Enhanced Active Anti-roll Control of a Single Unit Heavy Vehicle Using Neuronal Network

S. Babesse, and D. Ameddah

***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, is designed, then a data collected from this controller is used as a training basis of a neuronal regulator. The ANN inputs are quite selected, and, the controller is thereafter applied for linear side force model, for constant and variable friction, which gives satisfactory results.

Then, one carried out extensions of simulations for different speed of travel in order to test the robustness of the regulator, the results remain satisfactory.

***Keywords*—** Friction coefficient, Neuronal networks, Rollover, Single unit heavy vehicle.

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 (Kim and Park, 2004).

Sampson in (Sampson, 2000) 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.

Babesse Saad is with the Electrical Engineering Department, Institute of Technology, Tiaret, 14000, Algeria (corresponding author's phone:(213) 0772821012 ; e-mail: babessesaf@yahoo.fr).

Ameddah Djemeleddine, is with the Electrical Engineering Department, Batna, 05000, Algeria, (e-mail: Abida_dj@live.fr).

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. 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].

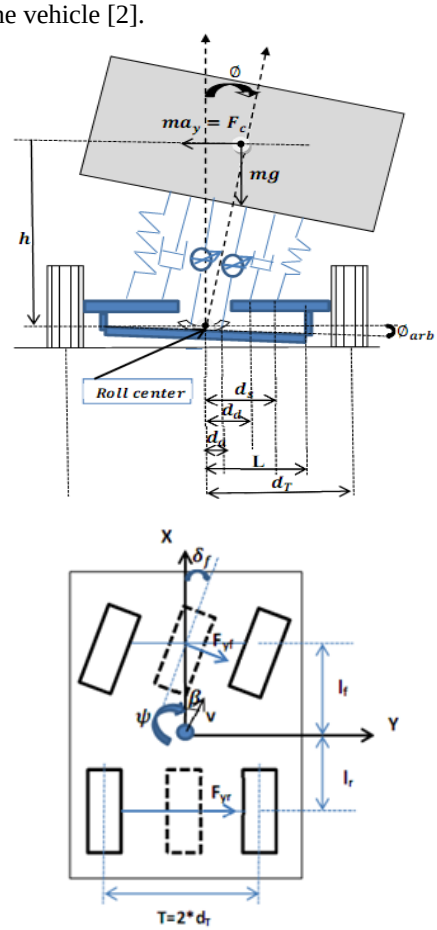

Fig. 1 coordinate system for a single unit heavy vehicle

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].

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

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

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

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

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

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

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:

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

The main input of the system is the steering angle. The steering angle applied in the training phase is a double lane change manoeuver (0-9s) followed by a step steering (10-20s), which is filtered at 4 rad/s to represent the finite bandwidth of the driver. The fig. 2 shows this input:

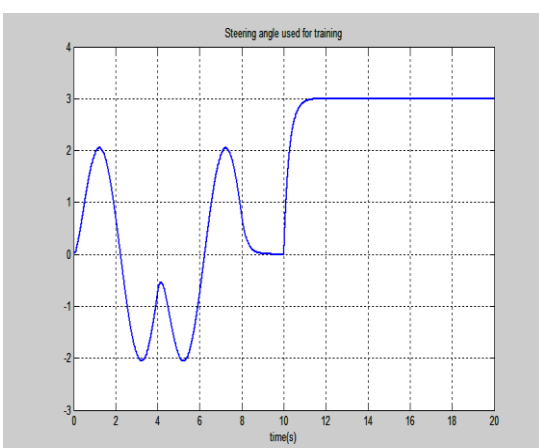

Fig. 2 Steering angle used in training phase

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 (Gaspar, 2005), 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 7º). 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.

a. 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.

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 $\left(R_m = \frac{R_f + R_r}{2}\right)$, and the change of the mean $\left(\frac{dR_m}{dt}\right)$and the roll angle of sprung mass (ϕ).

And as outputs the front and rear anti-roll moments (U_f, U_r)

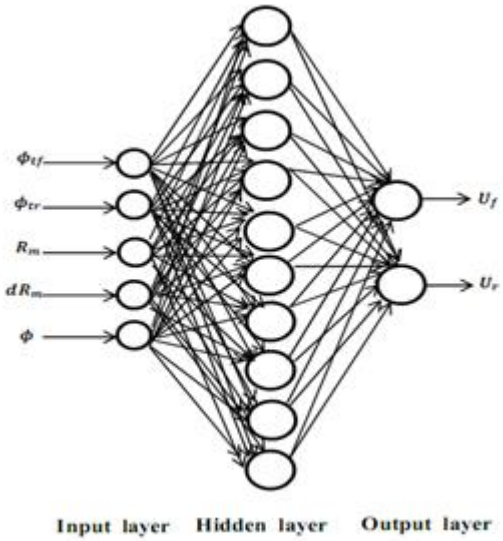

Fig. 3 Architecture of the neural network

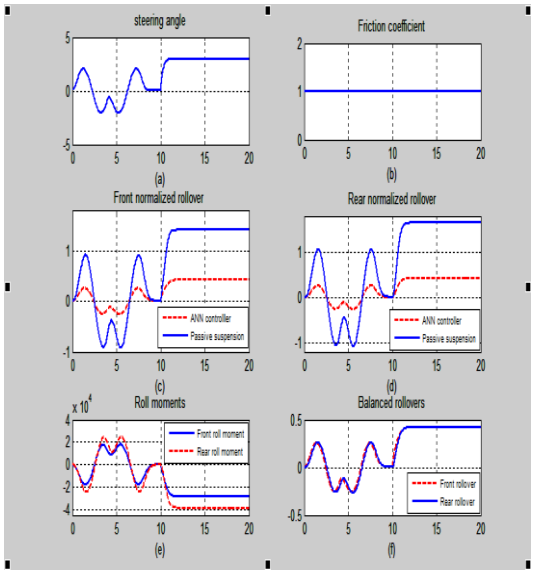

Fig. 4 ANN training results

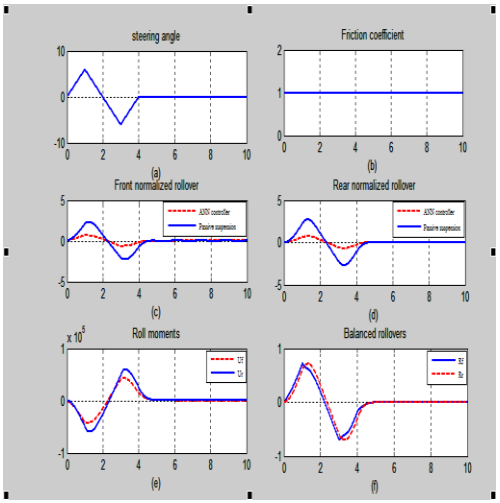

Fig. 5 Test1: Non-filtered double lane change manoeuver (NFDLCM) with constant friction coefficient.

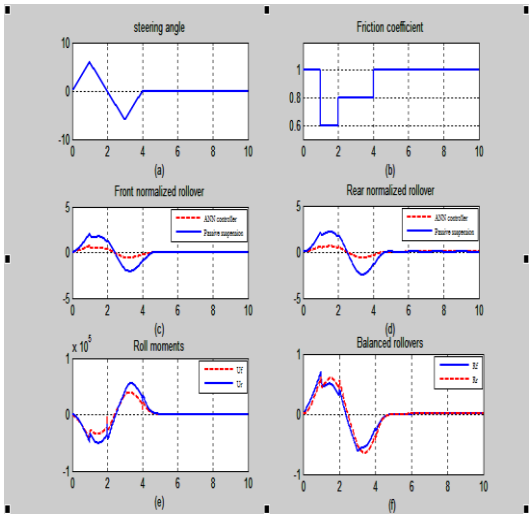

Fig. 6 Test 2: Non-filtered double lane change manoeuver (NFDLCM) with variable friction coefficient.

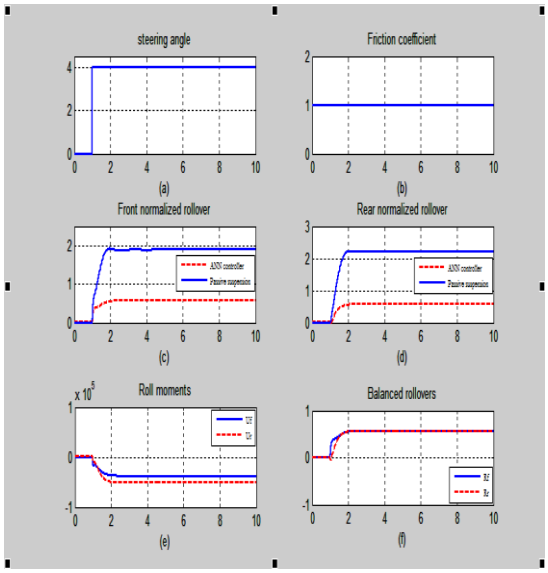

Fig. 7 Test3: Non-filtered step steering (J-turn) (NFJT) with constant friction coefficient

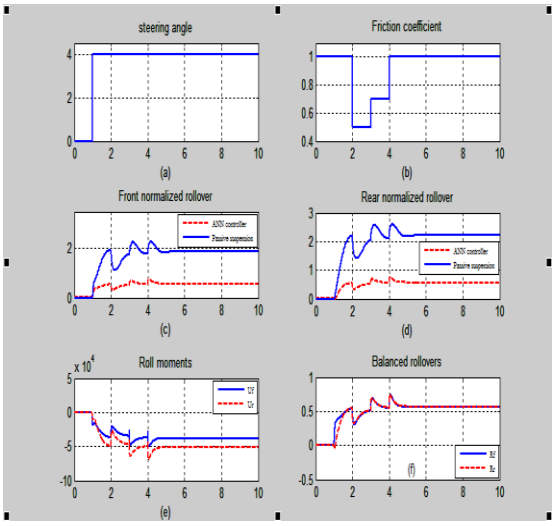

Fig. 8 Non-filtered step steering (J-turn) (NFJT) with variable friction coefficient.

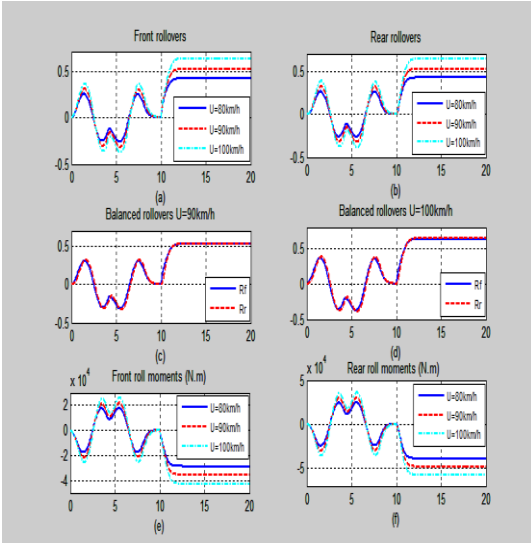

Fig. 9 Test of robustness of the neuronal regulator against the variation of U

TABLE I
THE HEAVY VEHICLE PARAMETERS

Parameter	Description	value
$m(Kg)$	Total vehicle mass	14193
$m_s(Kg)$	Sprung mass	12487
$m_{uf}, m_{ur}(Kg)$	Front unsprung mass	706, 1000
$h_{uf}, h_{ur}(m)$	Height of CG of unsprung mass from roll axis	0.53, 0.53
$h_r(m)$	Height of roll axis from ground	1.15
$h(m)$	Height of CG of sprung mass from roll axis	1.15
$C_f, C_r(\mathrm{kN/rad})$	tire cornering stiffness	582, 783
$k_f, k_r\left({}^{kNm}/_{rad}\right)$	suspension roll stiffness	380, 684
$k_{tf}, k_{tr}\left({}^{kNm}/_{rad}\right)$	Tire roll stiffness	2060, 3337
$b_f, b_r(\mathrm{kN/rad})$	Suspension roll damping	100, 100
$l_f, l_r(\mathrm{m})$	Length of the axle from the CG	1.95, 1.54
$I_{XX}(Kg.m^2)$	Inertia roll moment of sprung mass	24201
$I_{ZZ}(Kg.m^2)$	Inertia yaw moment of sprung mass	34917
$I_{XZ}(Kg.m^2)$	Yaw-roll product of Inertia of sprung mass	4200
$T(m)$	Vehicle width	2*0.93

In this paper, we proposed an intelligent regulator based on the training, and we chose as training data the best results obtained of a LQR regulator. The choice of the inputs, outputs and number of neurons in the hidden layer of the ANN regulator is obtained by trial and error. The side force coefficient is maintained constant in the training phase.

Figure 2 or the figure 4.a represents a fictitious steering angle, composed of two well-known steering angles: double lane changes manoeuver and steering angle which is filtered with 4rad/s to represent the finite bandwidth of the driver.

The results of training in figure 4 shows a perfect convergence of the neural network, with balanced rollovers. In the figure 4.f, the moments of the anti-roll bars are different because the front and the rear truck weights are different, but they always remain below the tolerated maximum (120000 N.m). Then, four tests were carried out in order to validate the utility of the neuronal regulator:

The first test and the second tests are shown in figure 5, with constant friction coefficient and figure 6, with variable friction coefficient respectively; it is non-filtered double lane change manoeuver, and it's often used to avoid an obstacle in an emergency. The figures 5.f and 6.f show good swinging of the rollovers, and the figures 5.e and 6.e show the required anti-roll bar moments which are smaller than their maximums.

The third and the forth tests are shown in figure 7, with constant friction coefficient and figure 8, with variable friction coefficient respectively; it is non-filtered J-turn manoeuver. Same remarks like previously.

In the Figure 9, we have tested the robustness of the regulator for a variation of U: 80km/h, 90km/h and 100km/h. therollovers are a little different but always check the two conditions: lower than the unit for the three cases, and with balanced front and rear rollovers.

In the other side, increase of the speed U required increase of the anti-roll bars moments.

IV. CONCLUSION

The ANN controller is successfully applied to control the semi-active suspension of the single unit heavy vehicle with the use of anti-roll bars mechanism, by using the collected data from the LQR controller. The four tests, for constant and variable friction coefficient, are given good results: balanced rollovers with values below the unity.

And as test of robustness; speed variation for the training steering angle is carried out, and show satisfactory results; balanced rollovers with values far from their thresholds.

For further simulation, one can control the anti-roll bars mechanism by using these neuronal regulator results.

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