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Modeling Lateral Motion of a Vehicle Using Neural Networks technique

نمذجة الحركة الجانبية للمركبة باستخدام تقنية الشبكات العصبية

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Abstract

In this research a neural model is proposed to predict the lateral force which affects the lateral motion dynamics of a vehicle during its travel. Neural networks technique is used to predict the lateral force through learning it the previous information about the relations among lateral force, variation in air pressure inside the tire, friction coefficient between tire and road, sideslip angle and normal load exerted on the tires. The results show that the model is capable of predicting the dynamic response to lateral motion represented by the dynamic response to yaw rate and side velocity when a vehicle negotiating a turn at different conditions. The lateral motion dynamics of a vehicle during its travel is affected by several parameters. The interaction between these parameters and states-variables is governed by nonlinear relations.

Keyword: Vehicle dynamics, Lateral motion of vehicle, Neural networks.

الخلاصة

استخدمت طريقة للشبكات العصبية للتنبؤ بالقوة الجانبية من خلال تعليمها على المعلومات المسبقة حول علاقة القوة الجانبية مع تغير ضغط هواء الاطار ومعامل الاحتكاك و زاوية الانزلاق الجانبية والحمل العمودي المسلط على الاطارات.اظهرت النتائج قابلية النموذج العصبي المقترح على التنبؤ بالاستجابة الديناميكية للحركة الجانبية متمثلة بالاستجابة الدينامكية لكل من لمعدل الدوران والسرعة الجانبية عند مختلف ظروف العمل التي تواجهة المركبة عند دورانها . ان دينامكية الحركة الجانبية للمركبة تتاثر بتغير عدد من البرامترات المركبة اثناء سيرها. كما ان تاثير هذه البارامترات ومتغيرات الحالة على بعضها البعض تحكمها علاقات لاخطية. في هذا البحث تم اقتراح نموذج عصبي للتنبؤ بالقوة الجانبية الموثرة على الحركة الجانبية للمركبة اثناء سيرها.

كلمات مفتاحية: ديناميكية المركبات، الحركة الخطية للمركبات ، الشبكات العصبية.

1-Introduction

The use of computer simulation of real systems has witnessed an increase in demand when these systems are tested whether they are plants, airplanes or vehicles etc. Computer simulation is now gaining ground because the traditional methods of testing are costly as well as risky, and take a long time to prepare. Furthermore, with simulation it is easy to change and modify the sample system and study all design possibilities, operation conditions, and the system response so that the designer can take the appropriate decision on the performance of the system components. Thus mathematical models are realized which are both reliable and trustworthy. The mathematical models are developedby finding out the relationship between all state variables, taking into consideration all changes in the related parameters when operation conditions change affecting the system dynamic response.[1]

Among the fields in which simulation is employed are vehicle manufacturing and testing. A vehicle prototype is simulated to test its performance and response to operation conditions on the road before it is manufactured, thus avoiding any error in design and getting the best performance when it is manufactured later. No doubt, this requires advanced mathematical models which describe the vehicle dynamics as accurately and realistically as possible.

A vehicle undergoes three types of motion. They are longitudinal, lateral and normal. They can be studied collectively or separately, in the latter case, the subject is simplified and acceptable results are obtained [18].

This paper is concerned with developing a model for vehicle lateral motion. Most literature on vehicle lateral motion depends on linear model [2-5]or on simplified nonlinear one [6-9]. These models are built on a specified operation condition and cannot be relied on when any vehicle parameter is changed. The lateral force generated duringvehicle lateral motion depends on and is affected by several parameterssuch as air pressure in the tires, normal load, coefficient of friction between vehicle tires and the road, slide slip angle and vehicle velocity[10].

The large number of variables affecting vehicle lateral motion as well as the nonlinear relations connecting them makes it difficult to create a simulation of the vehicle lateral motion using the traditional mathematical models such as partial differential equations and empirical equations.

Many attempts have been made to establish mathematical relations to describe the relation between lateral motion and one of the parameters such as tire pressure, coefficient of friction and normal load [11-12].

The motivation of this work is the most researches which studied the relation between variables affecting vehicle lateral motion explain it through performance curves without trying to build a complete mathematical model to describe vehicle lateral motion [13-16].

The fundamental essence of this research is to build a model for lateral force using neural network. This model covers all variables affecting vehicle lateral motion such as tire pressure, normal load, coefficient of friction between the vehicle and the road, slide slip angle and vehicle velocity.

The neural network system was learned to calculate the lateral force through learning the data published in the researches on the behavior of the force under various parameters during vehicle lateral motion. The dynamic response to side velocity and yaw rate under different operation conditions was studied and the results are compared with those obtained from linear model. The results show the nonlinear relations between lateral force and a number of compound parameters.

The remainder of this paper is organized as follows: Section two is a description of the mathematical model of the vehicle model. In section three, the proposed of neural network topology for calculating lateral force is derived. Simulations results of the neural network modelling are presented in section four and the conclusions are drawn in section five.

2- Mathematical Vehicle Model:

The model used in this work describes vehicle lateral dynamics in a turn lane, which is obtained from the bicycle model, shown in figure (1). The two-dimensional model with linear tire characteristics of the four wheels vehicle behavior can be described by the following differential equations [10].

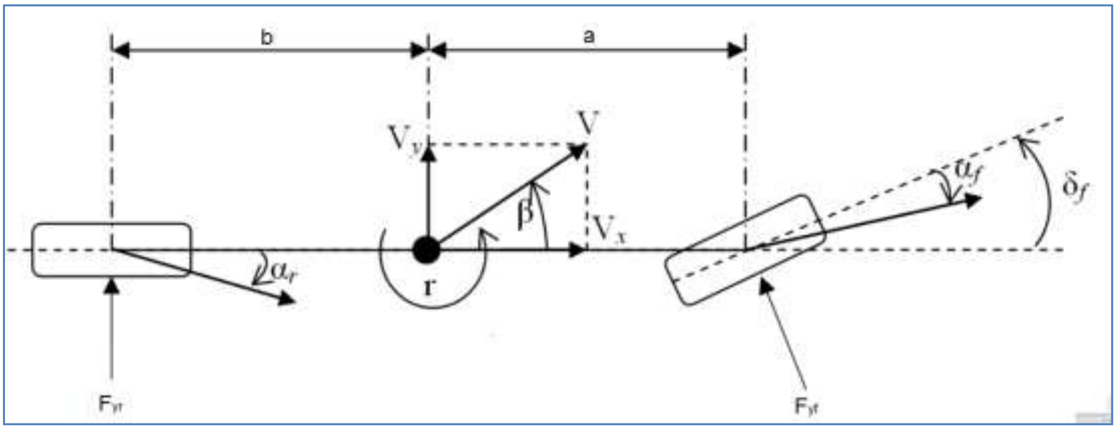


Figure (1) bicycle model and vehicle parameters

The equations of motion are formed using figure (1) [1]

$$\sum F_y = m\left(\dot{V}_y - rV_x\right) \rightarrow (2F_{yf})\cos\delta + 2F_{yr} = m\left(\dot{V}_y - rV_x\right) \qquad \ldots(1)$$

$$\sum M_Z = I_Z\,\dot{r} \rightarrow (2F_{yf})\cos\delta a - 2F_{yr}b = I_Z\,\dot{r} \qquad \ldots(2)$$

for small angle of β leads to $V_x = V$

For linear model of lateral forces is given

$$F_{YlL} = C_F\alpha_{Y1L}\ ,\ F_{Y1R} = C_F\alpha_{Y1R}\ ,\ F_{Y2L} = C_R\alpha_{Y2L}\ ,\ F_{Y2R} = C_F\alpha_{Y2R} \qquad \ldots(3)$$

The sideslip angles are calculated by the following equations

$$\alpha_{Y1L} = \left(\frac{V_y + ar}{V}\right) - \delta_f \qquad \alpha_{Y1R} = \left(\frac{V_y + ar}{V}\right) - \delta_f$$

$$\alpha_{Y2L} = \left(\frac{V_y - ar}{V}\right) \qquad \alpha_{Y2R} = \left(\frac{V_y - ar}{V}\right) \qquad \ldots(4)$$

But the production of the lateral force based on neural network will be discussed in next section is function of (P_r, N, μ, α, V).

The input of the lateral motion model is the front steer angle δ_f . The value of steer angle must take into consideration the maximum limit of the desired yaw rate for certain value of forward speed. At given vehicle velocity there is a minimum radius of maneuver that the vehicle can be turned without slipping or overturning.

3-Model of the lateral force based on neural network

The feed-forward neural is used to build lateral force model (NLF). The structure of this model is shown in figure (2), where a multi-layer perceptron with two hidden layers model is used [17].The nodes of input, hidden and output layers are highlighted and the outputs lateral force.

The training of the (NLF) is performed off-line depending on the training data come from published results [10-16].These relations are presented in the form of performance curves and not in mathematical or empirical relations because it is difficult to build a mathematical model which combines together.

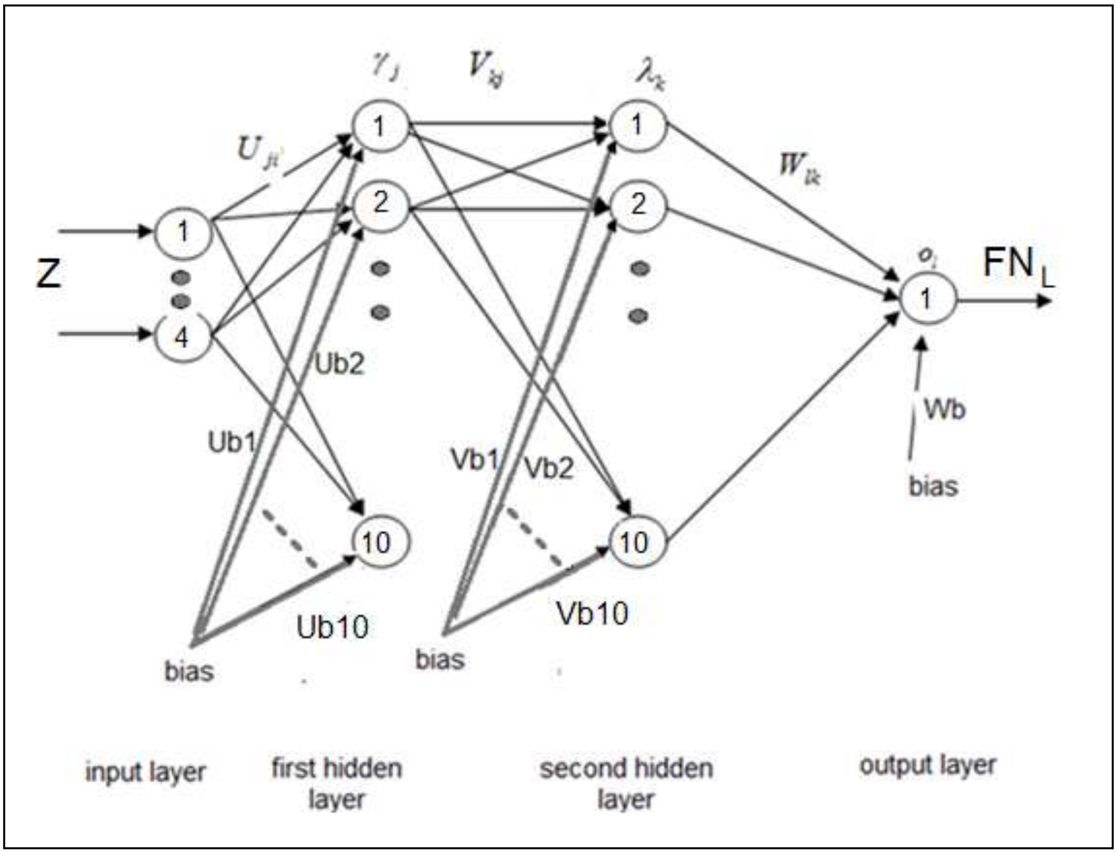


Figure (2) The multi-layer perceptron neural network of the direct neural controller.

In this work, the inflation pressure of tire, normal load, coefficient of friction between the tires and road, sideslip angle and vehicle velocity are input data of the (NLF).The mathematical analysis of the NLF is cleared as follow:

Consider the general j^{th} neuron in the first hidden layer. The inputs to this neuron consist of an *i*– dimensional vector, where *i* is the number of the input nodes. Ub_j is the weight vector for the bias of first hidden layer that is set equal to -1 to prevent the neurons quiescent. The output of the first hidden layer is calculated as[ ]

$$net1_j = \sum_{i=1}^{nh} U_{ji} \times Z_i + bias \times Ub_j \qquad \ldots(5)$$

where *nh* is the number of the hidden nodes Z is the input vector $Z = [P_r, N, \mu, \alpha, u]$.

Next the output of the neuron γ_j is calculated as the continuous sigmoid function of the net_j as:

$$\gamma_j = \frac{2}{1+e^{-net1_j}} - 1 \qquad \ldots(6)$$

For second hidden layer, also the output is calculated as the continuous sigmoid function of the $net2_k$ as

$$net2_k = \sum_{j=1}^{Nh} V_{kj} \times \gamma_j + bias \times Vb_k \qquad \ldots(7)$$

$$\lambda_k = \frac{2}{1+e^{-net2_k}} - 1 \qquad \ldots(8)$$

Once the outputs of the hidden layers are calculated, they are passed to the output layer. In the output layer, the linear neuron is used to calculate the weighted sum ($neto_l$) of its inputs.

$$net_l = \sum_{k=1}^{Nh} W_{lk} \times \lambda_k + bias \times Wb_l \qquad \text{…(9)}$$

where W_{lk} is the weight between the second hidden neuron λ_k and the output neuron. W_b is the weight vector for the bias of the output neuron. The linear neuron, then, pass the sum (net_l) through a linear function of slope 1 as:

$$O_l = L(neto_l) \qquad \text{…(10)}$$

The output of this neural solution is the lateral force FN_L.

The pattern of neural network output FN_L is compared with the pattern of actual output F_L and the weights are adjusted by the supervised back-propagation training algorithm until the pattern matching occurs, i.e., the cost function (E) becomes acceptably small.

The cost function (E) is the sum of the square of the differences between the actual output F_L and neural network output FN_L and given by equation (11) [18]:

$$E = \frac{1}{2}\sum_{i=1}^{np}(F_L - FN_L)^2 \qquad \text{...(11)}$$

where *np* is the number of patterns.

The adaptation equations of the direct neural controller's weights are shown below:

$$\Delta W_{lk}(m+1) = -\eta \frac{\partial E}{\partial W_{lk}} \qquad \text{…(12)}$$

$$\frac{\partial E}{\partial W_{lk}} = \frac{\partial E}{\partial FN_b(m+1)} \frac{\partial FN_b(m+1)}{\partial o_l} \frac{\partial o_l}{\partial net_l} \frac{\partial net_l}{\partial W_{lk}} \qquad \text{…(13)}$$

$$\Delta W_{lk}(m+1) = \eta \times \lambda_k \times e_l \qquad \text{…(14)}$$

$$W_{lk}(m+1) = W_{lk}(m) + \Delta W_{lk}(m+1) \qquad \text{…(15)}$$

$$\Delta V_{kj}(m+1) = -\eta \frac{\partial E}{\partial V_{kj}} \qquad \text{…(16)}$$

$$\frac{\partial E}{\partial V_{kj}} = \frac{\partial E}{\partial FN_b(m+1)} \frac{\partial FN_b(m+1)}{\partial o_l} \frac{\partial o_l}{\partial net_l} \frac{\partial net_l}{\partial \lambda_k} \frac{\partial \lambda_k}{\partial net2_k} \frac{\partial net2_k}{\partial V_{kj}} \qquad \text{…(17)}$$

$$\Delta V_{kj}(m+1) = \eta \times f(net_k)' \times \gamma_j \sum_{l=1}^{No} e_l W_{lk} \qquad \text{…(18)}$$

$$V_{kj}(m+1) = V_{kj}(m) + \Delta V_{kj}(m+1) \qquad \text{…(19)}$$

$$\Delta U_{ji}(m+1) = -\eta \frac{\partial E}{\partial U_{ji}} \qquad \text{…(20)}$$

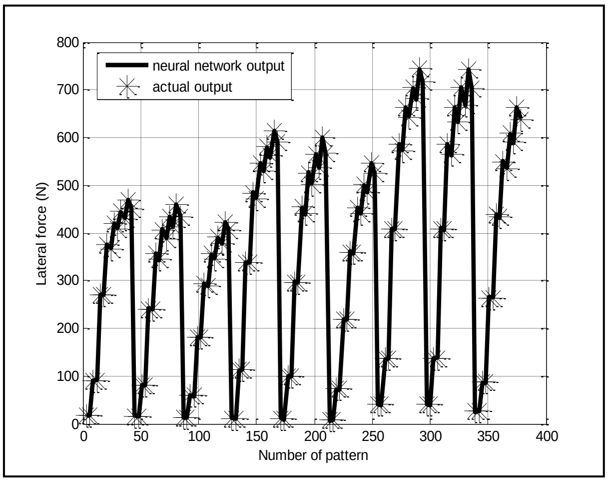
$$\frac{\partial E}{\partial U_{ji}} = \frac{\partial E}{\partial FN_b(m+1)} \frac{\partial FN_b(m+1)}{\partial o_l} \frac{\partial o_l}{\partial net_l} \frac{\partial net2_l}{\partial \lambda_k} \frac{\partial \lambda_k}{\partial net2_k} \frac{\partial net2_k}{\partial \gamma_j} \frac{\partial \gamma_j}{\partial net1_j} \frac{\partial net1_j}{\partial U_{ji}} \qquad \text{…(21)}$$

$$\Delta U_{ji}(m+1) = \eta \times f(net1_j)' \times Z_i \times \sum_{k=1}^{Nh} f(net2_k)' \times V_{kj} \times \sum_{l=1}^{No} e_l W_{lk} \qquad \text{…(22)}$$

$$U_{ji}(m+1) = U_{ji}(m) + \Delta U_{ji}(m+1) \qquad \text{…(23)}$$

The algorithm of the (NLF) is carried out using MATLAB version 2012.

A training set of 378 patterns has been used with a learning rate of 0.1 at different drive conditions (velocity, tire inflation pressure, slip angle and of friction between the tires and road). After 25 epochs, the output of the neural network is approximated to the actual output (lateral force) as shown in figure (3). The cost function (E) is equal to 5.5 e^{-5} for excellent learning of (NLF) as shown in figure (4).



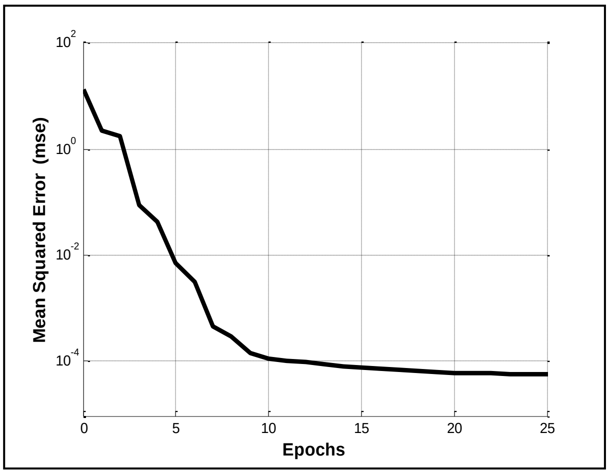


Figure (3) The response of the neural network brake force with the actual brake

Figure (4) Mean square error vs. epoch

4-Result and Discussion

The model of lateral motion which is used in the simulation was built by combining the equations of motion with neural model to calculate the lateral force. A neural network algorithm of the lateral force with Range Kutta method for the solutions of differential equations of lateral motion are programmed using Matlab language. Using the numerical values of the vehicle listed in Appendix (A), the response of lateral motion to rapid changes in the front steer angle is calculated.

The neural model which includes nonlinear relations between compound variables has been tested against the linear model

Figure (5&6) show the dynamic response of the side velocity and yaw rate at various vehicle velocities

From these figures, it is seen that as the velocity increases, the difference between the linear and neural models increases because of the increase in nonlinear effect between the variables of neural model.

The linear model is incapable of showing the effect of various vehicle velocities on dynamic response during its travel. On the other hand, the neural model can take into consideration all the changes in variables and their effect on some of them, thus this model shows response closer to reality.To validate the performance of the neural model of vehicle lateral motion, it was tested when changes took place in the compound parameters such as variation in tire pressure, normal load on tires and variation in coefficient of friction the tire and the ground. The simulation was carried out at constant speed of 70 km/h.

The figure (7) shows how the dynamic response of the side velocity and yaw rate changes with change in vehicle tire pressure. The less pressure in tire, the less stable the vehicle is as it turns a curve and it will slide off.

The coefficient of friction between the tire and the road effects on the dynamic response of the side velocity and yaw rate are illustrated in Figure (8).It can be seen that as the coefficient of friction decreases, vehicle slipping increases because of decrease in the cohesion between the tire and the ground.

The magnitude of normal load exerted on the tire plays a major role in the stability of the vehicle on the road. As the normal load increases, the cohesion between the tire and the ground increases. This is illustrated in figures (9). From this figure, it can be seen that as the normal load decreases, the vehicle lateral motion increases, the stability of the vehicle on the road decreases.

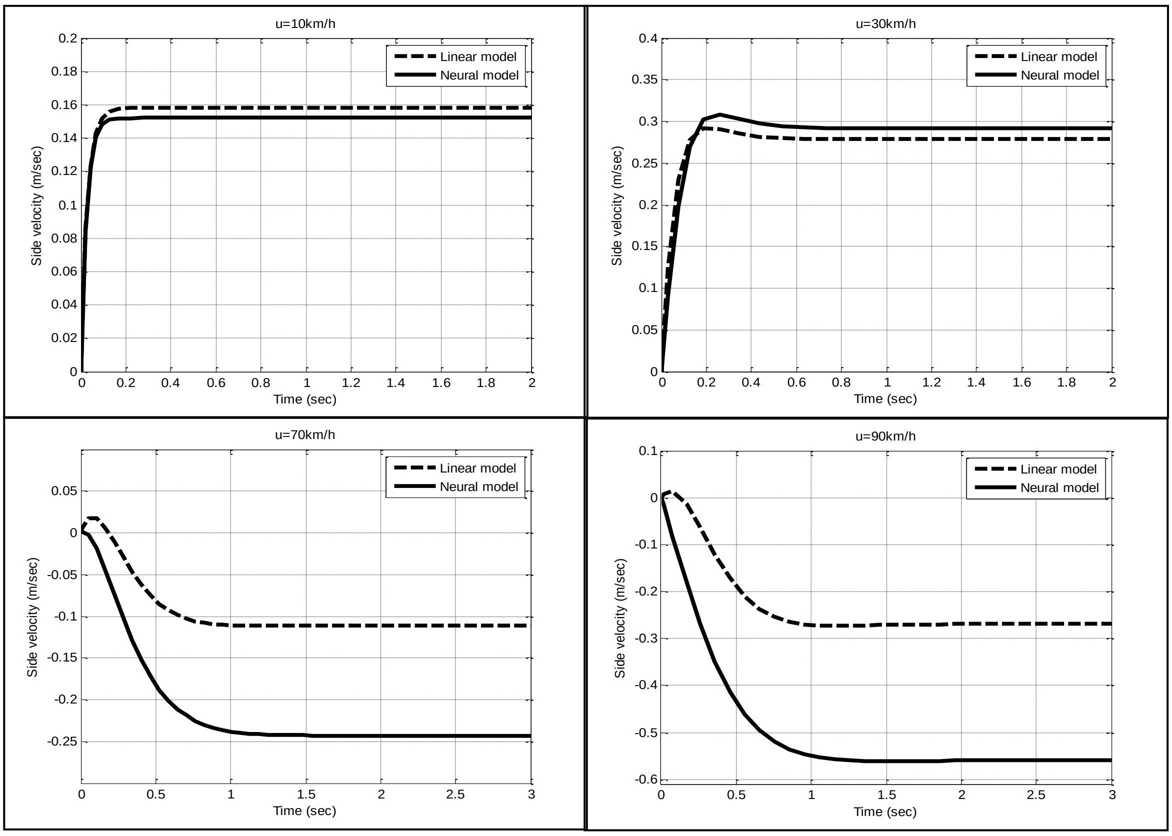


Figure (5) The responses of side velocity for linear and neural model at different velocities

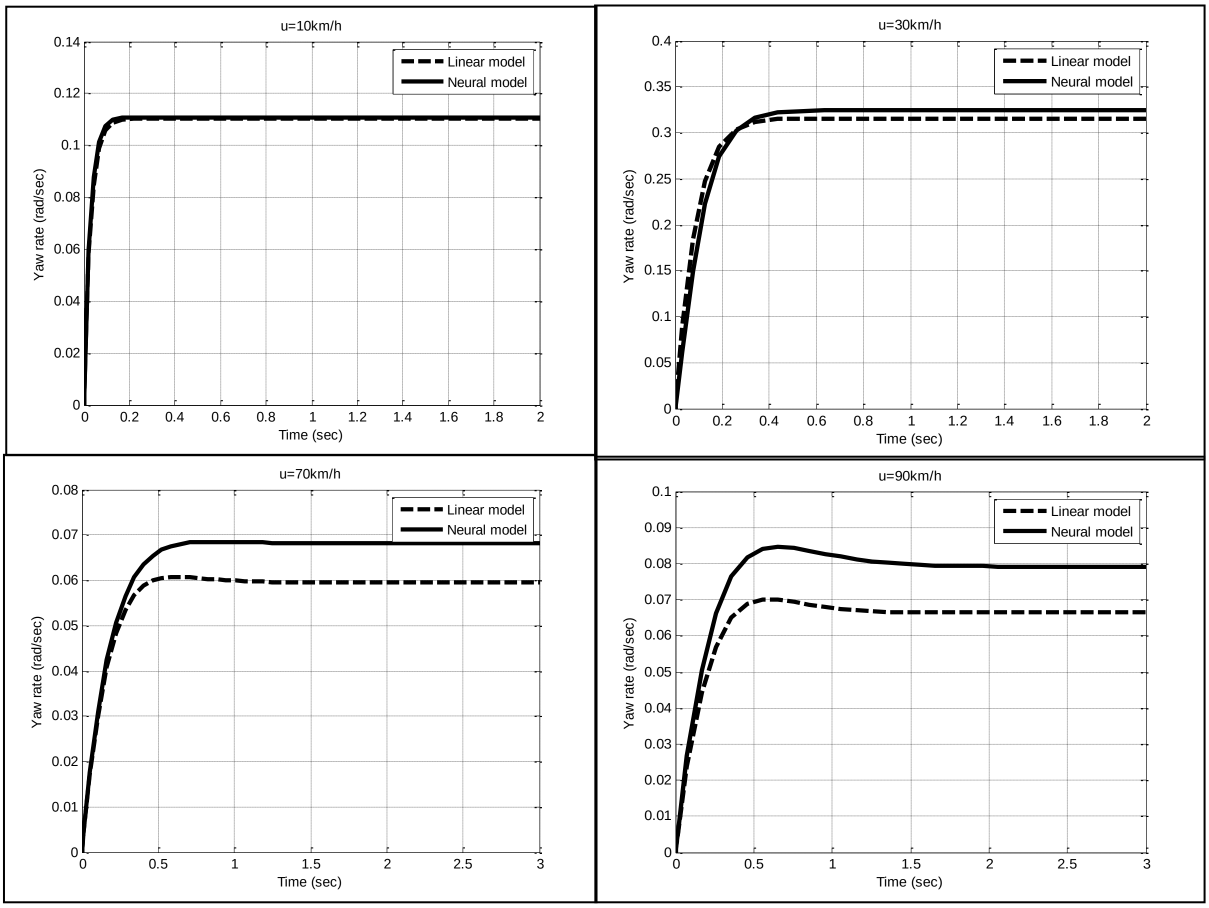


Figure (6) The responses of yaw rate for linear and neural model at different

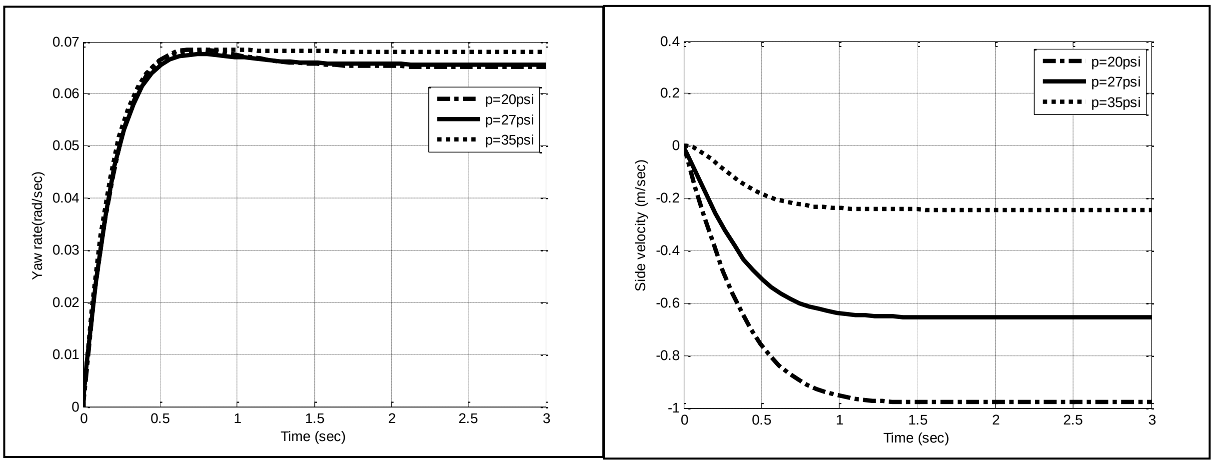


Figure (7) The responses of yaw rate and side velocity for neural model at different tire pressure

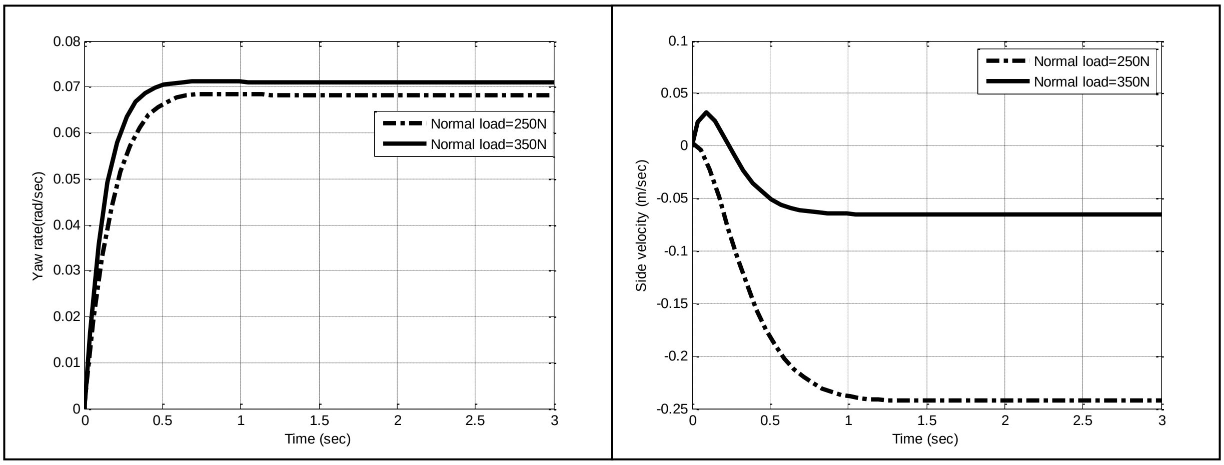


Figure (8) The responses of yaw rate and side velocity for neural model at different normal load

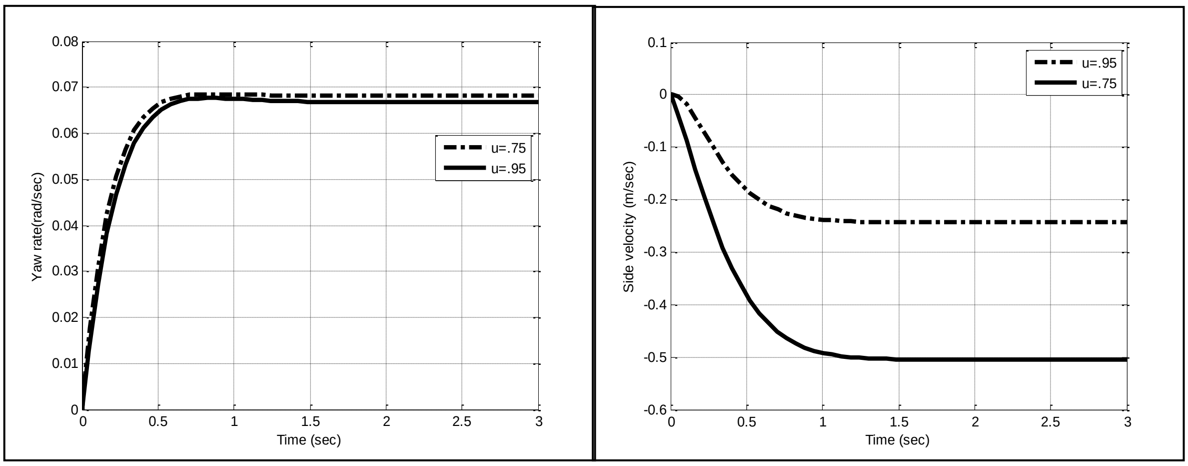


Figure (9) The responses of yaw rate and side velocity for neural model at different coefficient of friction

1-A new neural network based program for lateral motion has been created to predict lateral force. The system takes into consideration a number of parameters which affect the vehicle behavior during its lateral motion the neural model is learnt to calculate lateral force. The relation between the parameters and lateral force is nonlinear one therefore this neural model can be considered nonlinear model.

2- The results show that the proposed neural model for lateral motion is capable of predicting dynamic response for yaw rate, side velocity of the vehicle when tire pressure, normal load, coefficient of friction and vehicle velocity change.

3- The results show also that the behavior of nonlinear model is almost similar to that of linear one the other parameters are fixed but with increase in velocity, deviation and the difference between the two responses become clear

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Appendix (A)
List of symbols.

Symbol	Description	Value	Unit
A	Length from mass center to front axle	1	m
B	Length from mass center to rear axle	1.5	m
C_f	Front cornering coefficient (linear model)	55000	N/rad
C_r	rear cornering coefficient (linear model)	45000	N/rad
I	Mass moment of inertia	1500	Kg m^2
M	Vehicle mass	1000	Kg
R	Yaw rate	-	Rad/sec
V	Vehicle velocity	10	m/sec
V	side velocity	-	m/sec
δ_f	Front steering angle	-	rad