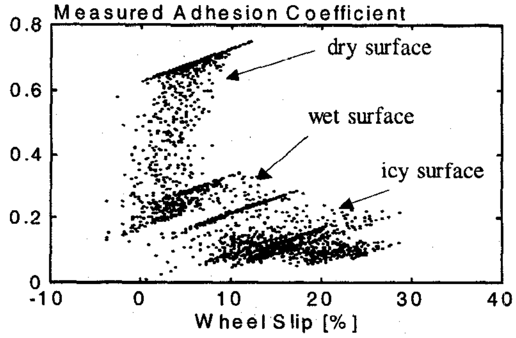


Figure 10: Fuzzy Sets for Surface Classification

In a second step a function has to be determined for each category defining a mapping from a pair of numerical data (s, μ) to a grade of membership GoM. The grade of membership of the pair (s, μ) to the category *dry* for example can be written as:

$$GoM_{dry} = f_{dry}(s, \mu) \in [0, 1] \qquad (8)$$

To find a suitable classification function f, probabilistic, fuzzy or neural methods may be considered. One possible approach is to use an empirical model of the adhesion characteristic $\mu(s)$ (figure 3) and to define f by the means of interpolation based on the fuzzy partition principle. Given a wheel slip s three adhesion coefficients are calculated from the characteristics $\mu_{dry}(s)$, $\mu_{wet}(s)$, $\mu_{icy}(s)$. These values define the three ordinary fuzzy sets *dry*, *wet* and *icy* (figure 10). The respective GoM's are the grades of membership of the calculated friction coefficient μ to these fuzzy sets.



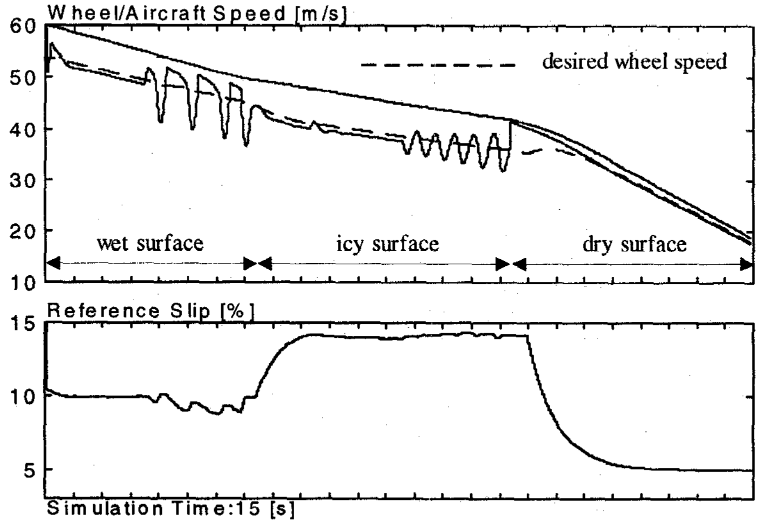


Figure 11: Braking on a Runway with Changing Surface Conditions

A second possibility which is currently studied is to use neural nets to define a classification function f directly from test flight data.

A simulation with the second supervisor is shown in figure 11. To test its capability of identifying the runway condition, a full braking on a runway with changing friction coefficient and varying optimum slip has been simulated. In addition to that, the calculated friction coefficient and the calculated wheel slip have been perturbed by white noise. The identification performance of the system is found to be very good. However, compared to the first supervisor, the system is not able to react to a varying optimum slip. This is due to the fact that only three rules have been used in the IPU.

4. Conclusions

In this paper an application of the fuzzy logic theory to an anti-skid control system of a commercial aircraft has been presented. The purpose was to define an "intelligent backup" in the form of an hierarchical controller for an existing conventional control system. By combining human experience and expert knowledge with conventional control techniques, it was possible to improve the performance of the original controller. Two possible versions of a supervisor have been proposed: The first one uses a classical fuzzy system to adapt the set-point value of the ABS. The simulation results show that the overall performance of the original system could be improved significantly, notably on runway surfaces with changing optimum slip. The integration of this supervisor into the *Braking and Steering Control Unit* of the Airbus A320/A321 is being prepared. Preliminary numerical simulations with the complete system on dry runways confirm the results achieved with the simplified ABS. The second version of the supervisor is based upon a direct classification of the runway surface. The overall performance was inferior to that of the first supervisor. However, concerning the classification of the runway surface itself, very promising results could be achieved.

Future work will concentrate on both the theoretical and the practical aspects of the validation of the supervising system. For this purpose the realization of the supervised ABS on a microprocessor and simulations on the Aerospatiale test facilities are presently being prepared.

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