

The equations of motion for the 5DOF vehicle model are:

$$mv(\dot{\beta} + \dot{\psi}) - m_s h \ddot{\phi} = F_{yf} + F_{yr} \quad (1)$$

$$-I_{xz} \ddot{\phi} + I_{zz} \ddot{\psi} = F_{yf} l_f - F_{yr} l_r + l_w \Delta F_b \quad (2)$$

$$(I_{xx} + m_s h^2) \ddot{\phi} - I_{xz} \ddot{\psi} = m_s g h \phi + m_s v h (\dot{\beta} + \dot{\psi}) - k_f (\phi - \phi_{t,f}) - b_f (\dot{\phi} - \dot{\phi}_{t,f}) + u_f - k_r (\phi - \phi_{t,r}) - b_r (\dot{\phi} - \dot{\phi}_{t,r}) + u_r \quad (3)$$

$$-h_r F_{yf} = m_{uf} v (r - h_{uf}) (\dot{\beta} + \dot{\psi}) + m_{uf} g h_{uf} \phi_{t,f} - k_{t,f} \phi_{t,f} + k_f (\phi - \phi_{t,f}) + b_f (\dot{\phi} - \dot{\phi}_{t,f}) + u_f \quad (4)$$

$$-h_r F_{yr} = m_{ur} v (r - h_{ur}) (\dot{\beta} + \dot{\psi}) - m_{ur} g h_{ur} \phi_{t,r} - k_{t,r} \phi_{t,r} + k_r (\phi - \phi_{t,r}) + b_r (\dot{\phi} - \dot{\phi}_{t,r}) + u_r \quad (5)$$

We consider first that the lateral tire forces in the direction of the wheel ground contact are approximated linearly to the tire slide slip angles, respectively:

$$F_{yf} = \mu C_f \alpha_f \quad (6)$$

$$F_{yr} = \mu C_r \alpha_r \quad (7)$$

and the tire side slip angles are approximated as:

$$\alpha_f = -\beta + \delta_f - \frac{l_f \dot{\psi}}{v} \quad (8)$$

$$\alpha_r = -\beta + \frac{l_r \dot{\psi}}{v} \quad (9)$$

The state vector is the following: $x = [\beta \ \psi \ \phi \ \dot{\phi} \ \phi_{t,f} \ \phi_{t,r}]^T$

The main input of the system is the steering angle. The steering angle applied in the simulation is a double lane change manoeuvre (0-7s) followed by a step steering (10-20s), which is filtered at 4 rad/s to represent the finite bandwidth of the driver. Fig. 2 shows this input:

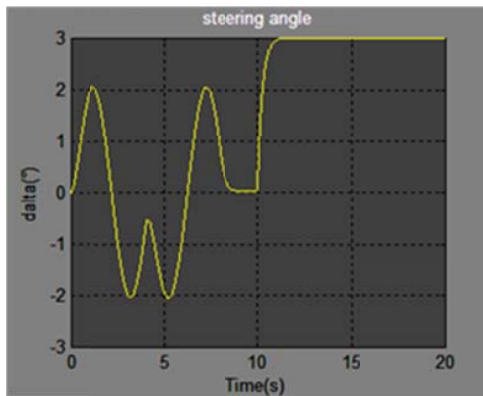


Fig. 2 Steering angle

III. CONTROL OBJECTIVES

The main objective of the proposed controller is to maximize the roll stability of the vehicle in both, linear and nonlinear, side force model. The roll stability is achieved by

limiting the lateral load transfers to below the levels for wheel lift-off.

First, we use the LQR active roll control, as described in [2], its objective is set the normalized load transfers at the steer and drive axles to be equal and below ± 1 , and to tilt the vehicle inwards to the maximum angle allowed by the suspensions (the relative roll angle of the suspension must be within 7°). Then, the collected data from the LQR controller are used for the training basis of the ANN controller.

We consider first the problem of optimal regulation in the presence of a constant deterministic disturbance $r(t)$, and consider a strictly proper linear dynamic system:

$$\dot{x} = Ax + B_0 u + B_r r, \quad z = C_1 x$$

Then, the problem is to find the control minimizing the index J such as:

$$J = \int_0^\infty (z^T Q z + u^T R u) dt$$

where: $C_1 = [0 \ 0 \ 0 \ 0 \ 1 \ 0; 0 \ 0 \ 0 \ 0 \ 0 \ 1]$; and the matrices Q and R are the relative weighting of the performance output trajectory z and the control input u respectively, their values, based on trial and error, are:

$$Q = [1000 \ 0; 0 \ 1685]; R = 10^{-9} \cdot [0.3830 \ 0; 0 \ 0.2590].$$

The optimal control law is provided by a feedback controller K_1 plus a feed-forward controller K_2 [4]:

$$u(t) = K_1 x(t) + K_2 r(t)$$

where

$$K_1 = -R^{-1} B_0^T S, \quad K_2 = R^{-1} B_0^T (A^T - S B_0 R^{-1} B_0^T)^{-1} S B_r$$

and S satisfies the Riccati equation:

$$S A^T + A^T S - S B_0 R^{-1} B_0^T S + C_1^T Q C_1 = 0$$

Therefore:

$$S = \begin{bmatrix} 21.2332 & -2.0901 & -4.6467 & -1.8981 & 1.3984 & 2.0605; \\ -2.0901 & 0.4337 & 0.0124 & 0.1088 & -0.6861 & -0.1485; \\ -4.6467 & 0.0124 & 3.5798 & 0.6636 & 0.2066 & 0.6474; \\ -1.8981 & 0.1088 & 0.6636 & 0.2040 & -0.0187 & -0.2172; \\ 1.3984 & -0.6861 & 0.2066 & -0.0187 & 18.6364 & 0.1172; \\ 2.0605 & -0.1485 & 0.6474 & -0.2172 & 0.1172 & 19.4957 \end{bmatrix}$$

IV. CONTROL BASED NEURONAL NETWORK

Artificial neural networks use a dense interconnection of computing nodes to approximate nonlinear functions. Each node constitutes a neuron and performs the multiplication of its input signals by constant weights, sums up the results and maps the sum to a nonlinear activation function; the result is then transferred to its output. A feed-forward ANN is organized in layers: an input layer, one or more hidden layers and an output layer [5].

The ANN is trained by a learning algorithm which performs

the adaptation of weights of the network iteratively until the error between target vectors and the output of the ANN is less than an error goal. The most popular learning algorithm for multilayer networks is the back-propagation algorithm and its variants. The latter is implemented by many ANN software packages such as the neural network toolbox from MATLAB [6]. The Sampling period of the simulation is 0.0002s.

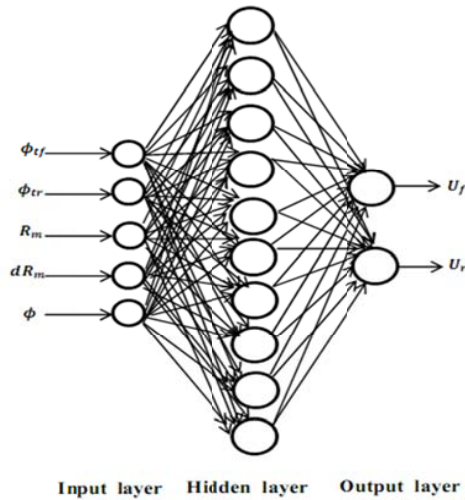


Fig. 3 Structure of the neural network architecture

Neural network, in Fig. 3, has been devised having as inputs the roll angle of the unsprung masses (ϕ_{tf}, ϕ_{tr}), the mean of the rollovers ($R_m = \frac{R_f + R_r}{2}$), and the change of the mean ($\frac{dR_m}{dt}$).

And the roll angle of sprung mass (ϕ). And as outputs the front and rear anti-roll moments (U_f, U_r).

A. With Constant Adhesion Coefficient

Fig. 4 shows front and rear normalized rollovers for the linear side force model with constant adhesion coefficient

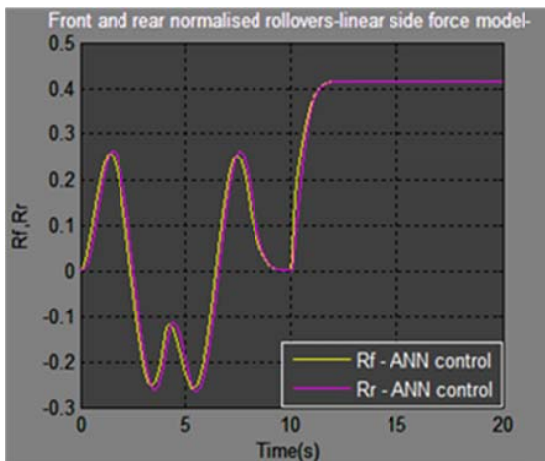


Fig. 4 Front and rear normalized rollovers with ANN controller

The front and rear normalized rollovers for the passive suspension, the active suspension with LQR, and with ANN are shown in Figs. 5 and 6 respectively:

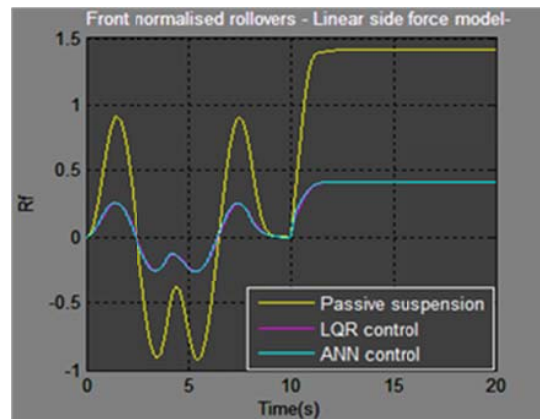


Fig. 5 Front normalized rollovers

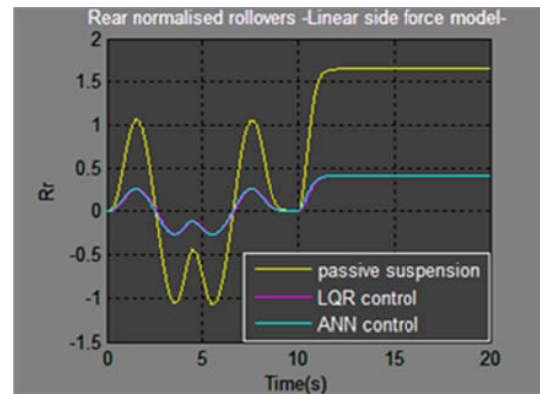


Fig. 6 Rear normalized rollovers

The moments generated by the front and rear anti-roll bars are shown in Fig. 7.

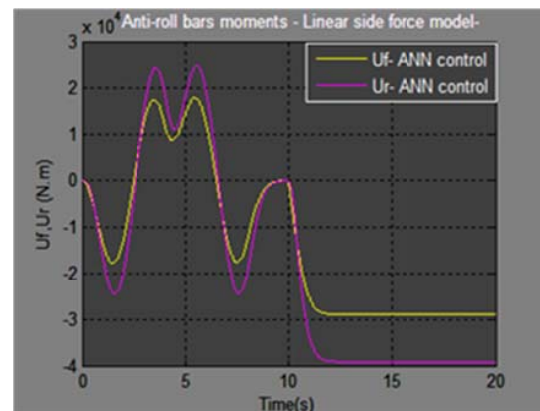


Fig. 7 Moments generated by the Anti-Roll Bars

The side slip angle β for the three cases: Passive, LQR, ANN are shown in Fig. 8.

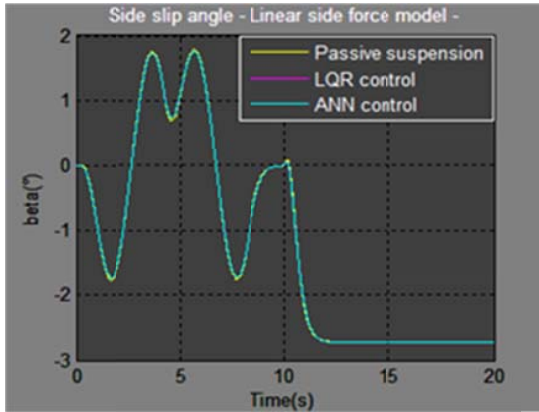


Fig. 8 Side slip angle

In this part of simulation, one can note that the neural network is successfully converged, since the LQR and the ANN controllers give the same results, for the rollovers and the side slip angle. In addition, the front and rear rollovers are balanced within the tolerated values.

The side slip angle for the three cases are the same, since the controllers work with the roll states and not with the yaw ones.

B. With Variable Adhesion (Friction) Coefficient

Here, we consider that the adhesion coefficient μ is varied to simulate the terrain variation. Fig. 9 shows this variation.

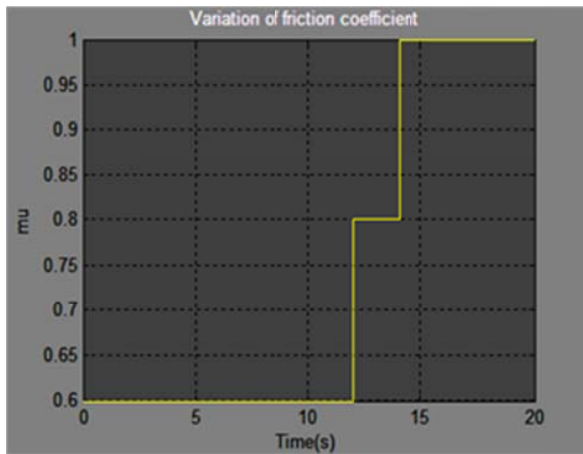


Fig. 9 Variation of adhesion coefficient

The LQR matrices must be changed and adapted with the variation of adhesion coefficient, and the new values of the gains K_1, K_2 become:

$$\text{For: } \mu = 0.6 \rightarrow K_1 = [-9.5730 \cdot 10^4; -5.1859 \cdot 10^4]$$

$$K_2 = 10^5 \cdot [1.7811 \ 0.0024 \ -1.1576 \ -0.3197 \\ -4.9145 \ 0.1387; 2.4802 \ -0.1324 \ -1.8974 \\ -0.3999 \ -0.1318 \ -7.2983]$$

$$\text{For: } \mu = 0.8 \rightarrow K_1 = [-1.260610^5; -0.710010^5]$$

$$K_2 = 10^5 \cdot [2.2989 \ -0.0077 \ -1.1677 \ -0.3248 \\ -4.8960 \ 0.1383; 3.1935 \ -0.1846 \ -1.9047 \\ -0.4055 \ -0.0967 \ -7.2876]$$

Figs. 10 and 11 show the normalized rollovers for the three cases: passive, LQR, ANN:

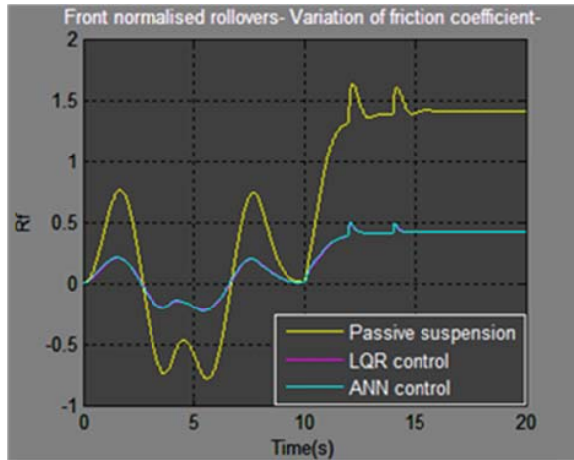


Fig. 10 Front normalized rollovers

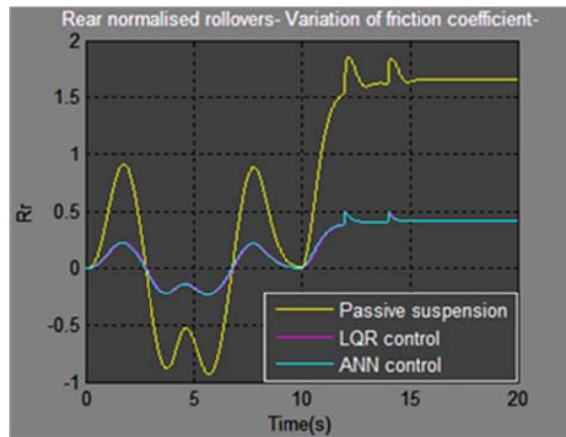


Fig. 11 Rear normalized rollovers

Fig. 12 shows the moments generated by the anti-roll bars.

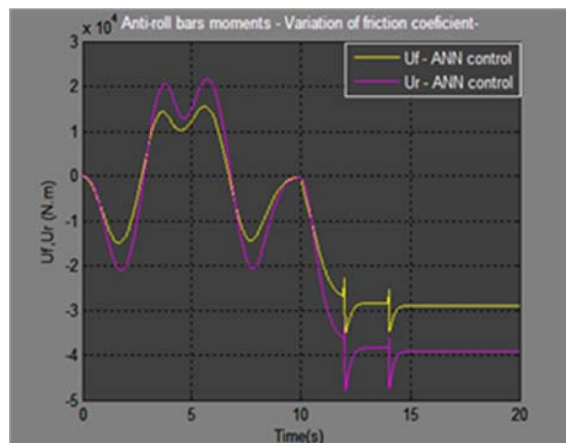


Fig. 12 Moments generated by the anti-roll bars

We can note that the LQR controller and the ANN

controller give the same satisfactory results, and the rollovers are within the allowed values. However, the LQR controller requires a parameter adaptation.

C. With Nonlinear Side Force Model (Kiencke and Nielson Model):

In this simulation, we consider that the lateral force is described by the Kiencke model [7]:

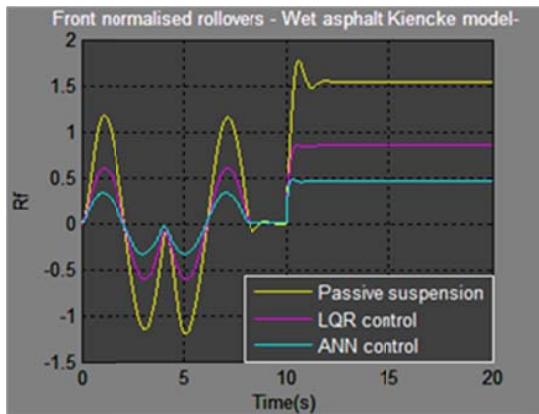


Fig. 13 Front normalized rollovers

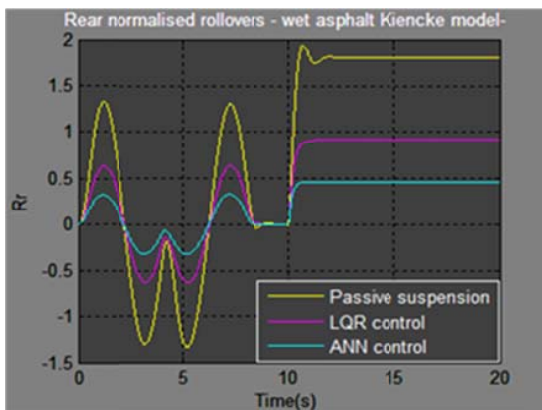


Fig. 14 Rear normalized rollovers

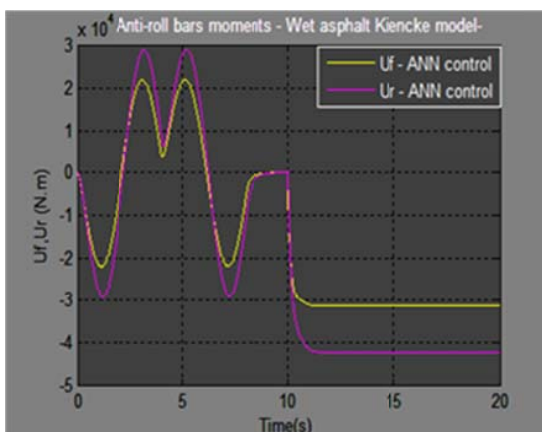


Fig. 15 Moments generated by the anti-roll bars

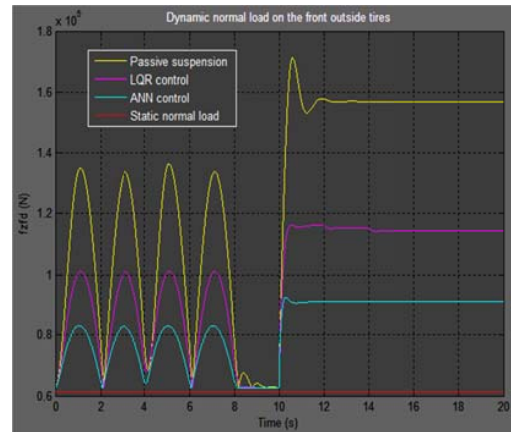


Fig. 16 Normal load on the front outside tire in a cornering

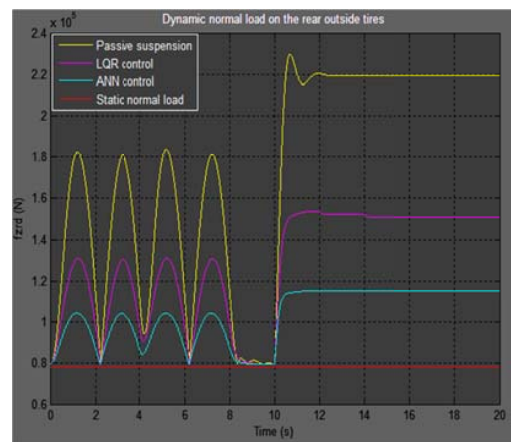


Fig. 17 Normal load on the rear outside tires in a cornering

The process is simulated for a “wet asphalt”, and it remains valid for any other ground. The results show the advantage brought by the ANN controller compared to the LQR, it's obviously noted, the LTR are always located in the range $[-0.5, 0.5]$ for the ANN controller, however the LQR controller loses its performance, and the LTR's have maximums close to their critical values 0.9.

V. CONCLUSION

The two controllers, LQR and ANN, are successfully applied to control the semi-active suspension of the single unit heavy vehicle with the use of anti-roll bars mechanism. These controllers give similar performance, for constant and variable friction coefficient; however, the LQR controller requires gain adaptation. The ANN controller is very advantageous in the nonlinear side force case.

By observing the normal forces supported by the outside tires in a cornering, one can conclude that the ANN can reduce successively and considerably these loads, and thus, to preserve usefully the rubber of the wheels and to protect the environment.

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