ADAPTIVE NEURAL CONTROLLER FOR VEHICLE LATERAL POSITION BASED ON GENETIC ALGORITHM[+]

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Abstract

In this paper, neural controller is proposed to control on the vehicle lateral position. The structure of the controller used consists of modified Elman recurrent neural networks that learned on-line by using genetic algorithm teachings. Using of both right and left braking forces simultaneously has automatically kept the vehicle in the correct path when the vehicle is going through an emergency situations. Therefore, it is used as feedback neural controller that is learned on-line in order to control the transient state output of the system by minimizing the error between the actual output of the system and the model reference output. The evolutionary techniques based on this algorithm are employed for the model-reference adaptive control scheme for this system. The variations of the vehicle parameters are addressed in controller. Computer simulation results, using a nonlinear vehicle model are included, and show the feasibility of the proposed controller.

المستخلص :

في هذا البحث تم تقديم مسيطر عصبي يسيطر على انحراف المركبة الجانبي .هيكلية المسيطر المستخدم تتكون من الشبكة العصبية المرجعة المحسنة أيلمن المتعلمة باستخدام الخوارزمية الجينية بطريقة On-Line .تتم عملية السيطرة على الانحراف الجانبي للمركبة أثناء سير المركبة على مسار مستقيم من خلال توزيع قوة الفرملة على عجلات الجهة اليمنى وعجلات الجهة اليسرى للمركبة.

يعتمد عمل المسيطر العصبي ذات التغذية الراجعة للسيطرة على الحالة العابرة لإخراج المنظومة من خلال تقليل الخطأ بين النموذج المرجع والإخراج الحقيقي للمنظومة.

وقد تم تطوير التقنية التي أساسها الخوارزمية الموضوعة للمسيطر المتكيف للنموذج المرجع لهذا النظام.

1-Introduction:

The stability of vehicle during motion is one of the important cases that the designers and researchers must take in vehicle design consideration.The means of vehicle stability is that, the driver can steer the vehicle in the correct path easily and without large effort. The steering of vehicle becomes more difficult when the vehicle is going through an emergency situations such as explosion one of the tires, side wind effect on the vehicle and when the driver gives the steer angle more than required to turn a maneuver. Therefore many automatic control

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systems are developed and used to help the driver to control on the vehicle and keep it in the right path.

Dejan [1]. tried many neural network algorithms to prove that it is possible to learn driving patterns from previous driving experiences ; to demonstrate that the successful prediction of future driving events is possible based on learned driving patterns, and that it is possible to detect potential problems ; to develop a model of a system which would help a driver to avoid potential errors. The driving patterns can be characterized by measuring the values of lateral and longitudinal acceleration. The suggested neural network algorithms predict future values of lateral and longitudinal acceleration based on current measurements of these values. His results indicted to the prediction capabilities for short time in advance are very good and that predicted accelerations are very close to actual ones, but the prediction error increases substantially for larger prediction orders, and networks are not able to correctly predict accelerations for driving events such as turns. It is important to note that Dejan [1] used the neural network algorithms as prediction device not as controller.

H.Sabah[2] investigated the use of independent front and rear wheel steering to control the vehicle to track a desired lateral velocity. Thomas Hessburg [3] controlled on lateral motion of vehicle during turning a maneuver by fuzzy controller.

Van Zanten [4] suggested controller to regulate the engine torque and the wheel brake pressures to minimize the difference between the actual and the desired motions. Tom [5] proposed the use of brake steer system (BSS) that uses differential brake forces for steering intervention to control on lateral position. The PID controller is used to explore (BSS) feasibility and capability.

Lin [6] presents the design and experimental implementation of a genetic fuzzy controller for automatic steering of a small-scaled vehicle. Fuzzy PD feedback controller was proposed to guarantee the stability of the system by using the genetic algorithm method to optimize the parameters of the fuzzy control to guarantee performance.

Aytekin[7] presented an efficient and fast tuning method based on a modified genetic algorithm (MGA) structure to find the optimal parameters of the proportional-integral-derivative (PID) controller so that the desired system specifications are satisfied. This controller used to maintain the vehicle in correct direction when the vehicle in crosswind.

Zhul [8] presented formulation of a neural network (NN) vehicle model for estimating vehicle behavior on sloping terrain. A training method combined with genetic algorithm and back propagation algorithm was used to train the NN vehicle model. The model was validated by comparing the simulated results with the experimental ones. His results indicated to the changes of field and soil conditions (e.g. rain) decrease the accuracy of the model, so the controller was not robust.

Stephen[9] developed fuzzy controller to control both the speed and direction of the vehicle. The parameters of the discourse sets for the fuzzy controller were optimized using a primitive form of Genetic Algorithm.

Wenzel [10] described the development of a hybrid approach to estimate the states and parameters of a vehicle. The parameter estimator is based on a genetic algorithm in conjunction with a bank of extended Kalman filters, which are simultaneously utilized to estimate the states of the system.

Lateral position is an important element of the vehicle dynamic that influences the driver's perception of vehicle handling and safety features. The lateral position of vehicle can be known by measuring the lateral acceleration [11].

Practically, a vehicle model of lateral motion dynamics is nonlinear model and heavily influenced by vehicle parameters such as vehicle speed, vehicle mass and road-tire interaction. These vehicle parameters vary during operation. Therefore the nonlinearity of model and variations of parameters must be taken into considering in controller design.

Most of the above researches used a linear vehicle model and the variations in parameters of the vehicle are not addressed in controller design. This gives unacceptable performance because the controller become robustness when the vehicle parameters change as mass, forward velocity and cornering stiffness.

This paper explores the use of differential braking as means to control on the lateral position to keep the vehicle in straight line on the road when any emergency situations are happened. The variations of parameters are taken into considering in controller design.

The controller structure used in this paper is adaptive neural controller based on genetic algorithm. The modified Elman neural network (MENN) is learning on line . This network structure is simple compared with Hidden Markov models (HMM) as example which is considering very complex for learning where it needs forward and backward calculation OFF-Line learning [1].

The learning algorithm used is Genetic Algorithm non supervisory technique while the popular Baum-Welch re-estimation method was used to learn neural networks supervisory technique [1]. The genetic algorithm is modern than the popular Baum-Welch re-estimation method

2-Nonlinear Mathematical Vehicle Model:

The non-linear dynamics of vehicle lateral motion depends on many parameters such as vehicle speed, vehicle mass and tires state on road. The lateral motion can be controlled by one of these control inputs " four wheel steering system, braking forces, and torque driving wheel" [12].

In this paper, the focus is on the vehicle lateral position as the desired and the differential braking is the control action. The brake system is a challenging control problem because the vehicle-brake dynamics are highly non-linear with uncertain time-varying parameter. Intelligent controllers, such as neural or fuzzy, overcome these issues [13]. Neural controllers have the benefit of not requiring a mathematical model of the plant, while still being highly robust. Also, certain neural control designs or to adapt themselves to improve its performance. Because of these features, neural controllers have been successfully implemented in the automotive field for controlling both wheel dynamics and vehicle dynamics [14].

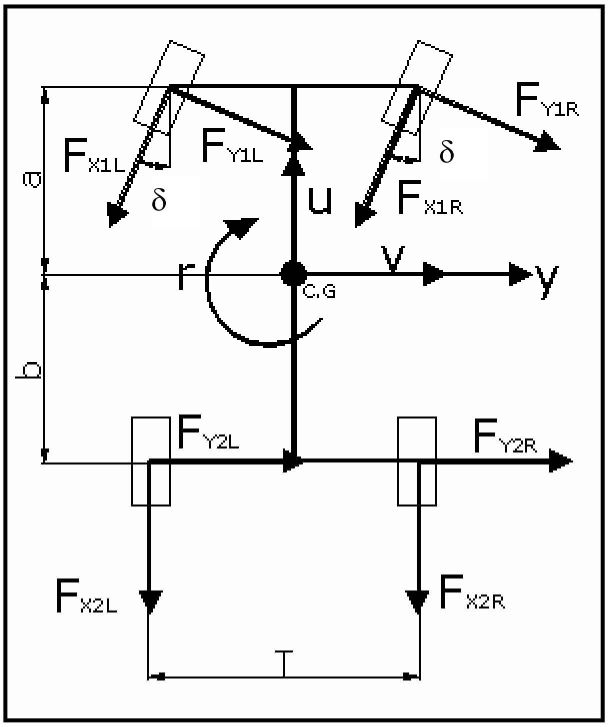


Fig.(1) Vehicle model.

The nonlinear vehicle model proposed by Tom [5]is used in this paper.

The equations of motion are formed using figure (1)

$$\sum F_x = m\left(\dot{u} - rv\right)$$

$$(F_{X1L} + F_{X1R})\sin\delta + (F_{Y1L} + F_{Y1R})\cos\delta + F_{Y2L} + F_{Y2R} = m\left(\dot{u} - rv\right)$$

$$\sum M_Z = I_Z\,\dot{r}$$

$$[(F_{X1L} - F_{X1R})\cos\delta - (F_{Y1L} - F_{Y1R})\sin\delta]\frac{T}{2} + [(F_{X1L} + F_{X1R})\sin\delta + (F_{Y1L} + F_{Y1R})\cos\delta]a$$

$$+(F_{X2L} - F_{X2R})\frac{T}{2} - (F_{Y2L} + F_{Y2R})b = I_Z\,\dot{r} \qquad \ldots(1)$$

The resulting lateral forces are determined by

$$F_{YIL} = C_F\alpha_{Y1L} \qquad F_{Y1R} = C_F\alpha_{Y1R}$$

$$F_{Y2L} = C_R\alpha_{Y2L} \qquad F_{Y2R} = C_F\alpha_{Y2R} \qquad \ldots(2)$$

The sideslip angles are calculated by the following equations

$$\alpha_{Y1L} = \tan^{-1}\left(\frac{v + ar}{u - 0.5Tr}\right) - \delta \qquad \alpha_{Y1R} = \tan^{-1}\left(\frac{v + ar}{u + 0.5Tr}\right) - \delta$$

$$\alpha_{Y2L} = \tan^{-1}\left(\frac{v - ar}{u - 0.5Tr}\right) \qquad \alpha_{Y2R} = \tan^{-1}\left(\frac{v - ar}{u + 0.5Tr}\right) \qquad \ldots(3)$$

The goal of this research is to learn and predict lateral vehicle motion. The lateral acceleration in the vehicle frame at the center of gravity is given by

$$\ddot{y} = \dot{v} + ur \qquad \ldots(4)$$

By double integration for equation (4) the lateral position y can be calculated.
Practically, accelerometers is used to measure the vehicle's lateral acceleration.
In this work, the vehicle must move in straight path (there is no steering angle input, $\delta=0$) so the lateral forces generated by the sideslip angles provide acceleration needed to vary the lateral position of the vehicle.
From equations (1) it can be seen that the effect of right front longitudinal braking force on the yaw rate is the same effect when brake is applied on the right rear tire. This note is true also for left side. Therefore we can consider the $F_{XR}=F_{X1R}+F_{X2R}$ and $F_{XL}=F_{X1L}+F_{X2L}$ and use F_{XL} and F_{XR} as controller output.
The brake system response is modeled as a first order lag with time constant ($\tau=0.1$)[5] such that

$$\dot{F}_b = -\frac{F_b}{\tau} + \frac{F_{b\,comanf}}{\tau} \qquad \ldots(5)$$

The model can be interpreted as the dynamic lag between a brake force command ($F_{b\ command}$) and the resulting brake force(F_b)

3-Modified Elman Neural Networks/Genetic Algorithm Learning:

Recurrent neural networks (RNN) have one or more feedback connections, where each artificial neuron is connected to the others. The RNN structures are suitable to channel equalization and multi-user detection applications, since they are able to cope with channel transfer functions that exhibit deep spectral nulls, forming optimal decision boundaries and are less computationally demanding than multi layer percepetrons (MLP) networks for these applications [15]. Among the available recurrent networks, modified Elman networks as shown in figure (2) is one of the simplest types that can be trained using genetic algorithm and it is used to minimize the oscillation or even instabilities to the training controller. The output of the jth context unit in the modified Elman network is given by:

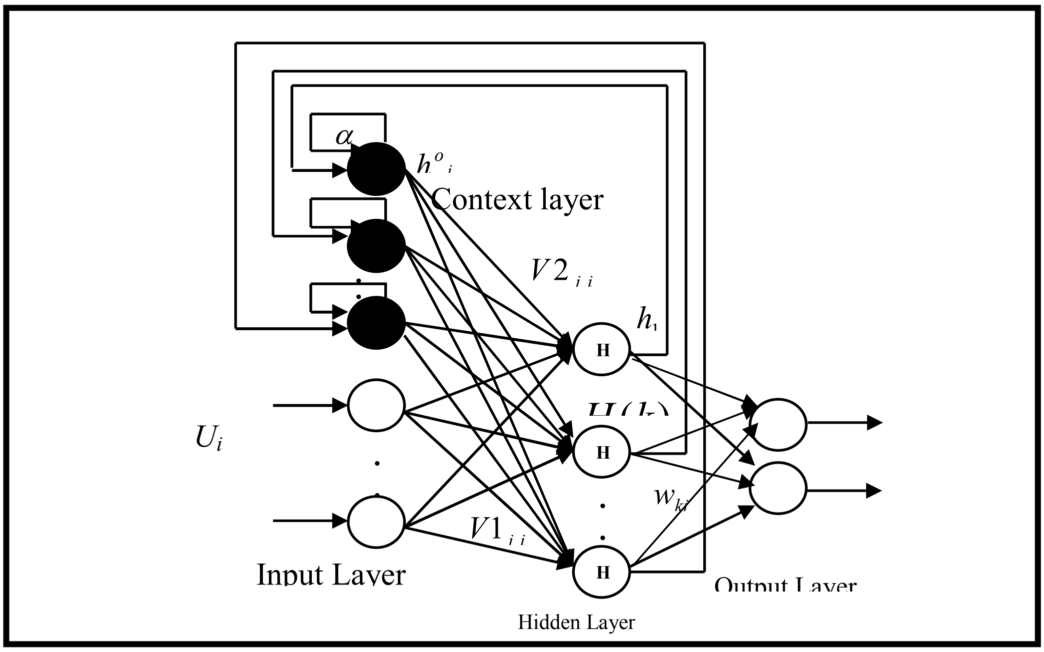
$$h_j^o(k) = \alpha h_j^o(k-1) + h_j(k-1) \qquad \ldots(6)$$

where $h_j^o(k)$ and $h_j(k)$ are respectively the output of the jth context unit and jth hidden unit and α is the feedback gain of the self-connections. The value of α adopted is the same for all self-connections and is not modified by the training algorithm. The value of α is between 0 and 1. A value of α nearer to 1 enables the context unit to aggregate more pat outputs. The input and output units interact with the outside environment. While the hidden and context units do not. The input units are only buffer units " Scales". The output units are linear units, which sum the signals fed to them. The hidden units can have nonlinear activation functions such as sigmoidal activation functions. The context units are used only to memorize the previous activation's of the hidden units and can be considered to function as one-step time delays. From the figure (2) it can be seen that the following equations:

$$h(k) = F\{V1X(k), V2h^o(k)\} \qquad \ldots(7)$$

$$O(k) = Wh(k) \qquad \ldots(8)$$

where V1,V2 and W are weight matrices and F is a non-linear vector function. The multi-layered modified Elman neural networks shown in figure (2) that is composed of many interconnected processing units called neurons or nodes.
where: $V1$: Weight matrix of the input units. $V2$: Weight matrix of the context units.
W : Weight matrix. L: Denotes linear node. H: Denotes nonlinear node with sigmoidal function.



As can be seen the net consists of three layers: An input layer (buffer layer as scales), a single hidden layer and a linear output layer. The neurons in the input layer simply store the scaled input values. The hidden layer neurons perform two calculations. To explain these calculations, consider the general j'th neuron in the hidden layer shown in figure (3). The inputs Xi and h_i^o to this neuron consist of an ni – dimensional vector and (ni is the number of the input nodes). Each of the inputs has a weight *V1* and *V2* associated with it. The first calculation within the neuron consists of calculating the weighted sum net_j of the inputs as:

$$net_j = \sum_{i=1}^{ni} V1_{j,i} \times X_i + V2_{j,i} \times h_i^o \qquad \ldots(9)$$

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

$$h_j = \mathrm{H}(net_j) \qquad \ldots(10)$$

$$\mathrm{H}(net_j) = \frac{2}{1+e^{-net_j}} - 1 \qquad \ldots(11)$$

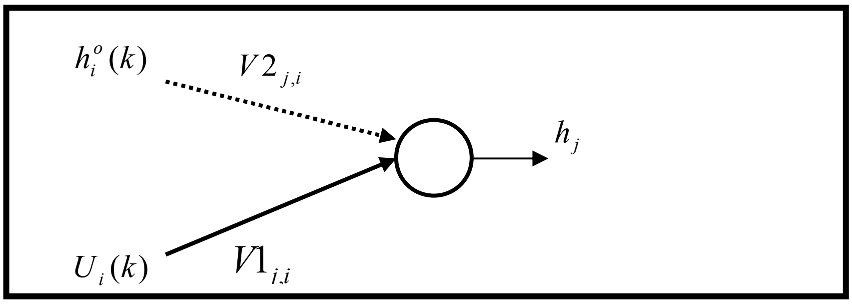


Fig (3): Neuron j in the hidden layer.

Once the outputs of the hidden layer are calculated, they are passed to the output layer. In the output layer, a single linear neuron is used to calculate the weighted sum (neto) of its inputs (the output of the hidden layer as in equation (12))..

$$\text{neto}_k = \sum_{j=1}^{nh} W_{k,j} \times h_j \qquad \text{…(12)}$$

where nh is the number of the hidden neuro (nodes) and $W_{k,j}$ is the weight between the hidden neuron h_j and the output neuron. The single linear neuron, then, passes the sum (neto_k) through a linear function of slope 1 (another slope can be used to scale the output) as:

$$O_k = L(neto_k) \text{ where } L(x)=x \qquad \text{…(13)}$$

Thus the outputs at the output layer are F_{XL} ,F_{XR} which are denoted by O1 and O2 respectively.

In this work, the GA with real coding rather than binary is used as follows: Each chromosome is considered as a list (or "vector") of the total weights of neural networks. The encoding is shown in figure (4) and the weights are read off the network in a fixed pre-defined order and placed in a vector. Each "gene" in the chromosome is a real number. To calculate the fitness of a given chromosome, the weights in the chromosome are assigned to the links in the corresponding modified Elman networks, the network is run on the training set, and an objective function is returned. An initial population of weight vectors was chosen to be 120 individuals, with each weight being between –1 and +1. The mutation operator adds a random value between –0.75 and +0.75 to the selected weight on the link. The crossover operator two mating vectors and exchanges the information by exchanging a subset their components. The result is a new pair of vectors, each of which carries components from both of the parent vectors. The mean square of error (MSE) for multi-input multi-output (SISO) is used as an objective function to be minimized with the GA:

$$MSE = \sum_{k=1}^{Np} \frac{(y_{mr}(k) - y_p(k))^2}{Np} \qquad \text{…(14)}$$

where:

y_p (k) is the first output of the plant at sample k.

y_{mr} (k) is the first output of the linear model reference at sample k.

Np is the number of the training patterns.

Since the GA maximizes its fitness function, it is necessary therefore to map the objective function (MSE) to a fitness function. It is used objective to fitness transformation is of the form [16].

$$fitness = \frac{1}{objectivefunction + \mu} \qquad \text{…(15)}$$

Where μ is a constant chosen to avoid division by zero.

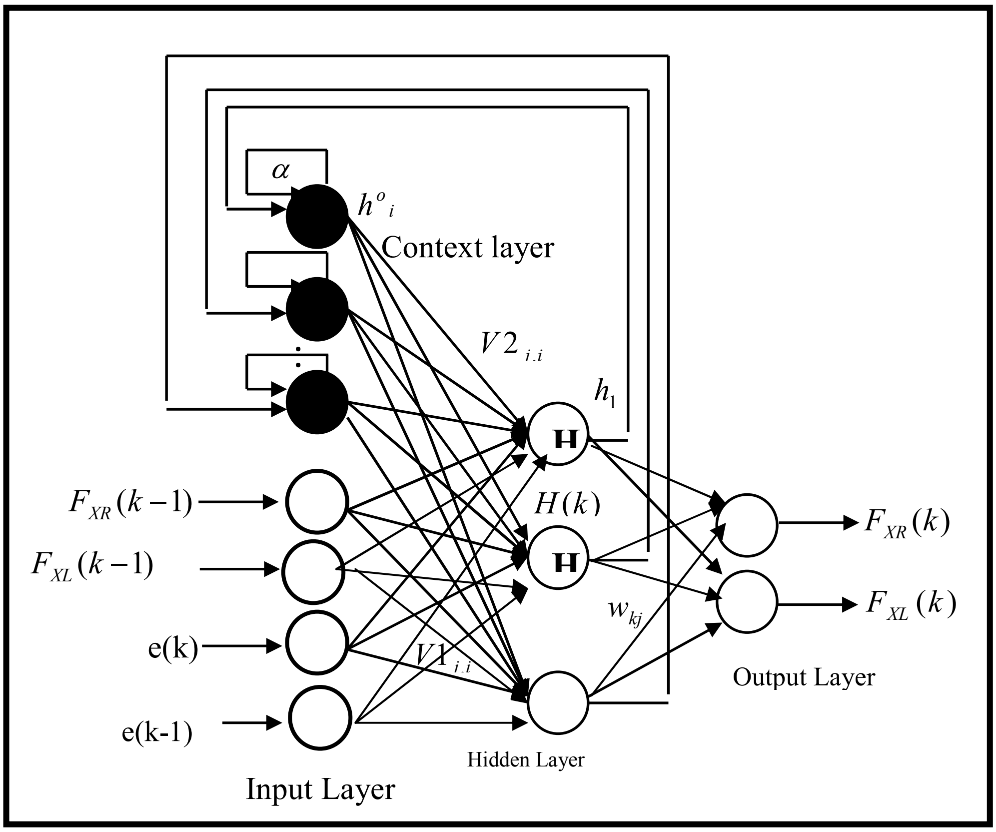
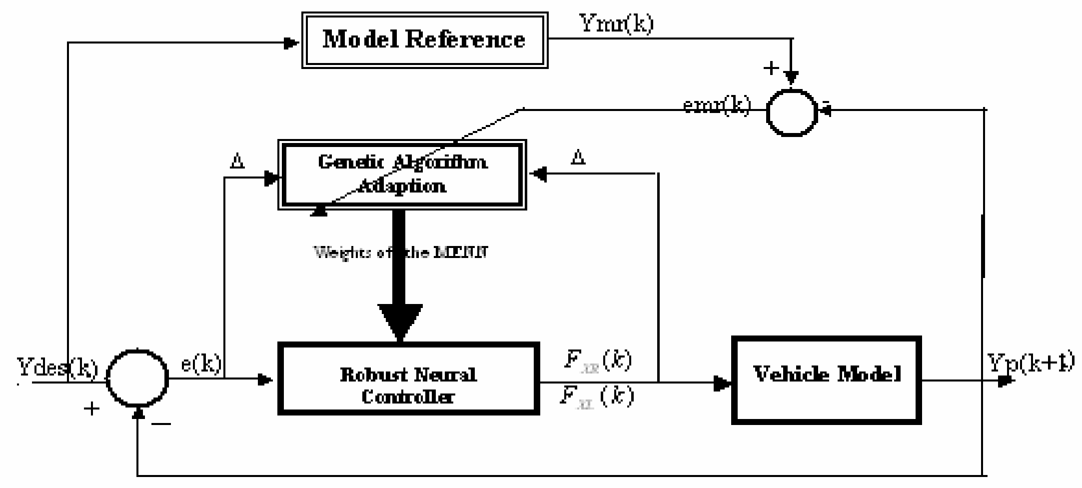


Fig (4): The structure weights of the neural controller as MENN

4-Feedback Robust Neural Controller

The control of the multi-variable nonlinear system is considered in this section. The approaches used to control the system does not depend on the information available about the system *"does not use identification to the system"*. The feedback neural controller is very important because it is necessary to stabilize the tracking error dynamics of the system when the output of the system is drifted from the input reference. The feedback neural controller is used based on the minimization of the error between the model reference & the actual output system in order to achieve good tracking of the reference signal with minimum time and to use minimum effort. In direct model reference adaptive controller (MRAC) with parallel model reference used here for the feedback neural controller, the adjustable parameters of neural network controller are adapted by genetic algorithm technique [17]. The integrated control structure that consists of the model reference and neural controller type modified Elman recurrent neural networks thus brings together the advantages of the neural model with the robustness of feedback. The general structure of the neural controller can be given in the form of the block diagram shown in figure (5).



Δ is defined as a delay mapping from a sequence of scalar inputs and outputs

Fig (5): The General Proposed of the Robust Neural feedback Controller

5-The Proposed Algorithm For The Adaptive Neural -Controller

The following genetic procedure is introduced for training the modified Elman recurrent neural network controller for the **(SISO)** plant to track the reference model trajectory:

Step 1: Initialize the genetic operators: the crossover probability Pc, the mutation probability Pm, the population size, and the maximum number of generations.

Step 2: Generate the initial population randomly.

Step 3: For each individual in the population, compute the objective function MSE, and then calculate the fitness function as in equation (14), where μ will be chosen as an input coefficient equal to 1.

Step 4: Put in descending orders all the chromosomes in the current population.

Step 5: Select individuals using hybrid selection method (Roulette Wheel plus deterministic selection). The real coded genetic operators of mutation and crossover (single point) is applied.

Step 6: Stop if a maximum number of generations of genetic algorithms are achieved, otherwise increment the generations by one and go to Step 3.

In order to overcome a numerical problem that is involved within real values. Scaling function has to be added at the neural network terminals to convert the scaled values to actual values and vice versa. Therefore the signals entering to or emitted from the network have been normalized to lie within (-1 & +1).

In this simulation, the proposed control scheme is applied to the vehicle model and the real-coded genetic algorithm is set to the following parameters:

Population size (N_{POP}) is equal to 60.

Crossover Probability (Pc) is equal to 0.8.

Mutation Probability (Pm) is equal to 0.05.

Maximum number of generations is 2000.

The training pattern (Np) used was taken as 240 as the desired trajectory. The modified Elman recurrent neural networks are used to minimize the performance error between the model reference and the actual output. For more stability and without any oscillation in the response, the equation of the model reference is taken as:

$$y_{mr}(k+1) = 0.45 y_{mr}(k) + 0.3 y_{des}(k+1) \qquad \ldots(16)$$

Convergence is achieved when the performance error falls below a pre-specified value.

$$e_{mr}(k+1) = y_{mr}(k+1) - y_p(k+1) \qquad \ldots(17)$$

where $e_{mr}(k)$ is the model reference error output.

The proposed algorithm for the adaptive neural-controller is shown in appendix (A).

The number of weights that are resulted from the genetic algorithm are sixty during one running of the computer program (turbo C++ program). For example, the variations of the values of the three different weights during the learning time are shown in table (1).

Table (1) The values of the three different weights

Time (sec.)	Lateral position (m)	Brake force (N)	$V1_{1,1}$	$V2_{1,1}$	$W_{1,1}$
٠	٠,٥	٠	-0.4	0.5	٠,٧
٠,٥	٠,٤٣٢٥٢٥٦	-٤٠٨٧,٦٣	0.131	0.115	.0.957
١	٠,٢٠٩٤٩٠٨	٣٠٢٧,٤٨٧	0.645	-0.331	0.845
١,٥	٠,٠٣١٥	٣٦٥٢,٤٨٥	0.458	-.659	0.716
٢	-٠,٠٢٢	١٢٥٩,٢٧	0.204	-0.291	0.381
٢,٥	-٠,٠١٢	-٢٣٠,٢٤٥٦	-0.704	0.233	0.575
٣	٠,٠٠٣٩٦	-٣٠٤,٥٣٤٥	0.361	0.324	0.206
٣,٥	٠,٠٠٤١٢	-٢٨,٧٦٠١٩	0.175	0.036	0.329
٤	٠,٠٠٠٠٩٥٥	٦٨,٩٣١٨٨	-0.471	0.589	0.849
٤,٥	-٠,٠٠٠٠٥٧٥	٣٨,٧٠٧٨٥	-0.638	0.282	0.371
٥	-٠,٠٠٠٠٤٧٣	-٠,١٤٣٣٧٥٣	0.339	0.562	0.981
٥,٥	-٠,٠٠٠٠٠٥٣٩	-٩,٧٠٤٨٦٧	0.541	0.398	0.448
٦	٠,٠٠٠٠٠٩٩≈0	-1.٠٥١٣٢٨	0.307	0.078	0.169

6-Simulations.

In this section, the vehicle constant that appear in appendix (C) are taken to clarify the features of the neural controller explained in section three ,four and applied the algorithm in section five.

After substitution the parameters of the vehicle in appendix (C), in the nonlinear equations (1,2,3,4,5) and use fourth order Rung Kuta method to solve these equations with the sampling period (*h*) is equal to 0.1.The performance of the neural controller is evaluated using closed loop step response for the nonlinear vehicle model including the variations of the vehicle parameters. The desired lateral position must be zero to prevent the vehicle from sliding out the correct path. So the initial lateral position is considering as input (disturbance) to the system and the task of proposed controller must achieve the desired lateral position .

Four cases are studied to test the neural controller

Case-1

The vehicle velocity is changing (*u=10,15,20,25 m/sec*) while the mass and front, rear cornering coefficients are constant. The lateral position for this case reaches to desired value (0 m) at short transit time as shown in figure (6). . We can see the overshot increases when the velocity increases because the vehicle approaches the unstable limits at high velocity. The maximum overshot does not exceed 0.05m.

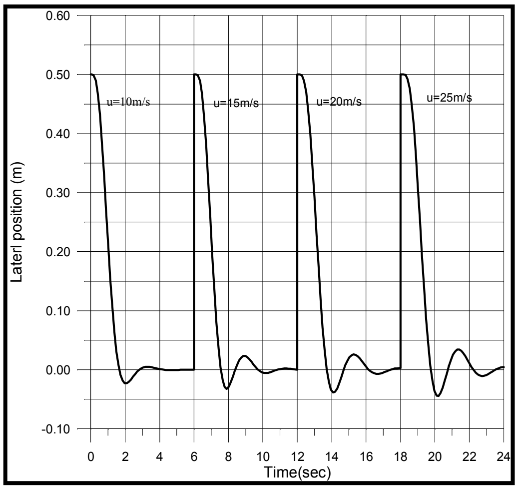


Fig. (6) Lateral position response for different velocity values.

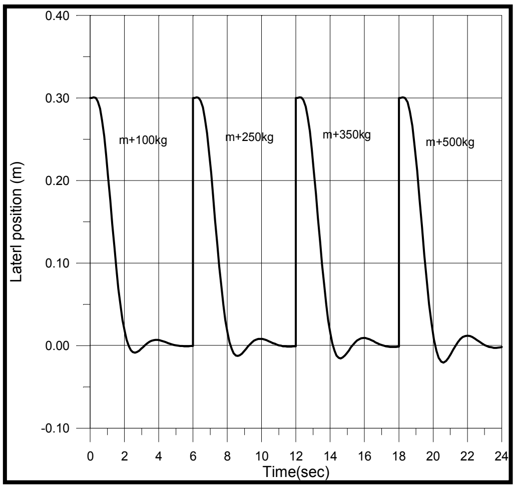


Fig. (7) Lateral position response for different mass values.

#Case-2

The mass of the vehicle varies according to the number of the passengers and loads. Therefore, the mass variations are taken as a case. Figure (7) shows the lateral position responses when mass is changing (1920,2070,2170,2320 kg) and other parameters are constant. As shown in figure (7) the lateral position responses at different masses are similar approximately. This inducts the proposed controller is very robust controller in this case.

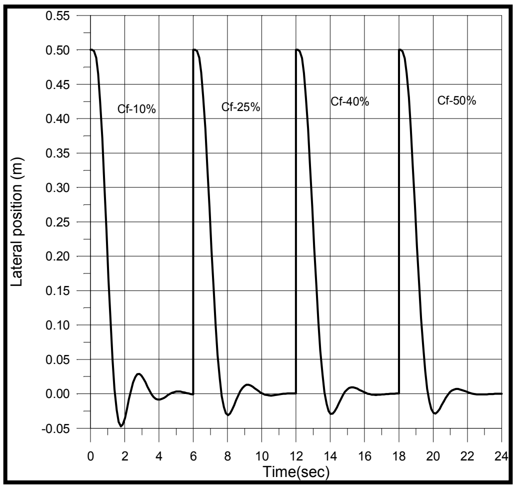


Fig. (8) Lateral position response for different front cornering stiffness values.

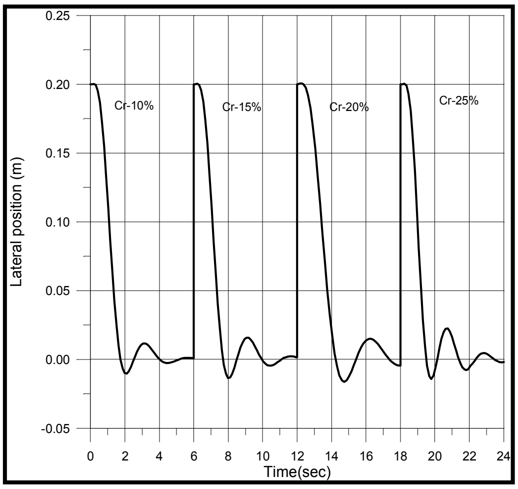


Fig. (9) Lateral position response for different rear cornering stiffness values.

#Case-3

The pressure of tires is very important parameter that affects on the vehicle dynamic behavior and so the values of cornering stiffness are related directly to pressure of the vehicle tires [18]. Therefore the variation of cornering coefficient gives a good indication to the variation of tire pressure.

In this case the front cornering stiffness is changing and other parameters are constant. Figure (8) shows the lateral position when the front cornering stiffness is reducing (10%-25%-40%-

50%) from normal of it value. The lateral position responses reach to desired value (0m) with values of overshot does not exceed –0.025m in worst responses.

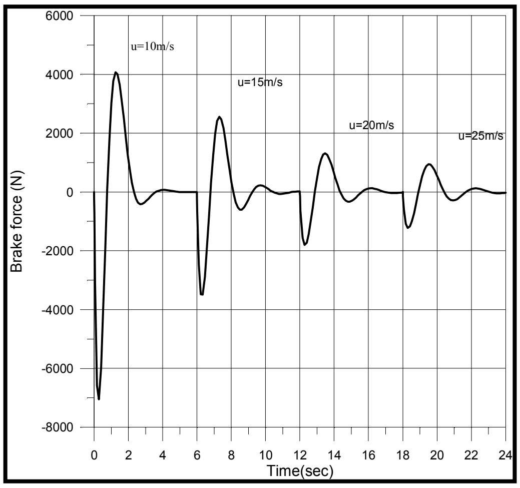


Fig (10) Brake force response for different velocity values.

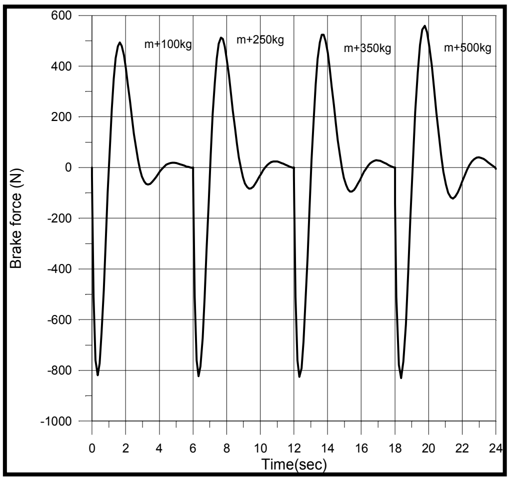


Fig (11) Brake force response for different mass values.

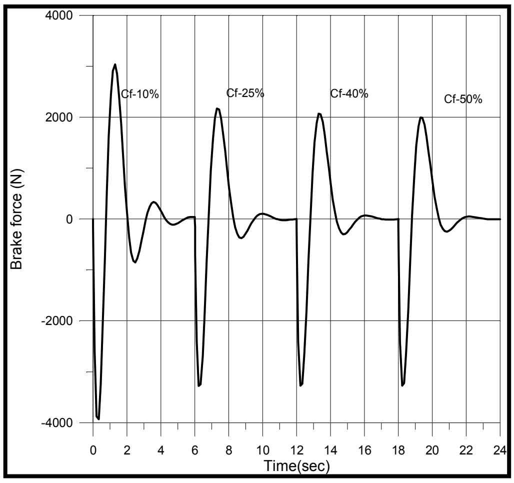
#Case-4

This is worst case because the direction stability of vehicle will be lost when the bunger or explosion is happened in the rear tire. This leads to reduce the value of the rear cornering stiffness. Figure (9) shows the lateral position responses when the rear cornering stiffness is reducing (10%-15%-20%-25%) from normal of it value. It is important to note that the reducing of rear cornering stiffness is less than reducing of front cornering stiffness in case three because the reducing of the rear cornering stiffness more make the vehicle dynamic behavior reaches to unstable limits. From Figure (10) it can be seen that the proposed controller achieves the desired lateral in spit of the oscillations that appear in transit time. These oscillations remain under ±0.025m so this result is acceptable practically.

When the vehicle velocity, mass, and front cornering stiffness are increasing and rear cornering stiffness is reducing the directional stability of a vehicle is increasing [18].

The effect of the vehicle parameters changing in the vehicle stability can be seen very clearly in figures (10,11,12,13). The values of braking force must be increased when the vehicle becomes more stable to move the vehicle to the right direction figures (10,11,12,). Also a little force can move the vehicle when it is unstable figure (13).It is important to note that the positive regions in figures(10,11,12,13) are right brake force and negative regions are left brake force

Figure (14) is described the best objective function ***MSE*** for the ***SISO*** system.



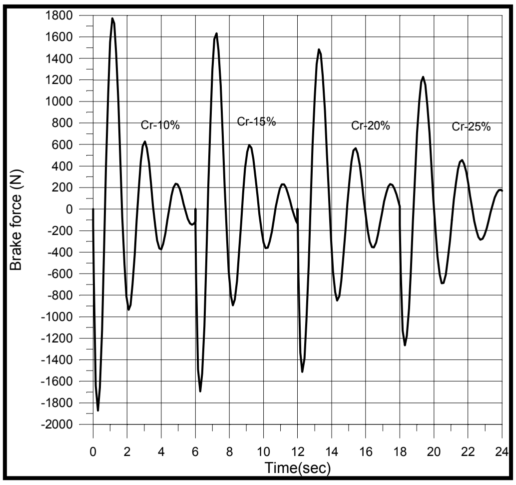


Fig (12) Brake force response for different front cornering stiffness values.

Fig (13) Brake force response for different rear cornering stiffness values.

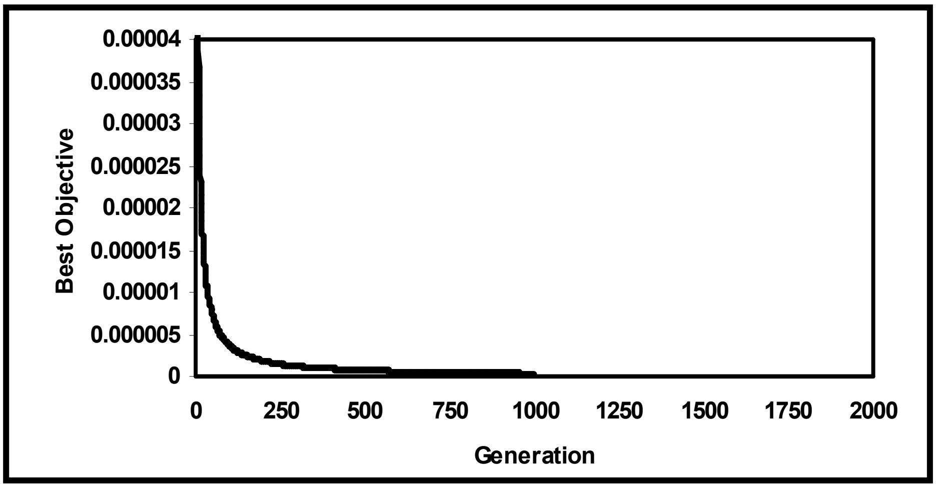


Fig (14): The best mean square error for the plant SISO

7-Conclusions

1-The dynamics change due to vehicle velocity, mass, and cornering stiffness variation was addressed in controller design ,therefore the proposed controller became more robust.

2-In lateral control motion problem, the taken of lateral position as state variables is more effective than lateral velocity state because the lateral position of the vehicle is a more objective indicator of vehicle deviation from the right path..

3- A nonlinear vehicle model for simulation is used. Therefore the adaptive neural controller is used in this work so these types of controllers have good ability to control on nonlinear system than classical controllers.

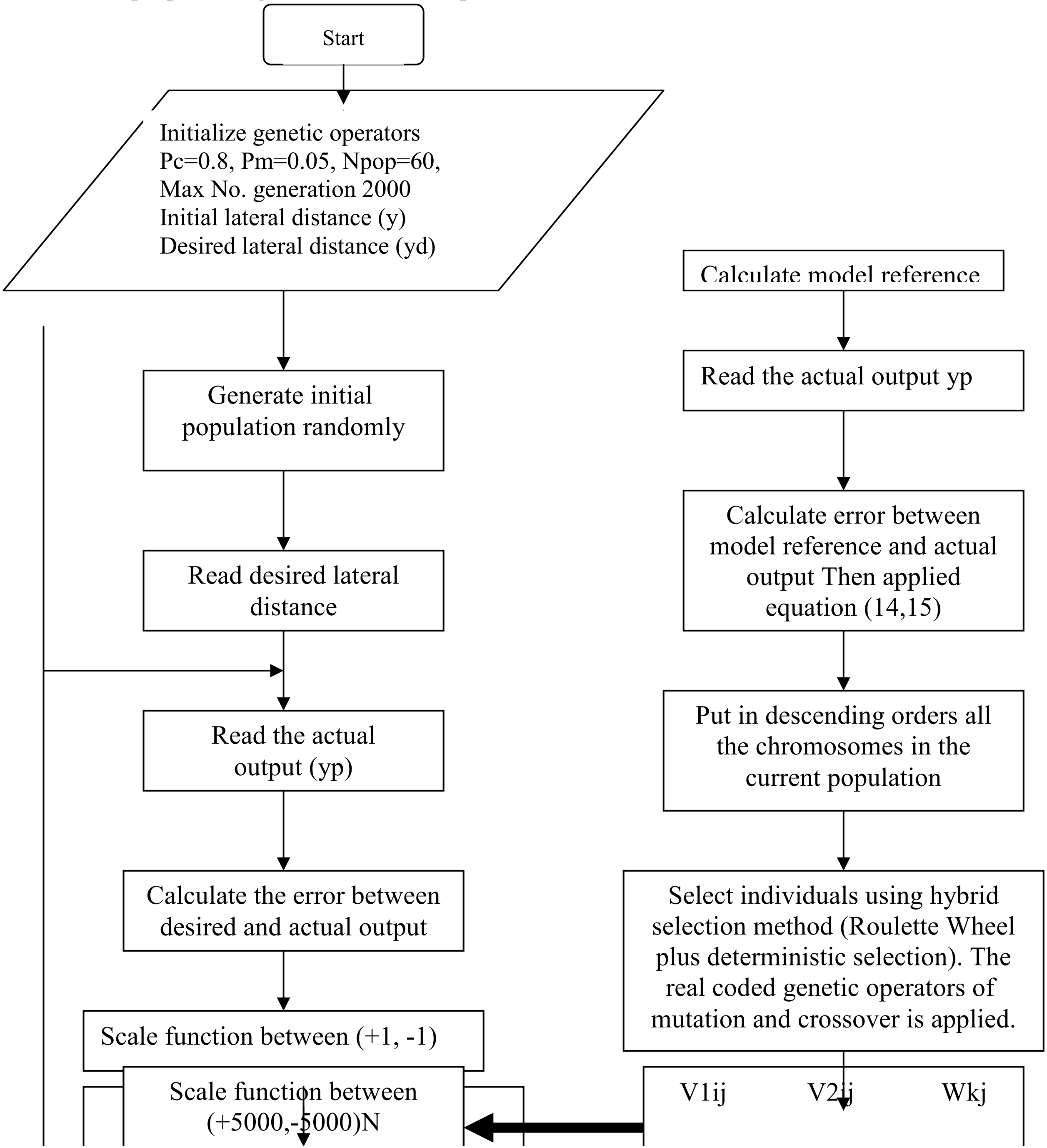
4- The structure of the neural (MENN) controller based genetic algorithm technique has been designed and successfully simulated to the dynamical vehicle model with very fast learned.

5- Among the available recurrent networks, modified Elman networks is one of the simplest types that can be trained using genetic algorithm and it used to minimize the oscillation or even instabilities to the training controller.

6- The proposed control structure has shown the ability to minimize the error between the desired output and the actual output of the vehicle as well as the control action, excellent set point tracking.
7- One of the most important in the proposed control structure does not depend on the information available about the system therefore does not need identification to the system.
8- It is used a model reference technique in order to obtain more stability and without any oscillation in the response.
9-The results of lateral motion simulation show that the controlling on lateral position by controller proposed have been achieved at different values of vehicle parameters. 10-Interviewing the results of simulations, the lateral position is fluctuating around the desired during the transient response. This fluctuating may be acceptable because it is so small value .
11-The lateral position responses that are obtained in this paper are too similar the results of Tom [5].

Appendix (A).

The proposed algorithm for the adaptive neuro-controller



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