

A Symbolic Sensor for an Antilock Brake System of a Commercial Aircraft

B. Ewers, J. Bordeneuve-Guibé

E.N.S.I.C.A., Département Avionique et Systèmes
1, place Emile Blouin
31056 Toulouse Cedex, FRANCE.
Tel: +33 (0)5 61 58 75 31 - email: bernd@ensica.fr

Corinne Langlois

Aérospatiale, Branche Aéronautique
316, Route de Bayonne
31060 Toulouse Cedex 03, FRANCE

Abstract

The design of a *symbolic sensor* that identifies the condition of the runway surface (dry, wet, icy, etc.) during the braking of a commercial aircraft is discussed. The purpose of such a sensor is to generate a qualitative, real-time information about the runway surface to be integrated into a future aircraft Antilock Braking System (ABS). It can be expected that this information can significantly improve the performance of ABS. For the design of the symbolic sensor different classification techniques based upon fuzzy set theory and neural networks are proposed. To develop and to verify these classification algorithms data recorded from recent braking tests have been used. The results show that the symbolic sensor is able to correctly identify the surface condition. Overall, the application example considered in this paper demonstrates that symbolic information processing using fuzzy logic and neural networks has the potential to provide new functions in control system design. This paper is part of a common research project between E.N.S.I.C.A. and Aérospatiale in France to study the role of the fuzzy set theory for potential applications in future aircraft control systems.

1 Introduction

Recently there has been a growing interest in intelligent control techniques for the design of aircraft and road vehicle Antilock Brake Systems (ABS). In particular, rule-based, fuzzy logic controllers have been applied to this problem and successfully tested in simulation [8], [9], [11], [3]. In fact, the use of non-linear, fuzzy control techniques appears to be particularly appropriate for the ABS control problem because of the high non-linearity of the system and the lack of a precise physical model of the friction force between tyre and runway. In addition to that, the controller must operate at an unstable equilibrium point to achieve an optimal braking performance.

The most important problem in ABS control design - fuzzy or conventional - is that the optimum adhesion coefficient varies significantly with the surface condition (i.e. dry, wet, icy, etc.) of the runway. Because the latter is unknown, it is extremely difficult to define a controller that guaranties an optimal braking performance for all types of runway conditions .

Therefore a key issue in ABS design today is to integrate a real-time information about the actual runway condition into the ABS and to adapt the control algorithm on the bases of this information. Matsumoto [8] and Ewers [3], for instance, suggest an adaptive, rule-based supervising system, which uses the brake pressure as an indicator for the friction force. Another approach is proposed by Mauer [9], where the surface condition is estimated explicitly using a discrete logic element.

This paper focuses on the design of a *symbolic sensor* for an ABS of a commercial aircraft to evaluate an explicit, real-time information about the actual runway surface condition during the braking procedure. The term symbolic sensor stands for a numeric-linguistic converter which gives a qualitative description of a physical context generating a linguistic information from basic, single numerical measurements.

This paper is organized as follows: In the first part, the physical context of aircraft braking and antilock control will briefly be outlined. Particular attention is given to the modelisation of the friction characteristic between tyre and runway surface. The second part of the paper concentrates on the design of a runway surface classifier to be used in symbolic sensor. After a general outline of the symbolic sensor concept different classification approaches including fuzzy interpolation and neural network classification will be presented. The sensor is tested with flight test data from dry and wet runway surfaces. Finally, the integration of the symbolic runway surface sensor into an ABS will briefly be discussed.

2 Physical Model

The braking performance of an 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.

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

$$F_r = \mu \cdot F_z \quad (1)$$

The adhesion coefficient depends on the wheel slip s , the relative difference between the aircraft forward speed v and the translational wheel speed $\omega \cdot R$:

$$s = \frac{v - \omega \cdot R}{v} \quad (2)$$

where R is the radius of the wheel and ω its rotational speed. Representing the adhesion coefficient as a function of the wheel slip yields the adhesion characteristic $\mu(s)$, which primarily depends on the runway surface. Typical adhesion characteristics for different runway surfaces are shown in figure 1. It can be observed that all curves $\mu(s)$ start at $\mu=0$ for zero slip, which corresponds to the non-braked, free rolling wheel. With increasing slip the adhesion coefficient increases up to a maximum value which is located between a slip ratio of 3% and 20%. Beyond this maximum value the slope of the adhesion characteristic is negative. At a slip ratio of 100% the wheel is completely skidding, which corresponds to the locking of the wheel.

The adhesion characteristic plays an essential role

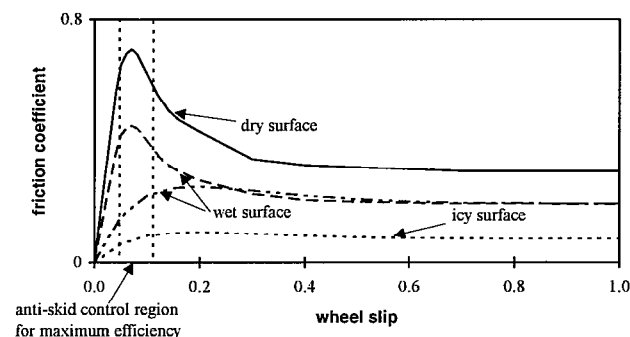


Figure 1: Adhesion coefficient vs. slip

for both the design and the validation of an ABS. It is noted, though, that the curves $\mu(s)$ in figure 1 are simplified models of the friction coefficient. Especially on wet and icy surfaces it is extremely difficult to obtain a reliable representation of the friction characteristic. A theoretical-empirical model of the runway characteristic is given by Pacejka's formula [10], which is based upon an exponential function approach. This formula can be used to determine $\mu(s)$ from flight test data by applying a curve fitting algorithm.

Finally, a physical model of the system tire-runway is derived from the equations of motion applied to a rotating wheel. From figure 2 it follows that:

$$\dot{\omega} I = F_r \cdot R - T \quad (3)$$

where T is the brake torque.

3 Conventional ABS

The role of the ABS is to control the wheel speed in order to prevent the wheels from locking and to assure a maximum braking force. This is of major importance when the runway is slippery or very short.

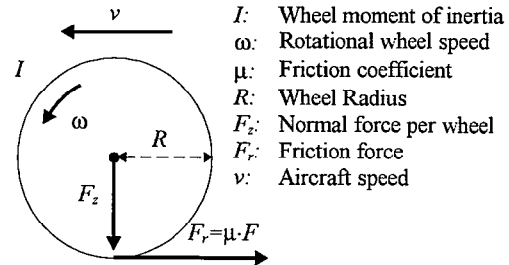


Figure 2: Forces acting on a braked wheel

On dry runways wheel skidding must be avoided in order to minimize the wear of the tyres and to prevent them from bursting.

The ABS commands the brake pressure as a function of the difference between the measured and the reference wheel speed. The latter is calculated from the measured aircraft speed and the desired wheel slip s_c using equation 2. At the moment, when the pilot pushes the brake pedal the brake pressure and the wheel slip increase provoking a ground force between tyre and runway. Assuming the case of full braking, the ABS will control the wheel speed to its reference value. To achieve a maximum braking force the reference slip should be chosen close to the optimum slip. However, when the pressure level in the brakes becomes too high, the wheel slip slides beyond the optimum of the adhesion curve and the system tyre/runway (eq. 3) becomes unstable. The slope of $\mu(s)$ being negative, the wheel immediately starts to lock. In this case, 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).

The principle problem in ABS design is, that the optimum slip and the exact shape of the adhesion characteristic depend on the runway surface and further parameters, which cannot be measured, such as the condition of the tyres or the dynamics of the normal forces. Recent flight test data also show that the location of the optimum slip value significantly varies with the aircraft forward speed on wet or icy runway surfaces. Bearing in mind that the optimum slip value may vary between 3% and 20%, it is clear that the choice of the reference slip value is crucial for a safe and efficient ABS. If it is too small the braking force might become insufficient, if it is too high, wheel lock-up occurs. More recent ABS therefore include some kind of adaptation logic to adjust the reference slip. Overall, to improve the functioning of an ABS it is desirable to have some real-time information about the adhesion characteristic.

4 Ground Surface Sensor

General Remarks The objective of the following section is to propose a framework for the design of a

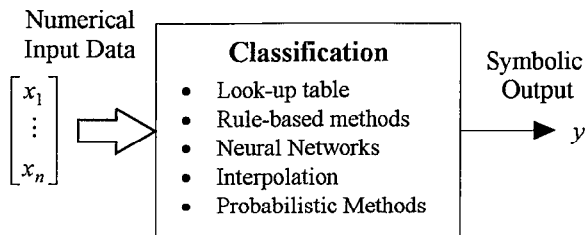


Figure 3: Symbolic sensor

symbolic sensor to "measure" the actual runway condition during the braking of a commercial aircraft. The concern of this paper is to present the principle of a symbolic sensor and to give an outline of two classification approaches applied to the surface identification problem. It must be noted, though, that these methods are still being tested and analyzed with new test data. In this paper we are less concerned about the real-time aspect of the sensor design. To integrate the sensor into an ABS we aim at sample times of about 20 to 30 [ms]. The verification of the feasibility for an real-time application of the sensor will be the subject of a forthcoming publication.

Symbolic Sensors The general structure of a symbolic sensor is depicted in figure 3. The objective is to generate a qualitative information in form of a linguistic description of a physical context from a number of basic, single measurements. One way of representing this numerical to linguistic conversion is to apply Zadeh's principle of a *linguistic variable* [12]. In fuzzy control and approximate reasoning a linguistic variable is a physical quantity whose domain of numerical values is mapped to a number of linguistic expressions represented by fuzzy sets. This concept can be extended to the symbolic sensor by representing the linguistic values of the sensor output signal as fuzzy relations on the Cartesian product of the physical domains of the numerical sensor input signals. In analogy to the representation of a linguistic variable (see [2] for example) the symbolic sensor can be associated with the following framework:

$$\langle Y, \mathcal{L}Y, \mathcal{X}, R_{\mathcal{X}} \rangle \quad (4)$$

where Y denotes the symbolic name of the sensor output signal and $\mathcal{L}Y$ its vocabulary, i.e. the linguistic values that Y may take. $X = X_1 \times \dots \times X_n$ is the Cartesian product of the physical domains X_i of the sensor inputs x_i . Finally, $R_{\mathcal{X}}$ is a fuzzy relation that performs the numeric-linguistic conversion from X to $\mathcal{L}Y$ defined as:

$$R_{\mathcal{X}} = \int_{X_1 \times \dots \times X_n} \mu_{R_{\mathcal{X}}}(x_1, \dots, x_n) / (x_1, \dots, x_n) \quad (5)$$

where $\mu_{R_{\mathcal{X}}} : X_1 \times \dots \times X_n \rightarrow [0, 1]^m$ is the n -dimensional membership function of the relation $R_{\mathcal{X}}$.

Surface Sensor Applying this framework to the surface sensor problem the symbolic name for the output signal Y , for instance, becomes the *surface condition* taking the symbolic values:

$$\mathcal{L}Y = \{icy, wet, dry\} \quad (6)$$

The numerical input signals are the estimated adhesion coefficient $x_1 = \hat{\mu}$ defined on $[0, 1.2]$, the wheel slip $x_2 = s$ defined on $[0, 1.0]$ and the aircraft forward speed $x_3 = v$, defined on the domain $[0, 80 \text{ m/s}]$. Assuming that the wheel speed and the aircraft speed are constantly measured, the wheel slip can directly be calculated from equation 2. To estimate the adhesion coefficient it is necessary to measure the brake torque. A real-time estimation of the adhesion coefficient can then be performed by the means of an recursive least squares (RLS) estimator. This approach has been studied by Kiencke [7] and German [4]. Equation 3 can be represented in the form of the following discrete regression model:

$$\frac{\omega(n) - \omega(n-1)}{T_s} + \frac{T(n)}{I} = \frac{F_z(n)}{RI} \cdot \hat{\mu}(n) \quad (7)$$

$\hat{\mu}(n)$ is the estimated adhesion coefficient, T_s is the sample time and n is the n^{th} time step. Since the normal force is not measured it has to be approximated using the constant load:

$$F_z \simeq k \cdot \frac{m_a g}{N_w} \quad (8)$$

where m_a is the known aircraft mass and N_w the number of braked wheels. The factor k is the ratio between the charge acting on the main landing gear wheels and the charge acting on the nose wheel. The estimate of the adhesion coefficient $\hat{\mu}(n)$ can be evaluated using a classic RLS algorithm with exponential forgetting (see [1] for example). The forgetting factor λ is adjusted with respect to the wheel slip using a simple adaptation logic. In addition to that, a condition to discard outlying measurements has been used.

The essential step in designing the symbolic sensor is to determine the relation $R_{s,v,\hat{\mu}}$ that defines the mapping from the numerical domain of $\hat{\mu}$, v and s to the symbolic expressions *dry*, *wet* and *icy*. Hereafter, two approaches will be outlined.

In the following paragraphs it will be necessary to distinguish between the adhesion coefficient and the grade of membership, both usually denoted as μ . In order to avoid confusion, we will use the notation GoM for the grade of membership and μ for the adhesion coefficient.

Fuzzy Interpolation The following method defines a relation R by the means of an interpolation based on the fuzzy partition principle. For the sake of simplicity it is first assumed that R does not depend on the aircraft speed v . The numerical domain s, μ is divided into the three zones *dry*, *wet* and *icy*, limited by the respective adhesion characteristic $\mu_{dry}(s)$, $\mu_{wet}(s)$, $\mu_{icy}(s)$. These limiting functions have been previously identified on the bases of

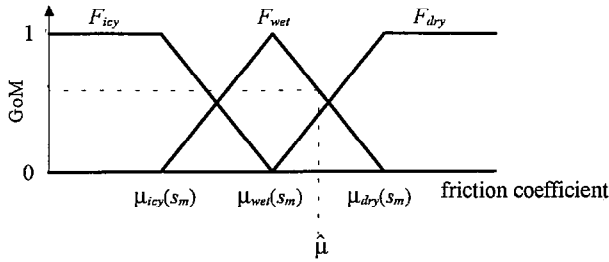


Figure 4: Fuzzy interpolation

the Pacejka model and flight test data. Given the measured wheel slip s_m and the estimated adhesion coefficient $\hat{\mu}$ the objective is to classify this pair into the above categories and to associate it a grade of membership. The latter is determined from the three triangular membership functions F_{dry} , F_{wet} and F_{icy} as shown in figure 4. The values $\mu_{dry}(s_m)$, $\mu_{wet}(s_m)$ and $\mu_{icy}(s_m)$ correspond to the adhesion coefficients calculated by putting s_m in the respective adhesion characteristics.

As it has been pointed out earlier the adhesion characteristic of a wet or an icy runway depends on the aircraft speed, which must therefore be taken into account in the classification algorithm. In fact, this can easily be done by adjusting the limiting curves μ_{wet} and μ_{icy} as a function of the aircraft speed. If the adhesion characteristics are given in form of discrete points, μ_{wet} and μ_{icy} are obtained by the means of a 2-D lookup table. The curve μ_{dry} can be considered as independent on v .

Neural Network Classifier Feedforward multi-layer neural networks have proven to be an appropriate tool for identification and classification problems. A typical feedforward neural network with one hidden layer is depicted in figure 5. Overall, a neural network can be viewed as a nonlinear mapping $f : R^n \rightarrow R^m$ relating the input-output pair (x, y) , $x \in R^n$ and $y \in R^m$. This neural mapping is dependent on the interconnection weights w . To find the appropriate mapping relationship the network is trained with example input-output pairs until the net has "learned"

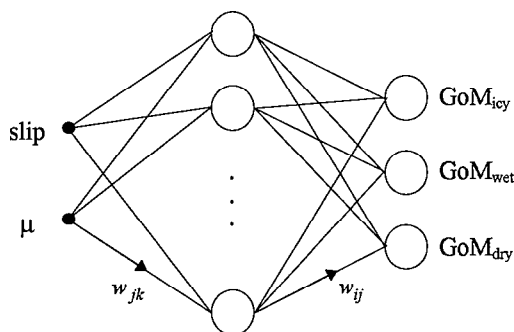


Figure 5: Feedforward neural network

to reproduce these input-output pairs as closely as possible. Training the network means to update its weights such that a quadratic performance criterion is minimized using a gradient search algorithm. This is referred to as *backpropagation* learning. A detailed description about neural networks can be found in [5] or [6] for example.

If the output of the network is chosen from the interval $[0, 1]^m$ the mapping relationship induced by the neural network corresponds to the desired fuzzy relation of the symbolic sensor (eq. 5). For the runway surface sensor a three layer feedforward network with 2 neurons in the input layer, 3 neurons in the output layer, 7 neurons in the first and 5 neurons in the second hidden layer has been used. The input signals of the neural net are the wheel slip and the estimated adhesion coefficient. To take into account the influence of the aircraft speed the network has been trained separately for different reference speeds ($v_{ref} = 80, 60, 40$ and 20 [m/s]) yielding a set of network weights for each v_{ref} . During classification the weights are simply changed when the speed reaches these threshold values. The outputs of the network are the membership grades of the fuzzy categories *dry*, *wet* and *icy*. An initial configuration of the network is obtained by training the network first with data from the empirical adhesion models (fig. 1). In a second step the network is additionally trained with data from braking tests on different runway surfaces. It must be noted here, that this second phase has not completely been finished by the time of the submission of this paper, because too few reliable test data were available for wet and icy runways. For these runway conditions only empirical data have been used to train the network.

Simulation Results The afore described classification algorithms have been verified by numerical simulation using recorded flight test data. Figure 6 shows the results of the classification obtained with data recorded from a full braking on a dry runway surface. The braking starts after about 5 [s] of rolling. Both the fuzzy interpolation and the neural network approach yield correct results classifying the runway surface between 80 and 100% as dry. Similar results could be achieved for other braking recordings on dry runway surfaces.

Figure 7 shows a second simulation, where the surface sensor is presented braking test data recorded on a wet surface. It can be observed that during the beginning of the braking process, i.e. at high aircraft speed, the runway is classified between wet and icy. With decreasing aircraft speed the sensor indicates a wet surface (between 60 and 80%) with an increasing percentage of a dry surface and the classification score "icy" becoming negligible. At low speed the classification score lies between wet and dry. This result coincides with theoretical and experimental analyses suggesting that the friction coefficient on a wet runway increases with decreasing forward speed. This means that the adhesion characteristic of a wet surface as such does not exist and therefore it is very difficult to identify a purely wet surface. In fact, a

wet ground surface should rather be considered as an intermediate state between a low friction (=icy) and a high friction (=dry) surface. From this point of view the surface sensor yields a correct result. It must be noted, though, that these results have been obtained on the bases of very few test data. In order to complete the design and the validation of the surface sensor more braking test data from wet and icy runways are needed.

5 Integration of the Surface Sensor into an ABS

The symbolic ground surface sensor has been designed to estimate the actual runway condition as real-time information for an ABS. One way to integrate additional symbolic information about the runway surface into an ABS would be to introduce the symbolic surface sensor on a supervisory level in order to adapt the reference slip value and/or other parameters of the ABS controller. A simple adaptation logic for the reference slip s_c could be expressed by the following if-then rules:

If runway is dry then s_c is small (7%).
If runway is wet then s_c is medium (9%).
If runway is icy then s_c is big (12%).
If runway is unknown then s_c is default (12%).

These rules can be completed by additional rules using information about the system dynamics.

Rather than using the surface sensor information outside of the control loop, it could directly be incorporated into the ABS control law. If a rule-based controller is chosen, then the surface condition can be included in the antecedent of the control rules. For example two typical linguistic rules of a fuzzy antilock controller could be:

If speed error is big and runway is dry
then variation of output is negative big.
If speed error is big and runway is icy
then variation of output is negative small.

The development of an ABS that incorporates a symbolic ground surface sensor is presently being studied.

6 Conclusion

In this paper a symbolic sensor has been discussed for the acquisition of a real-time information about the surface condition of the runway during the braking of a commercial aircraft. From the measured, numerical input signals the sensor evaluates a degree of membership with respect to the three categories *dry*, *wet* and *icy*. Two classification approaches based on fuzzy logic and neural networks have been proposed and tested with data recorded from braking tests. Satisfactory results could be obtained for both methods. However, more test cases will have to be studied to verify the concept of the surface sensor for a wet runway. Overall, the application example studied in this paper demonstrates that the

integration of qualitative knowledge into a control system can provide new, interesting functions for control design. In this context, fuzzy logic and neural network approaches represent an appropriate framework for the processing and the representation of symbolic information. It can be expected that in future control systems both qualitative and numeric information will be processed in parallel. Nevertheless, it must be noted that symbolic data based systems are more difficult to validate, because they are often subjective and based upon heuristic or black-box type approaches. Therefore future research will have to concentrate on these issues. A further point of interest in the field of symbolic information processing is the interface between symbolic sensors and those system components that receive qualitative information (e.g. rule-based expert systems, deterministic controllers, etc.)

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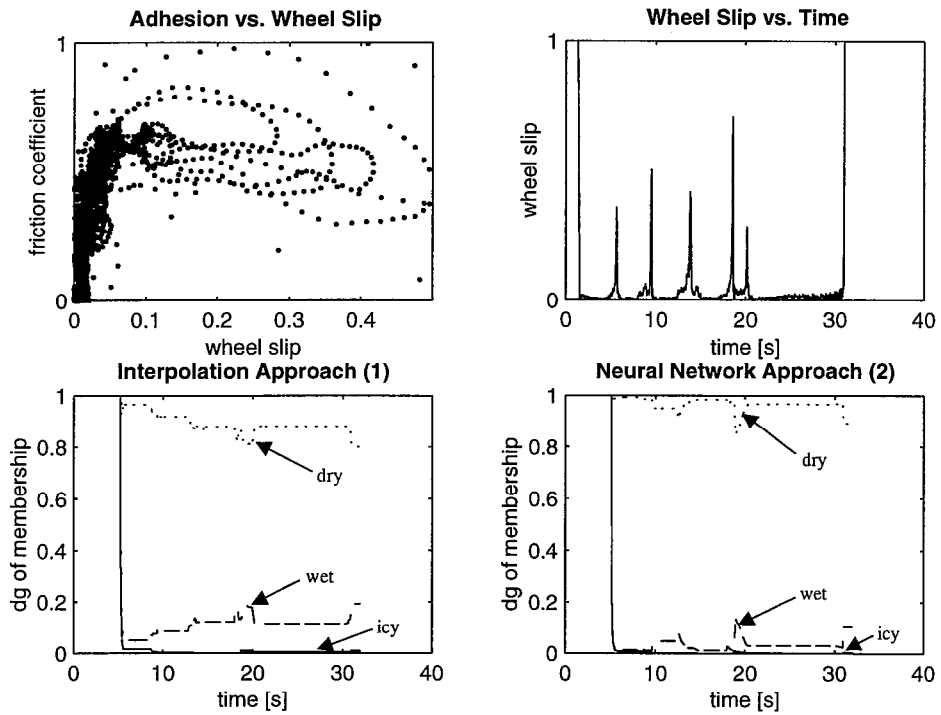


Figure 6: Classification results for a braking on a dry runway

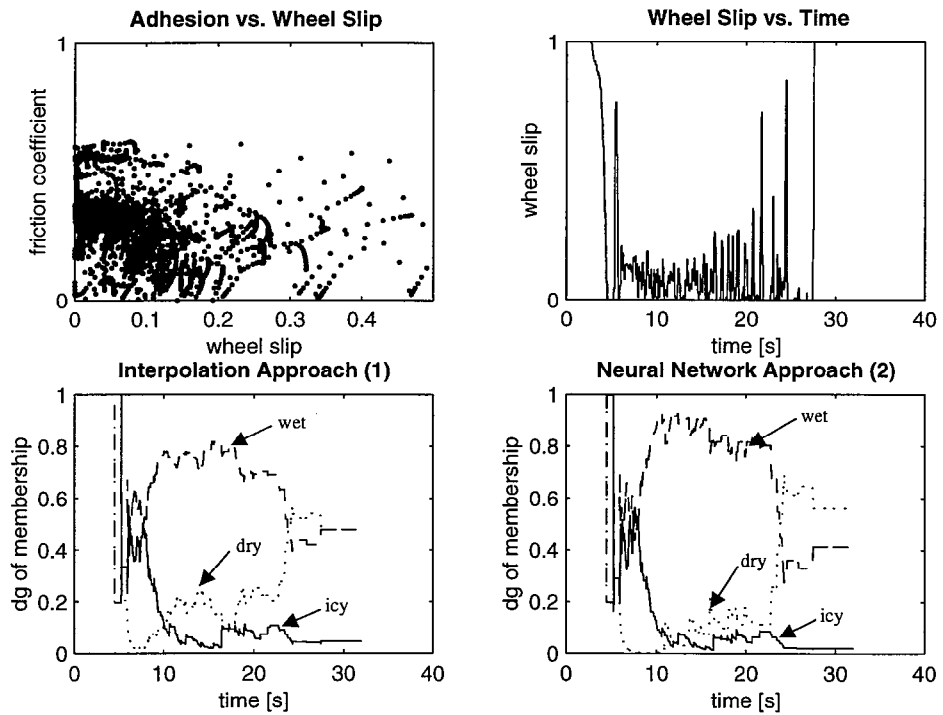


Figure 7: Classification results for a braking on a wet runway