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# Comparison between LQR and ANN Active Anti-Roll Control of a Single Unit Heavy Vehicle

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***Abstract*****—**In this paper, a learning algorithm using neuronal networks to improve the roll stability and prevent the rollover in a single unit heavy vehicle is proposed.

First, LQR control to keep balanced normalized rollovers, between front and rear axles, below the unity, then a data collected from this controller is used as a training basis of a neuronal regulator. The ANN controller is thereafter applied for the nonlinear side force model, and gives satisfactory results than the LQR one.

***Keywords*****—**Rollover, single unit heavy vehicle, neural networks, nonlinear side force.

## I. Introduction

THE lateral stability loss is one of the main causes of traffic accidents in which heavy vehicles are involved. This can cause mainly a rollover, which is crucial and fatal when the tire-road contact force on one of the side wheels becomes zero.

At moderate levels of lateral acceleration, the heavy vehicles can lose roll stability, which means the ability of a vehicle to resist overturning moments generated during cornering, because of their relatively high centers of mass and narrow track widths.

In the literature, several active roll control strategies have been proposed in order to improve vehicle handling response and roll stability. The famous one is active anti-roll bars; these bars consist of a pair of hydraulic actuators which generate the adequate roll moment between the sprung and unsprung mass at each axle to balance the overturning moment [1].

Sampson in [3] defines an active roll control based on LQR (Linear Quadratic Regulator) approach to improve the roll and handling stability, this procedure has been used in this paper, but in our case, the best results of the LQR controller are exploited as a training data for the neuronal network.

The inputs and the number of the neurons in the hidden layer are selected after several trials and it is those which give the best performance in the phase of training.

## II. The Single Unit Heavy Vehicle Model

Fig. 1 shows the five-degree-of-freedom vehicle model used in this research. It represents a single unit heavy and it is modeled using three rigid bodies: the sprung mass and the two unsprung masses, one each for the front and rear axles [1], [2]. The vehicle as a whole can translate longitudinally, laterally and can yaw. The sprung mass can rotate about the roll axis fixed in the unsprung masses. The unsprung masses can also rotate in roll, enabling the effect of the vertical compliance of the tires on the roll performance to be included in the model. The motion is described using a coordinate system (x, y, z) fixed in the vehicle [2].

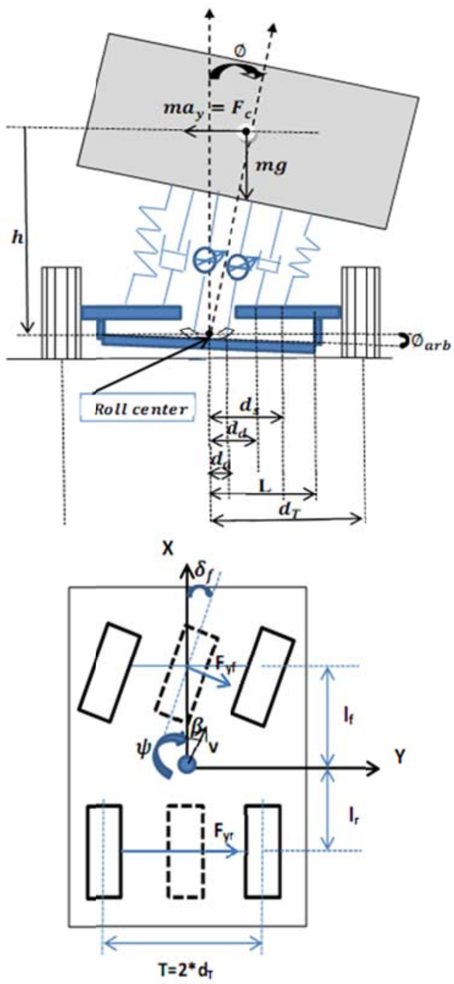


Fig. 1 Coordinate system for a single unit heavy vehicle

In this model, the forward speed of the vehicle is assumed to be constant during the lateral maneuvers $\left(U = 80\,{}^{Km}/_{h}\right)$. The roll stiffness and damping of the vehicle suspension systems are also assumed to be constant for the range of roll motions considered [3].

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

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

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

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

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

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

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: $x=[\beta \;\; \dot{\psi} \;\; \phi \;\; \dot{\phi} \;\; \phi_{t,f} \;\; \phi_{t,r}]^T$

The main input of the system is the steering angle. The steering angle applied in the simulation is a double lane change manoeuver (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:

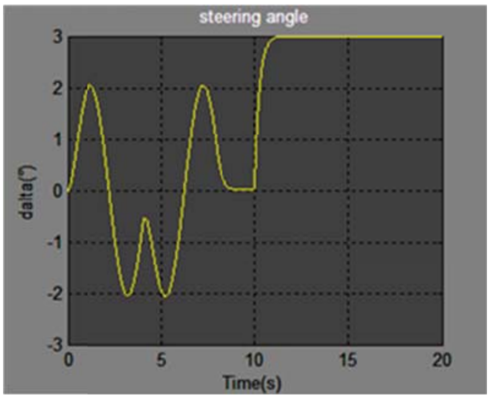


Fig. 2 Steering angle

## 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:

$$\dot{x}=Ax+B_0u+B_rr, \quad z=C_1x$$

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

$$J=\int_0^{\infty}(z^TQz+u^TRu)\,dt$$

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:

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

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

$$u(t)=K_1x(t)+K_2r(t)$$

where

$$K_1=-R^{-1}B_0^TS,\; K_2=R^{-1}B_0^T(A^T-SB_0R^{-1}B_0^T)^{-1}SB_r$$

and S satisfies the Riccati equation:

$$SA^T+A^TS-SB_0R^{-1}B_0^TS+C_1^TQC_1=0$$

Therefore:

S = [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]

## 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.

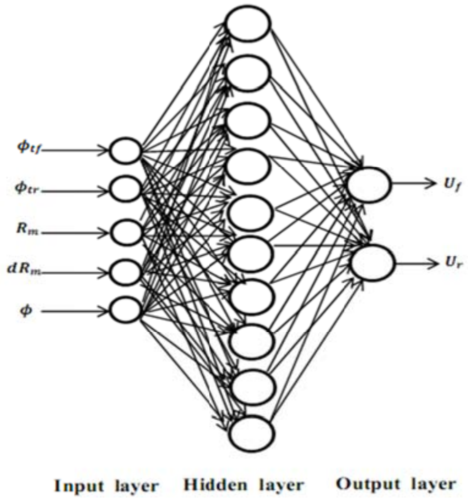


Fig. 3 Structure of the neural network architecture

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

And the roll angle of sprung mass $(\phi)$. 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

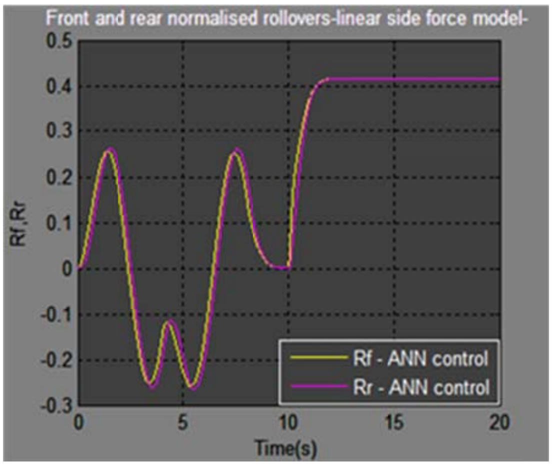


Fig. 4 Front and rear normalized rollovers with ANN controller

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:

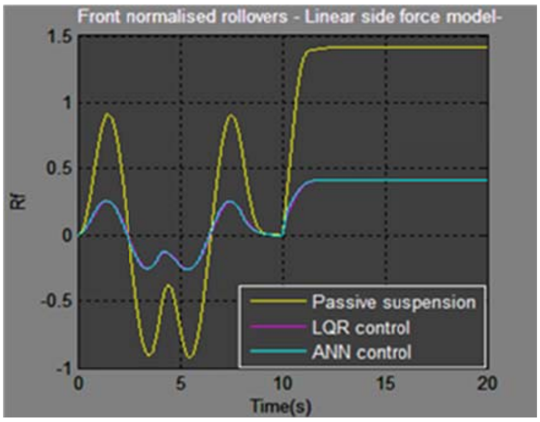


Fig. 5 Front normalized rollovers

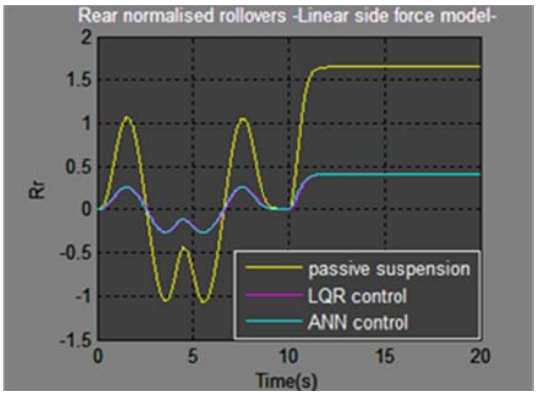


Fig. 6 Rear normalized rollovers

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

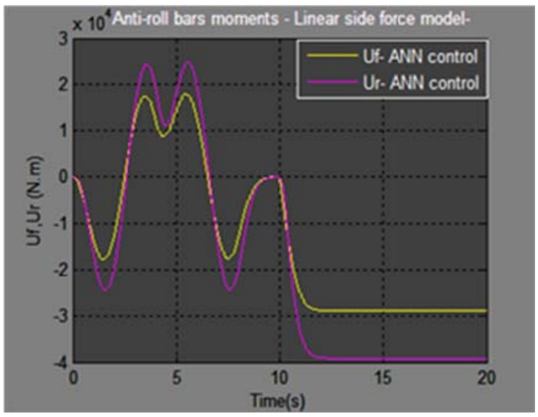


Fig. 7 Moments generated by the Anti-Roll Bars

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

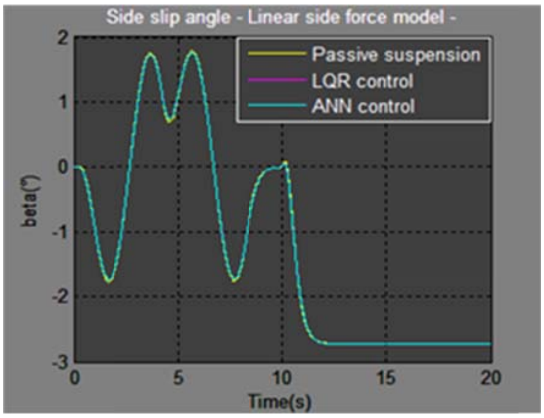


Fig. 8 Side slip angle

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 $\mu$ is varied to simulate the terrain variation. Fig. 9 shows this variation.

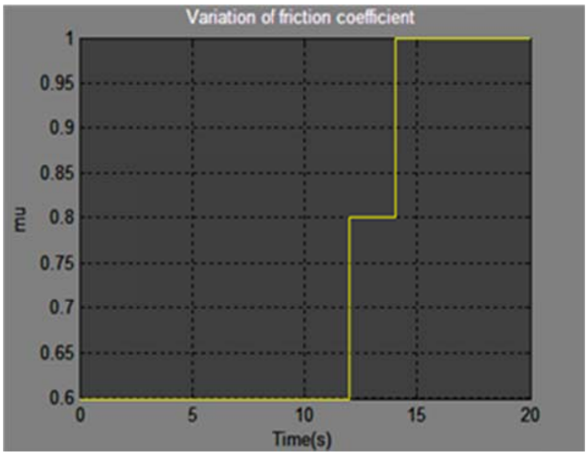


Fig. 9 Variation of adhesion coefficient

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:

For: $\mu = 0.6 \rightarrow K_1 = [-9.5730.10^4; -5.1859.10^4]$

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

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

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

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

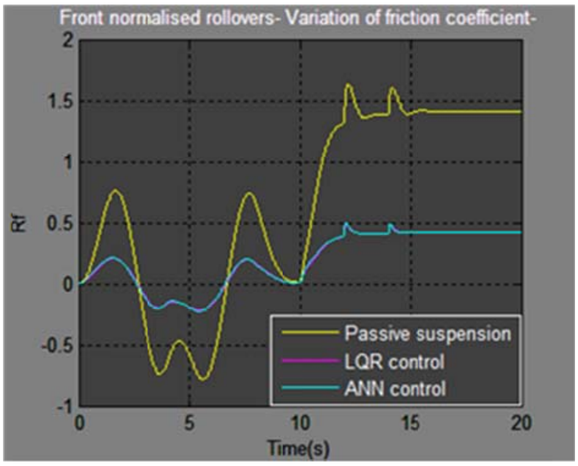


Fig. 10 Front normalized rollovers

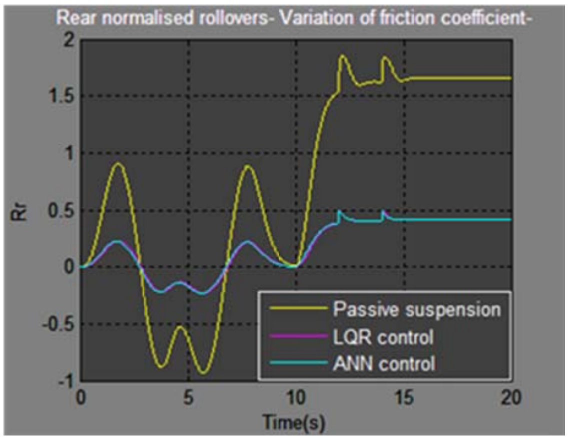


Fig. 11 Rear normalized rollovers

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

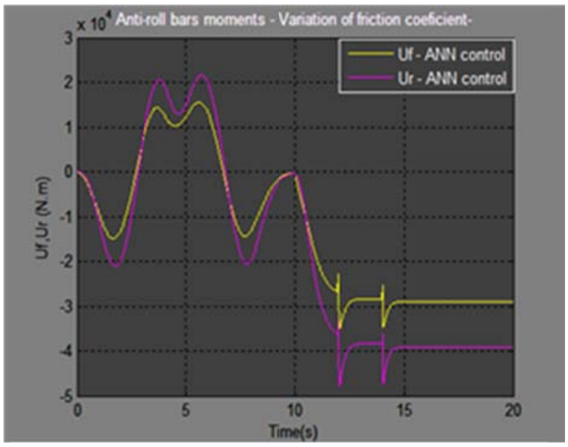


Fig. 12 Moments generated by the anti-roll bars

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]:

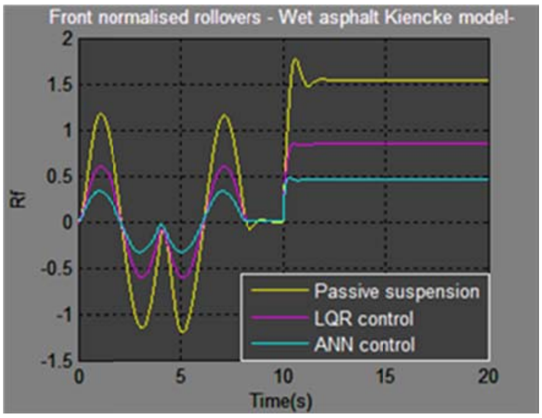


Fig. 13 Front normalized rollovers

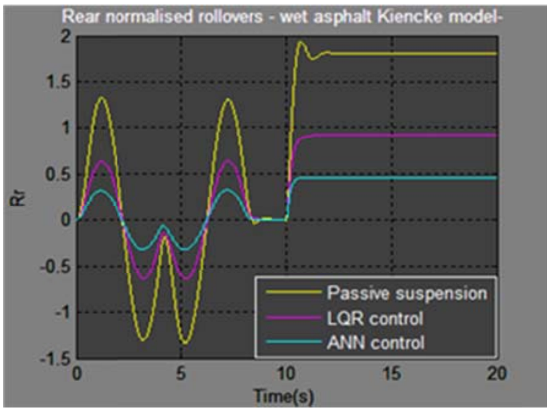


Fig. 14 Rear normalized rollovers

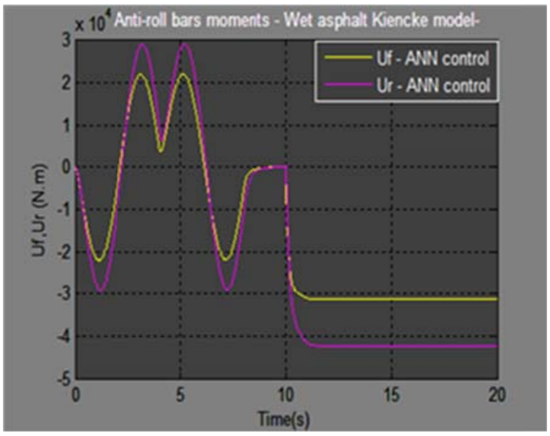


Fig. 15 Moments generated by the anti-roll bars

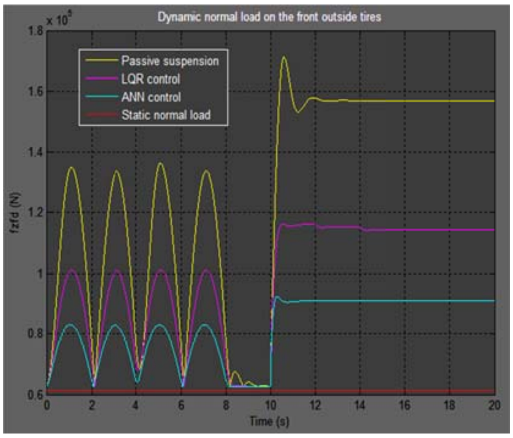


Fig. 16 Normal load on the front outside tire in a cornering

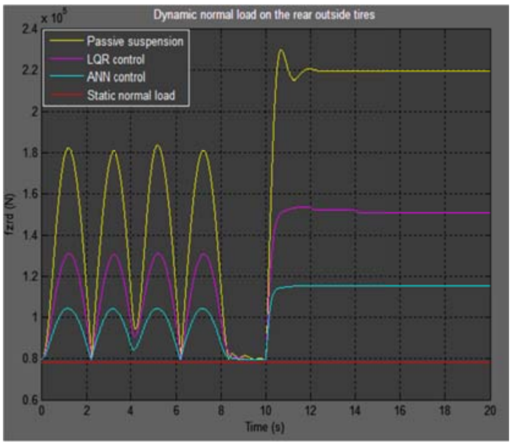


Fig. 17 Normal load on the rear outside tires in a cornering

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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