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# ESTIMATION OF THE PARTIAL WRENCH OF THE WHEEL ROAD INTERFACE

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Abstract: Nowadays, active safety has a significant place in the automotive field. Recent studies have shown that electronic driver assistance systems could be improved if the wheel-ground interface could be determined in real time from the driver's requests. So, the aim of this paper is to present a real time estimation of the forces exerted between the wheel and the road, using neural networks. The originality of this study consists in using a limited number of low-cost sensors for the partial wrench estimation. For the moment, the study only considers the estimation of forces Fx, Fy and Fz for purely lateral excitations of the vehicle. The results obtained from the test car of the laboratory are presented, as well as the future improvements to be made. *Copyright © 2002 IFAC*

Keywords: estimator, partial wrench, neural networks.

## 1. INTRODUCTION

The aim of car-manufacturers has always been to improve cars in terms of driving comfort and pleasure, as well as driving safety. That is why traffic has been increasing for several decades and the number of road accidents has risen at the same time. In the 1980's, road transport became a serious subject for research. It was the birth of PROMETHEUS (PROgraM for European Traffic with Highest Efficiency and Unprecedented Safety), the European road safety research program which is part of EUREKA, the European project. From then on, car manufacturers have tried to improve passive safety aimed at protecting the driver and the passengers from serious wounds in an accident.

The technological advances of the past years have particularly helped to improve active safety whose aim is to control vehicle behaviour in order to avoid critical driving conditions. Active safety is thus meant to avoid the crash. There are currently several electronic driver assistance systems (Bosch, 1999, …). The best known systems are Antilock Braking Systems (ABS) (to prevent wheel lock and thus ensure steerability of the vehicle), the Traction Control systems (TC) (to prevent wheelspin during a standing-start or a too sudden acceleration), and Electronic Stability Control (ESP) (device using the brake systems of a vehicle in order to direct it) (Zanten, 1996).

All these driving assistance systems try to avoid the loss of adherence of the vehicle in critical situations. The knowledge, in real time, of the stresses acting directly on the tyre would undeniably help to improve active safety, because the friction limits of the vehicle are expressed by the forces on the tyre. So, the aim of this paper is to know the real time estimation of the forces exerted between the wheel and the road.

The concept presented here allows the estimation of the 3 forces (Fx, Fy and Fz) acting between the right front wheel driving and the road. The different situations which were taken into account to train and to validate the estimator are those ones a normal driver can meet with : the steady state as well as dynamic situations, and particularly the critical situations (dangerous ones) like the strong under-steering situations and the strong over-steering situations. This concept uses a limited number of low-cost sensors measuring namely : the longitudinal and lateral accelerations, the steering wheel angle and the right and left wheel clearances. The method must take account of the highly non-linear behaviour of the vehicle. It was decided to use the neuromimetic networks which, contrary to fuzzy logic, do not need a precise knowledge of the non-linear behaviour of the system. The forces estimator then developed has been tested and validated on a test car.

## 2. LIST OF SYMBOLS

| Code | Unit | Meaning |
|---|---|---|
| Fx | N | longitudinal force |
| Fy | N | transversal force |
| Fz | N | normal load |
| $\dot{\psi}$ | rad/s | yaw velocity |
| γl | m/s² | longitudinal acceleration |
| γt | m/s² | lateral acceleration |
| αv | rad | steering-wheel angle |
| zd | - | right front wheel clearance |
| zg | - | left front wheel clearance |
| W | - | weight matrix of the network |
| b | - | biases matrix of the network |
| M | Kg | mass of the vehicle |
| H | m | height of the vehicle |
| V | m | track front |
| Sx | % | tyre slip ratio |
| δ | ° | tyre slip angle |
| µl | - | longitudinal friction coefficient |
| µt | - | lateral friction coefficient |

## 3. STRATEGY

As mentioned previously, the estimator developed uses neural networks for the prediction of the forces acting between the wheel and the road. After various tests, it appeared clearly that only one neural network was not able to predict the 3 forces Fx, Fy and Fz. The estimator was thus divided into 3 subsystems. Each of them (having its own neural network) represents the prediction of one of the 3 forces (Fx, Fy, Fz) (see figure 1).

The first subsystem helps to estimate the longitudinal stress (Fx) according to the 4 following input variables : $\gamma_l$, $\gamma_t$, zd and zg. The second uses the variables $\gamma_t$, αv, zd and zg for the estimation of the lateral stress (Fy). And the third subsystem helps to estimate the normal load (Fz) and uses the same inputs as those used for the estimation of Fy, namely: $\gamma_t$, αv, zd and zg.

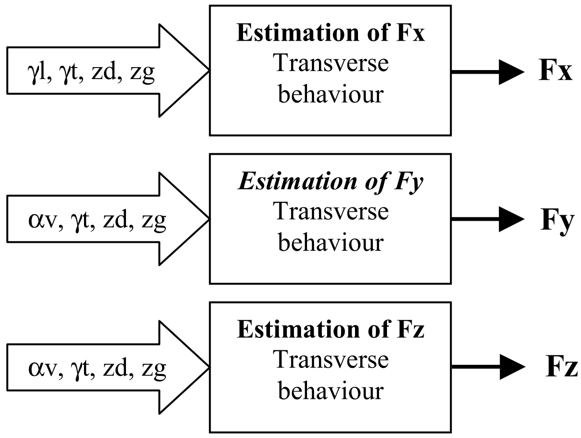


Fig. 1. Principal structure of the estimator of the forces acting between the wheel and the road.

The training of these 3 neural networks still remains an art as well as a science (Davalo and Naîm, 1989). Indeed, the predictive capacity of a neuromimetic network depends on several parameters such as the structure and the type of network, the number of neurons, the transfer function, the learning process and so on. After choosing these different parameters, the network tries to converge towards a reference behaviour according to the data which it is provided with him. It is thus necessary to first carry out various measurements in order to create a data base (also called *training set*) made up of the network's inputs and the network's output towards which this one must converge.

Once the training set has been defined, the learning process starts according to the following synopsis (see figure 2) :

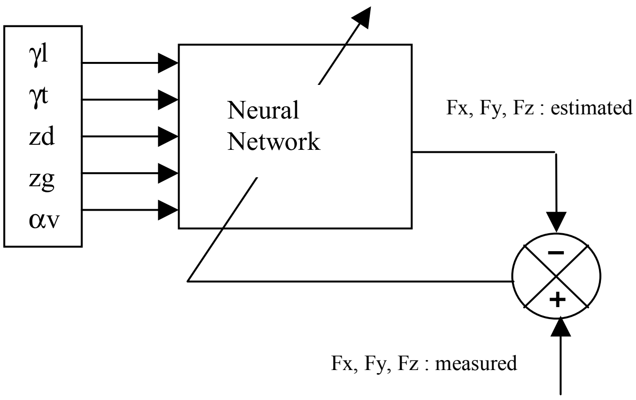


Fig. 2. Learning process of the neural network.

During the learning process, the network converges towards the reference forces while modifying the weight (w) for each neuron (Anderson, 1995).

## 4. MEASUREMENTS

A test-vehicle instrumented and equipped by the laboratory allowed these measurements. The different sensors and measurement parameters needed in the test car for these trials are shown in figure 3.

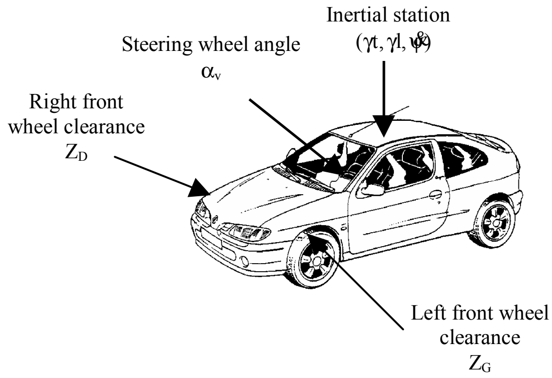


Fig. 3. Sensors and measurement parameters in the test car.

The choice of the different sensors is justified by the following items:

- The steering-wheel angle (αv) corresponds to the actions on the steering wheel by the driver.

- The vertical motion of the right front (zd) and left front (zg) wheels corresponds to the front vehicle clearance.

- The longitudinal (γl) and lateral (γt) accelerations help to find the friction potential of the tyre by drawing the diagram G-G (Milliken and Milliken, 1995).

The axis system chosen for the vehicle is displayed below in figure 4.

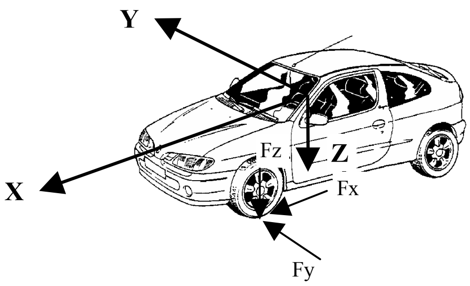


Fig. 4. Axis system chosen for the vehicle.

The data base, also called training set, which is obtained from these measurements is made up of the inputs and the output of the neuromimetic system. The longitudinal ($\gamma_l$) and lateral ($\gamma_t$) accelerations, as well as the steering-wheel angle (αv) and the right front (zd) and left front (zg) wheel clearance make up the network's input. $\gamma_l$ and $\gamma_t$ are provided by acceleration sensors located near the centre of gravity of the test car, and zd, zg as well as αv are measured by conditioned potentiometers. The output is composed of the 3 reference forces between the wheel and the road (Fx, Fy et Fz) which were measured by a wheel force sensor located on the right front wheel.

The tests carried out by the car to obtain the training set are presented below:

- Angular dynamic (DA) : the vehicle drives in a circle at really low speed (γt negligible). Then, the vehicle gradually increases its speed in order to increase γt, while maintaining its trajectory by correcting the steering wheel angle.

- Handing-over of the steering wheel angle (RAV) : the vehicle drives along a straight stretch of road with a continuous velocity, then the steering wheel angle increases slowly with a continuous velocity in order to generate an incline αv.

## 5. NEURAL NETWORK

### *5.1 Neurons.*

The network used is composed of several neurons. These neurons can be represented as follows :

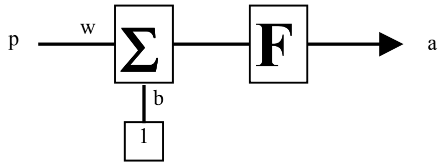


Fig. 5. Structure of a neuron with one input

The output ***a*** of the neuron depends on the following parameters : the transfer function ***F***, the input vector ***p***, the biases ***b***, and the weight of the neuron ***w***. The equation of output **a** is :

$$a = F(w.p + b) \qquad (1)$$

### *5.2 Network used.*

The prediction quality of the forces (Fx, Fy and Fz) provided by the network after the learning process depends on the following parameters :

- The network'structure : it was decided to use a Multilayer Perceptron with one hidden layer (see figure 6) , because according to the theorem of Stome-Weierstrass (Hérault and Jutten, 1994), this type of neural network is able to approximate any continuous function, provided that the transfer function is not a polynomial and that the number of neurons in the hidden layer is sufficient.

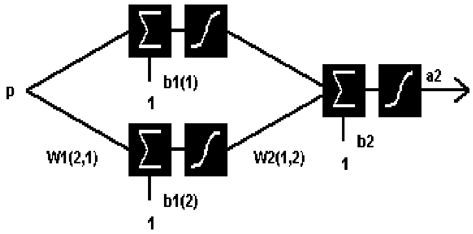


Fig. 6. Multilayer network.

- The number N of neurons in the hidden layer (Joduin, 1994) : after several manipulations for different values of N in the hidden layer, the most satisfactory results were obtained for N=50.

- The transfer function : it determines the behaviour of a neuron. It can be different from one layer to another, following the network's architecture and the data that are in input. After several tests, the transfer function « satlins » for the hidden layer and « purelin » for the output layer, provided the best results (see figure 7).

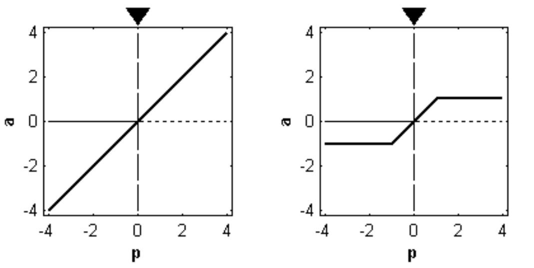


Fig. 7. Transfer functions accepted : Linear (left) and Symmetric Saturating Linear (right).

- The training set : thanks to the training set, the network converges towards a reference behaviour which it learnt. Several specific types of tests, such as handing-over of the steering-wheel angle (RAV) and the angular dynamic (DA), were assembled in a deterministic way in order to form the training set. All the measurements of these tests were then filtered using a Butterworth filter, then treated to remove the offsets, so that they could finally be standardized between 1 and -1. The neurons of the network which perceive these data are called *input neurons*.

- The learning process algorithm : the solution adopted is an important generalization of the gradient descent to a nonlinear, multi-layer feedforward network, called backpropagation. Backpropagation is a supervised algorithm which minimizes network error by modifying weights. This learning process algorithm which has been chosen, is the most often used for this type of network (Anderson, 1995).
  The backpropagation training algorithm is the one of Levenberg-Marquardt.

The training convergence used the mean square error. The training is stopped when the mean square error is stable after several iterations.

## 6. RESULTS

### *6.1 The estimation of the longitudinal stress (Fx).*

The learning process was carried out for angular dynamic tests and handing-over of steering-wheel angle tests, which involves low variations for the longitudinal force. For the network, it is thus more difficult to converge towards an optimal solution during the learning process, as the latter is much more sensitive to the non-linearities of the tyre due to too weak a signal/noise ratio. As a consequence, the prediction obtained for the longitudinal force (Fx) is not optimal. The results obtained for an angular dynamic (DA) test is given in figure 8, and the results obtained for an handing-over of the steering wheel angle (RAV) test is given in figure 9.

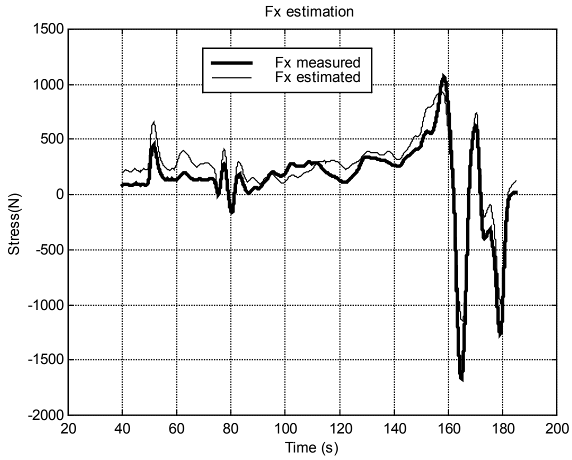


Fig. 8. Comparison between the estimated and measured longitudinal force (DA).

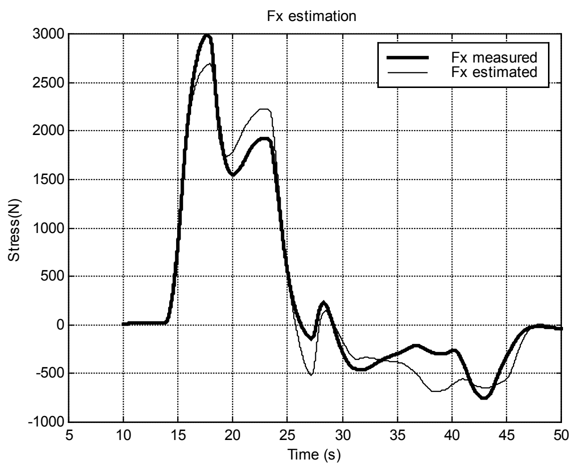


Fig. 9. Comparison between the estimated and measured longitudinal force (RAV).

### *6.2 The estimation of the lateral stress (Fy).*

The predictive capacity of the network used is more or less high according to the trajectory of the vehicle. Indeed, when the latter simulates a steering-wheel angle test (RAV) or an angular dynamic test (DA) for a negative steering-wheel angle (i.e. for a left turn), a load transfer $M.\gamma_t.\frac{h}{V}$ is carried out between the right front wheel and the left front wheel. The normal forces operating on the front vehicle are the following :

$$Fz_g = \frac{M.g}{2} - M.\gamma_t.\frac{h}{V} \qquad (2)$$

$$Fz_d = \frac{M.g}{2} + M.\gamma_t.\frac{h}{V} \qquad (3)$$

The right front wheel is thus more *loaded*. The coupling between the lateral force (Fy) and the normal load (Fz) which is defined as follows :

$Fz.\mu_t = Fy$ (with $\mu_t$ the lateral adhesion coefficient) shows that Fy depends on Fz. Moreover, there are induced phenomena acting on Fy such as, for instance, the deformation of the tyre (when the vehicle is stopped) thus generating a lateral stress, which is more or less negligible according to the load applied to the wheel.

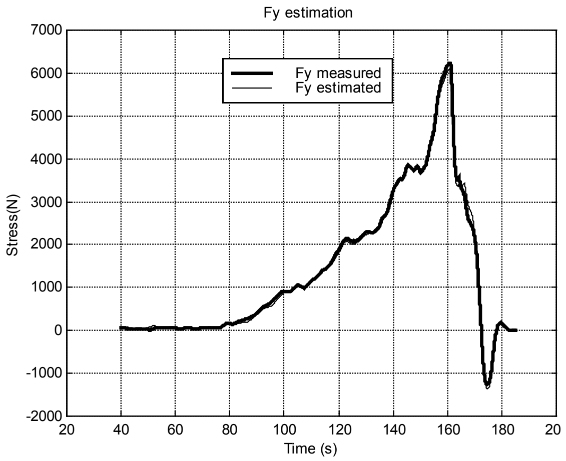


Fig. 10. Comparison between the estimated and measured lateral force (DA).

All this shows that the lateral stress estimation (Fy) is of better quality when the wheel is strongly loaded, because the induced phenomenon on the load transfer ratio is weaker. The results obtained for the estimation of the lateral force acting on the right front wheel of a vehicle during a left angular dynamic test, are shown in figure 10 and during a left handing-over of the steering wheel angle, are shown in figure 11.

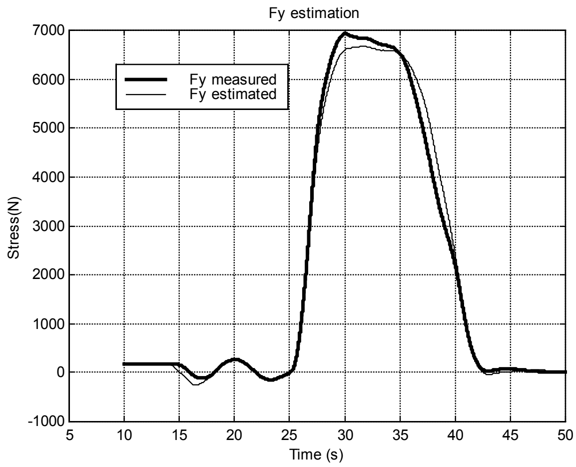


Fig. 11. Comparison between the estimated and measured lateral force (RAV).

*6.3 The estimation of the normal load (Fz)*

Referring to the previous equations (2) and (3), it can be noticed that the normal load applied to the wheel-ground interface mainly depends on the load transfer (in the case of lateral requests), and more particularly on the centrifugal force ($M.\gamma_t$). The estimator developed is able to correctly estimate Fz, whatever the type of trajectory followed by the vehicle (i.e. a left turn).

The results obtained for the estimation of the normal load acting on the right front wheel of a vehicle during an angular dynamic test are shown in figure 12 and during an handing-over of the steering wheel angle, are shown in figure 13.

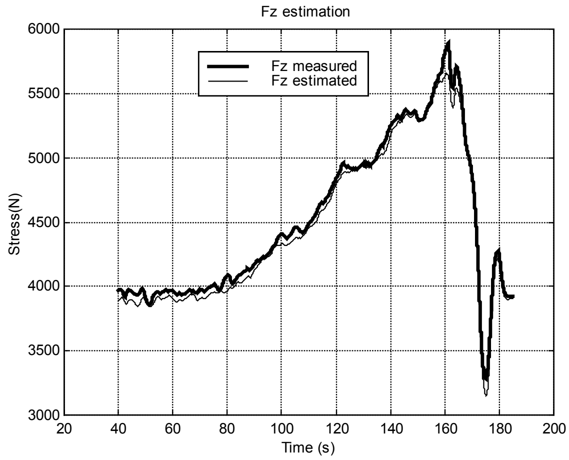


Fig. 12. Comparison between the estimated and measured normal force (DA).

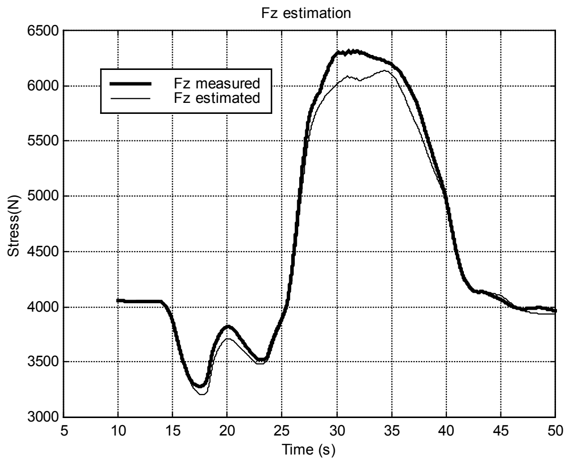


Fig. 13. Comparison between the estimated and measured normal force (RAV).

## 7. VALIDATION OF THE 3 ESTIMATORS (FX, FY, FZ)

As mentioned earlier, driver assistance systems try to avoid the loss of adherence of the vehicle in critical situations. It is difficult to implement such regulation systems because of the non-linear behaviour and the limited potential of the tyre. Different models of tyres have thus been developed. One of the best known and most often used, is Pacejka's algebraic model (Pacejka, 97).

To determine the friction limits of the tyre and thus of the car, the lateral friction characteristic of the tyre can be plotted on the ground.

The lateral friction curve is defined by the lateral friction coefficient ($\mu_t$) according to the tyre slip angle ($\delta$) :

$$\mu_t = f(\delta) \qquad \text{with}$$

$$\mu_t = \frac{Fy}{Fz} \quad \text{et} \quad \delta = \arctan(\frac{v_t}{v_l}) \quad (4)$$

The results obtained for the estimation of the lateral friction coefficient ($\mu_t$) of the right front wheel vehicle during an angular dynamic test are shown in figures 14 and during an handing-over of the steering wheel angle, are shown in figure 15.

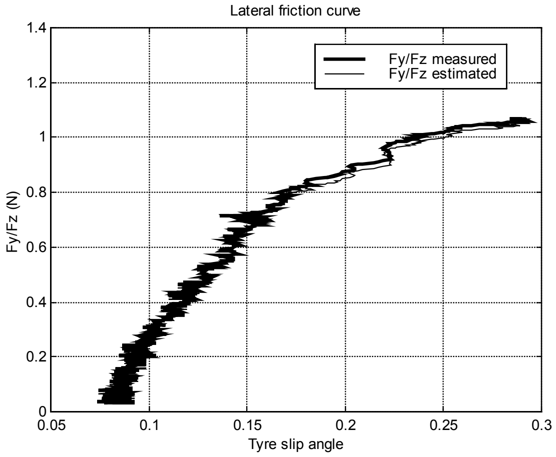


Fig. 14. Comparison between the measured and estimated lateral friction curve (DA).

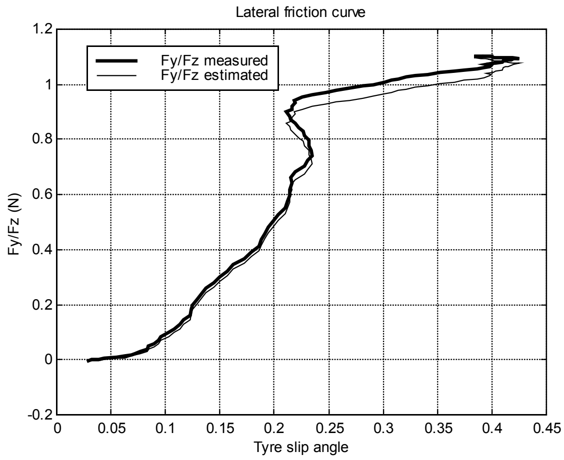


Fig. 15. Comparison between the measured and estimated lateral friction curve (RAV).

## 8. CONCLUSION

The present study has helped to determine the 3 forces that act between the wheel and the ground.

The aim of this paper is not to prove that a new tyre model can be developed only using neural networks, but to present a concept which allows the estimation of the partial wrench of the wheel ground interface, for a purely lateral trajectory of the vehicle, using a limited number of sensors. This study is based on a particular kind of neural network, called *multi-layer feedforward network,* which is composed of a hidden layer of neurons. The estimator is currently in the optimization phase. Indeed, as mentioned previously, the prediction of this neural network depends on several parameters. Therefore, the modifications of the neuronal network will be about :

- The number of neurons in the hidden layer which can still be modified to optimize the neural network prediction.
- The selection of the data files, chosen in a deterministic way which constitutes the training set, can be chosen in a random way in order to prevent that the network from not converging towards a local minimum.
- The choice of the input variables and the backpropagation training algorithm.

Two new estimators are currently being under developed for the estimation of the partial wrench of the wheel ground interface for various types of behaviour of the vehicle. The first one will simulate a purely longitudinal behaviour of the vehicle (i.e. for a zero steering-wheel angle) and the second one will simulate both a longitudinal and a lateral behaviour.

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