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IMPROVING AUTOMATIC BRAKE PERFORMANCE IN NONLINEAR VEHICLE USING ARTIFICIAL INTELLIGENCE TECHNIQUE

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ABSTRACT

This paper presents improving automatic brake performance in nonlinear vehicle using artificial intelligence technique. An an empirical study of a fuzzy logic based brake control system and achieved stability response time of 4.78s as total time it takes to bring a nonlinear vehicle at 0.4N coefficient friction to stability and speed of 75Km/hr was conducted. A neural network algorithm was adopted and used to develop an automatic brake control system and then implemented with simulink. The result when tested at the same condition with the characterized system showed a stability response time of 2.25s as against 4.78s in the characterized.

Keywords: Brake, Nonlinear Vehicle, Fuzzy Logic, Artificial Neural Network, Response Time

I. INTRODUCTION

In recent years, the number of road accident increase has raised great concerns across the globe and presents a major challenge for road traffic administrators. If serious solution is not proposed, in the next few years, road accident will be among the top five major causes of human mortality rate (Maninder and Amrit, 2014). It has been reported overtime that most of the car crashes along Nigerian high ways for instance are as a result of high speed. According to Federal Road Safety Commission (FRSC) in Nigeria report in 2016, the major causes of road accident are manmade, of which the top of the list is over speeding. The World Health Organization (2014) Report added that 4-5% of fatal road crash is as a result of over speeding.

According to Edison (2014), over speeding is a condition of which the vehicle engine is allowed or forced to run beyond its design limit. Various methods have been identified as the solution to this canker, which includes the implementation of automatic breaking systems, cruise control system, among others; however a complete control of vehicle under high speed is yet to be employed.

Recently, the car industries have turned to artificial intelligence to help solve the problem and bring about a complete intelligent cruise control, employing various controllers like the proportional integral controller, sliding controller, among other feedback control systems (Eneh and Uche, 2014). However, despite their contributions and controllability, the issues of response time remained a challenge. These problems of delay control and stability time were achieved in this paper using artificial neural network with the following setout objectives. These were executed by developing an adaptive brake control system using neural network and implementing the model using Simulink and evaluate the performance. Several articles reviewed were listed as table 1:

Table 1: Systematic Review

Trong et al. (2016)	Adaptive Tracking Control of Two-Wheeled Welding Mobile Robot (WMR) with Smooth Curved Welding Path	Adaptive Controller	Designed a tracking controller to drive the errors from WMR to zero as fast as desired.	Delay response time
Sun et al. (2016)	Robust lane-detection method for car-like robot	Robust lane-detection method	Worked on how to extract the edges of lanes in traffic scenarios, the authors adopt an adaptive thresholding strategy to binarized a gradient image and trace edges by using their local gradient information to enable lane detection	But the work showed low efficiency
Fekih et al (2016)	Fault tolerant vehicle control design for automatic path tracking in	Reference-based adaptive controller	The proposed method was applied to a ground vehicle following a rigid square-wave–shaped road under different faulty conditions in	The speed by which the system is able to recover from the fault and excellent tracking

	vehicle		the vehicle actuator.	performance under faulty conditions are the main positive features of the proposed approach.
Lin et al. (2016)	Adaptive Critic Anti-Slip Control Of Robot	Hybrid technique	Using dual heuristic programming and multi-layer perceptron neural networks, an adaptive critic anti-slip control design was developed for automatic driving control system enabling it comply with changes in slip conditions	The result shows that the performance was significantly better than traditional fuzzy control which was not characterized on the research and hence not justifiable.

II. METHODS

The materials used for the development of the new system are the case study vehicle, fuzzy controller, brake system, the vehicle simulator, decelerometer monitoring instrument (DVSA model) and the power supply. This research characterized the Innoson Vehicle Motors (IVM) using the chassis in figure 1 which was mounted on a system which modeled road surface at 0.4N coefficient of friction (which implied wet road) to conduct the empirical study of the brake control system at variable speed.

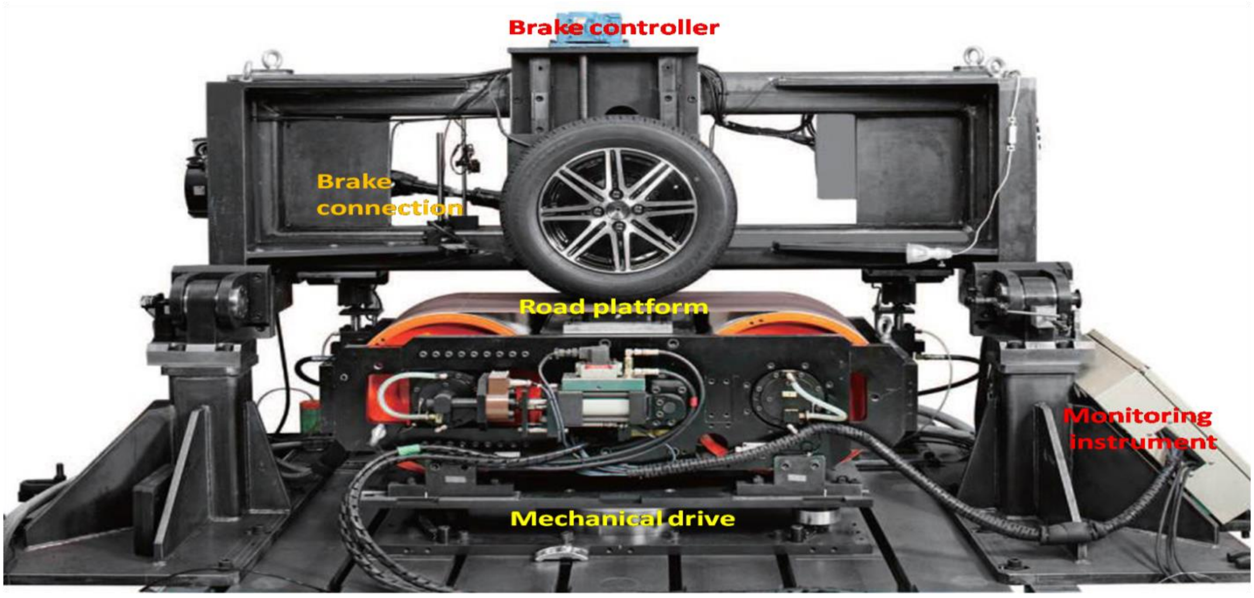


Figure 1: The testbed (Coutsey: Innoson)

From the mechanism, the vehicle chassis made up of the brake control system developed with fuzzy logic among other vehicle odometry was operated at varying speed from 40km/hr to 100km/hr and then analysis performance based on the standard of the Nigerian federal road safety commission. The result of the vehicles speed was measured for 18minuites with speedometer while the brake system was analyzed with the decelometer to determine the response time and reported in table 2.

Table 2: Characterized data

Time (min)	Vehicle Speed (km/hr)	Control time (s)	Vehicle behavior
1	40	3.90	Speed ok, dynamics ok
2	45	3.95	Speed ok, dynamics ok
3	50	4.02	Speed ok, dynamics ok
4	55	4.15	Speed ok, dynamics ok
5	60	4.26	Speed ok, dynamics ok
6	65	4.35	Speed ok, dynamics ok
7	70	4.40	Speed ok, dynamics ok
8	75	4.56	Speed ok, dynamics ok
9	80	4.72	Speed High , dynamics not ok
10	85	4.83	Speed High , dynamics not ok
11	90	5.01	Speed High , dynamics not ok
12	95	5.12	Speed very High , dynamics not ok
13	96	5.22	Speed very High , dynamics not ok
14	97	5.31	Speed very High , dynamics not ok
15	98	5.37	Speed very High , dynamics not ok
16	99	5.45	Slip very high, dynamics not good
17	99	5.71	Slip very high, dynamics not good
18	100	5.83	Slip very high, dynamics not good
Average	77	4.78	

From the data reported in table 2, the vehicle behavior was examined at a road with frictional coefficient of (0.7) which induces slip. The analysis was done based on the specification of the federal road safety crop (FRSC) which specified speed limit above 100km/hr as over speeding, 40 to 75km/hr as normal speed and 75 to 100km/hr as and high speed, while speed limit over 100km/hr is over speeding. The vehicle behavior is analyzed as shown below;

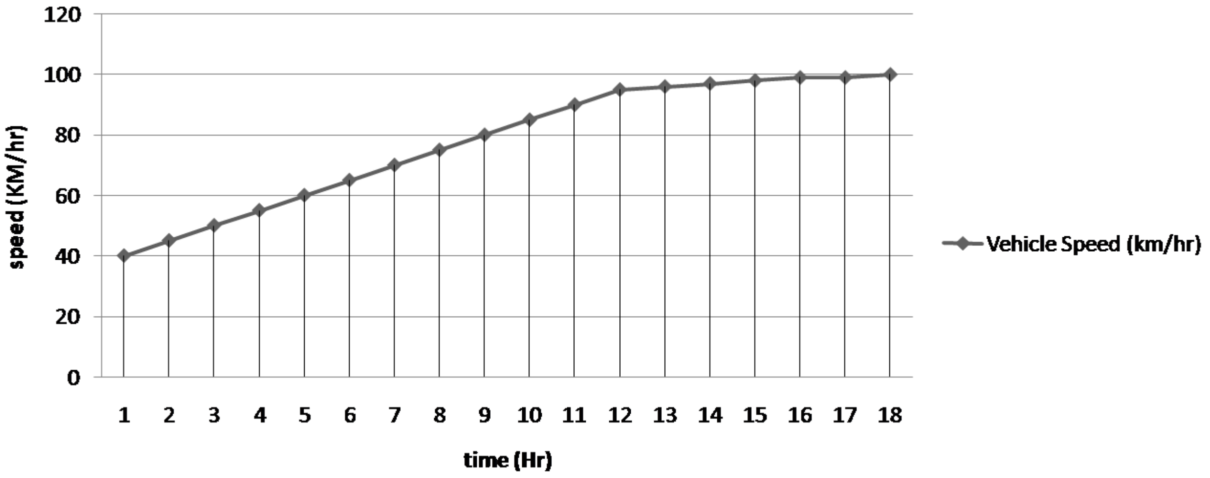


Figure 2: Characterized vehicle performance

From the result presented in figure 2, the behavior of the vehicle characterized was analyzed and during high speed the fuzzy logic based brake was applied at a force of 15N and the performance of the step response is presented in figure 3;

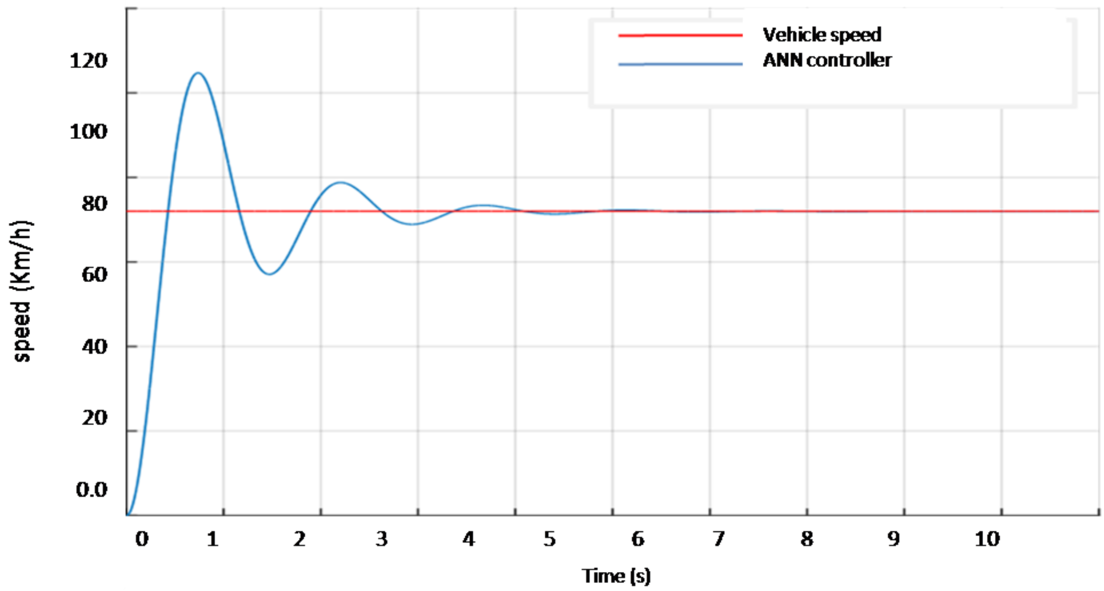


Figure 3: brake performance

From the result it was observed that the fuzzy logic bake controller reduced the speed at 4.78s when tested at an average speed of 75km/h. This result implied that the control system took the time to bring the vehicle to a steady state. This delay time needs to be reduced for improved control performance and will be achieved in this research using artificial neural network.

III. DEVELOPMENT OF THE AUTOMATIC BRAKE CONTROL SYSTEM

The Automatic Brake System (ABS) was developed with Artificial Neural Network (ANN). The ANN model was adopted from Eneh and Uche (2014) and used to train the vehicle data collected from the IEEE dataset in Wasin and Bernstein (1992). The block diagram of the system developed was presented in figure 4;

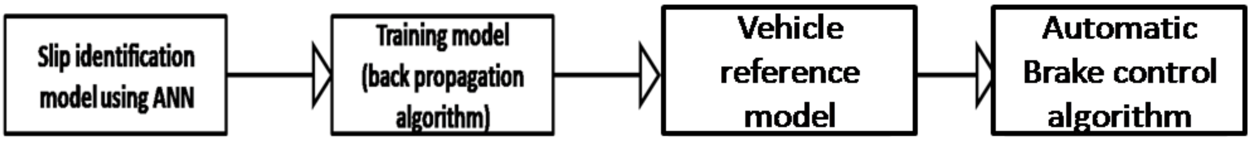


Figure 4: The system block diagram

The figure 4 presented the system identification of the neural network model adopted and trained with back–propagation algorithm presented in the figure 5 to generate the vehicle reference model used to stability the vehicle during nonlinear conditions as the automatic brake control algorithm.

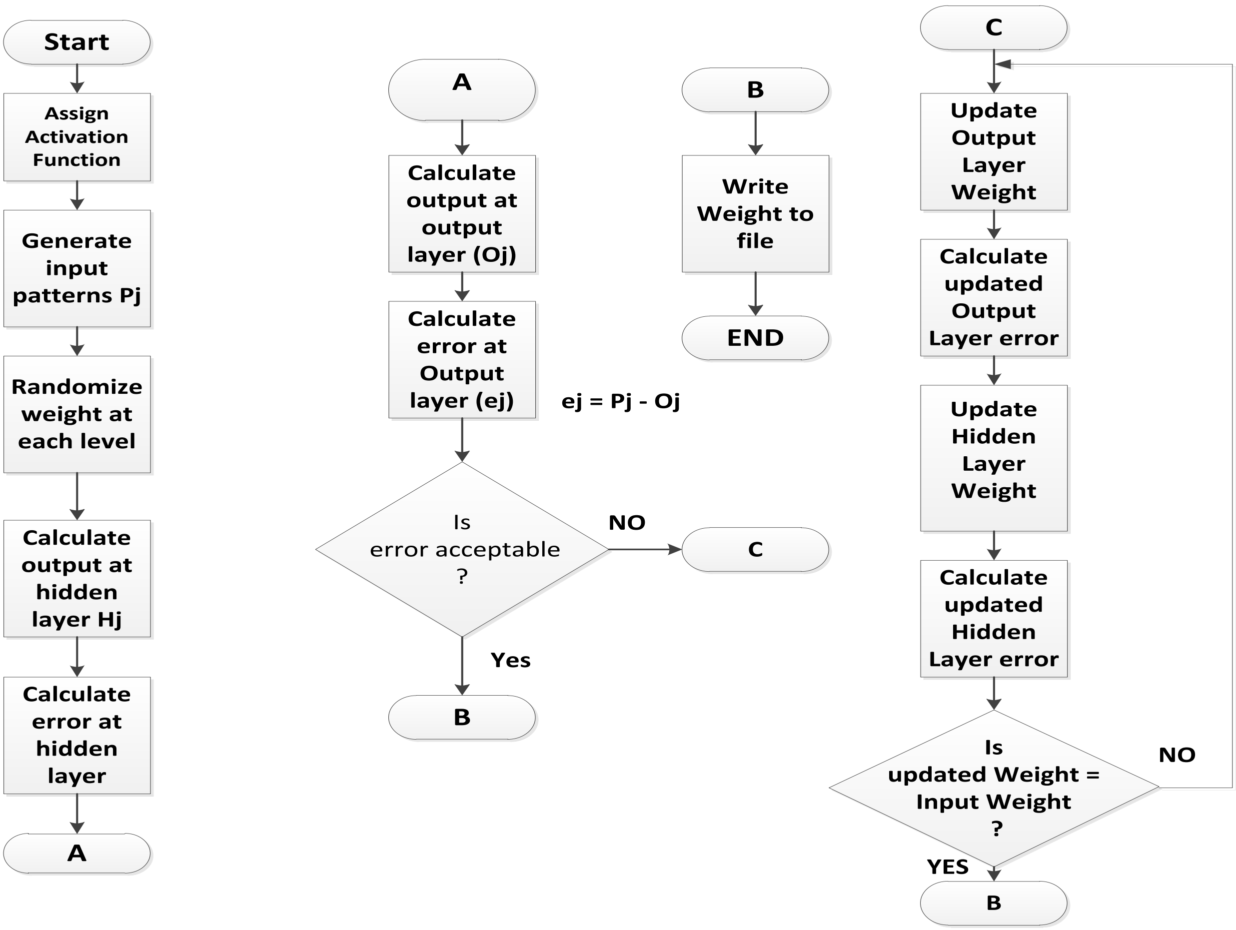
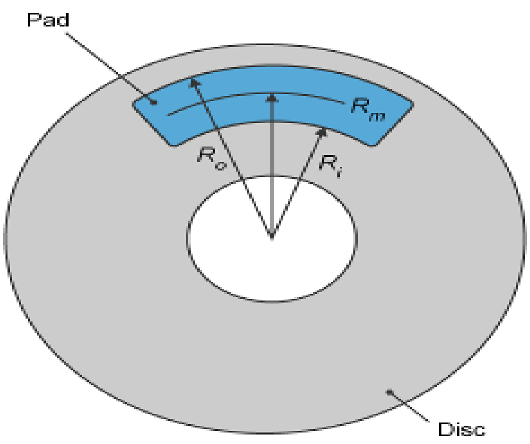


Figure 5: The training algorithm

Predictive model

To design an automated plant, there is need to distinguish disturbance which requires response from negligible noise. The noise model is presented to define the negligible noise characteristics using the plant model to generate measurement noise model of the form;

$$J = \sum_{j=N_l}^{N_2} y_r(t+1) - y_m(t+j))^2 + \; p\sum_{j=1}^{N_u}(u'(t+j-1) - u'(t+j-2))^2 \qquad 1.0$$



Where N_1, N_2 *and* N_u defines the specified horizon between the control increment and the tacking error. u' is control signal, y_r is the desired response, y_m is the network model response, p is the incremental control sum which squares has effect on the performance index, J is the prediction plant response.

The Brake Control mechanism

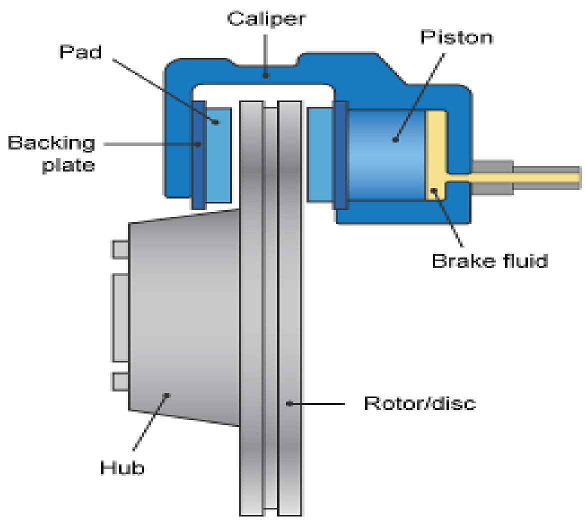


Figure 4: Brake Model

A disc brake converts the brake cylinder pressure from the brake cylinder into force. The disc brake applies the force at the brake pad mean radius. The equation that the block uses to calculate brake torque, depends on the wheel speed, *Ω*, such that when Ω≠0,

$$T = \frac{\mu k P \pi D b^{\wedge}2 * RmN}{4} \qquad 2.0$$

However when Ω=0, the torque applied by the brake is equal to the torque that is applied externally for wheel rotation. The maximum value of the torque that the brake can apply when Ω=0, is

$$T = \frac{\mu s P \pi D b^{\wedge}2 * RmN}{4} \qquad 3.0$$

In any case, $Rm = \frac{Ro+Ri}{2}$

Where: *T* is the brake torque; *P* is the applied brake pressure; *Ω* is the wheel speed; *N* is the number of brake pads in disc brake assembly; μ_s is the disc pad-rotor coefficient of static friction; μ_k is the disc pad-rotor coefficient of kinetic friction; D_b is the brake actuator bore diameter; R_m is the mean radius of brake pad l force application on brake rotor; R_o is the outer radius of brake pad, R_i is the inner radius of brake pad.

THE SYSTEM IMPLEMENTATION

The proposed system designed will be implemented using control system toolbox, predictive maintenance toolbox, optimization toolbox and Simulink. These tools were employed to implement the models developed as shown in the figure 7;

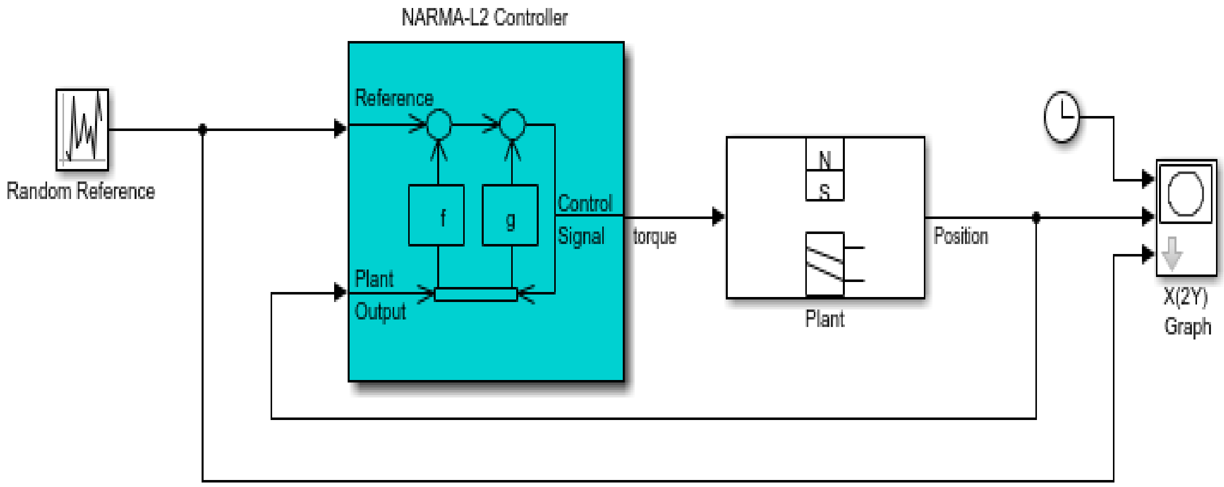


Figure 7: Simulink model of the improved brake control system

The neural network tool was configured with the neural network model adopted and used to develop the algorithm for the vehicle stability via brake control. The algorithm was simulated with data inspired from the testbed vehicle as reported in the table 3 and the result presented in the next section of this paper.

Table 3: Neural Network Parameters

Training epochs	10
Size of hidden layers	10
Controller training segments	30
No. delayed reference input	2
Maximum feature output	3.1
Maximum reference value	0.7

Continuation of Table 3: ANN Parameters

Maximum feature input	15
Number of non hidden layers	2
Maximum interval per sec	2
Speed	75Km/h
No. delayed output	1
No. delayed feature output	2
Minimum reference value	-0.7

V. RESULTS AND DISCUSSION

This section presented the Mean Square Error (MSE) performance of the neural network based vehicle stability algorithm developed. The MSE was used to check the error rate of the training process with the aim of achieving error value of approximately zero as in figure 8.

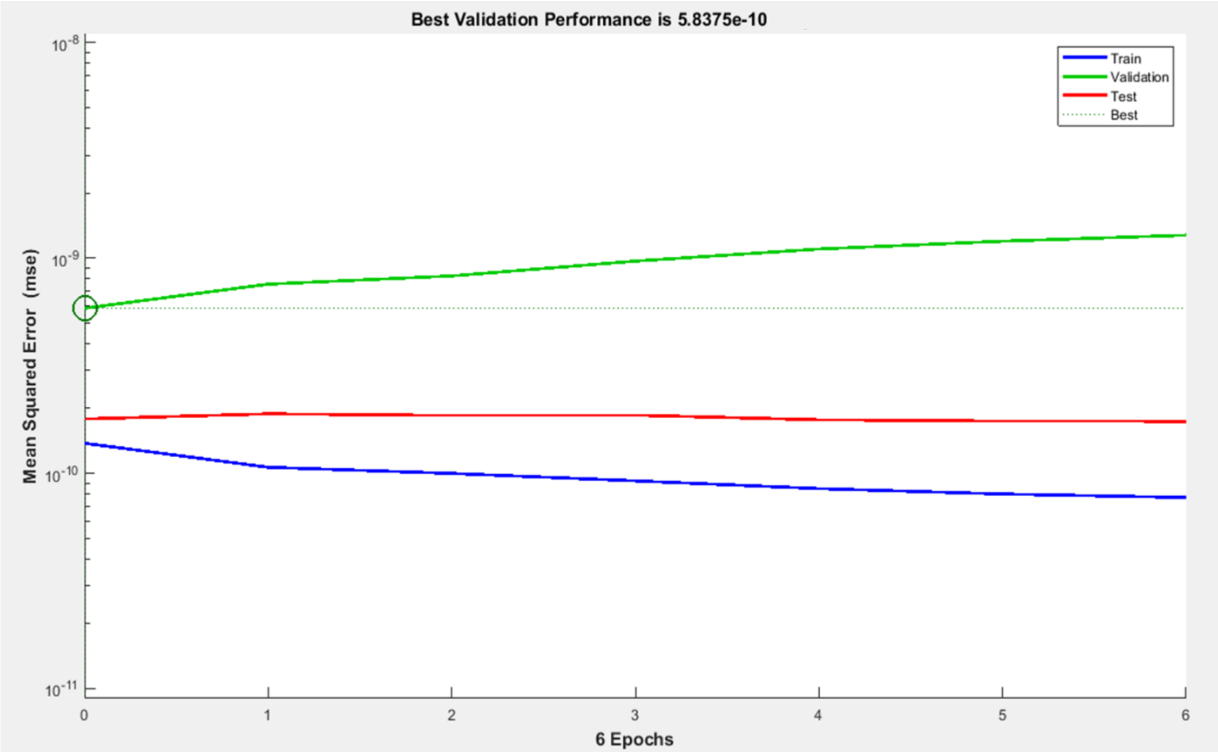


Figure 8: NN training MSE performance

The figure 8 presented the MSE performance of the training algorithm. The result showed that the training process achieved MSE of 5.8375e-10Mu. The implication of this result showed that error achieved was approximately zero which indicated good training performance. The next result presented the Regression performance of the system to detect nonlinear vehicle behavior and stability via the brake control as shown in the figure 9;

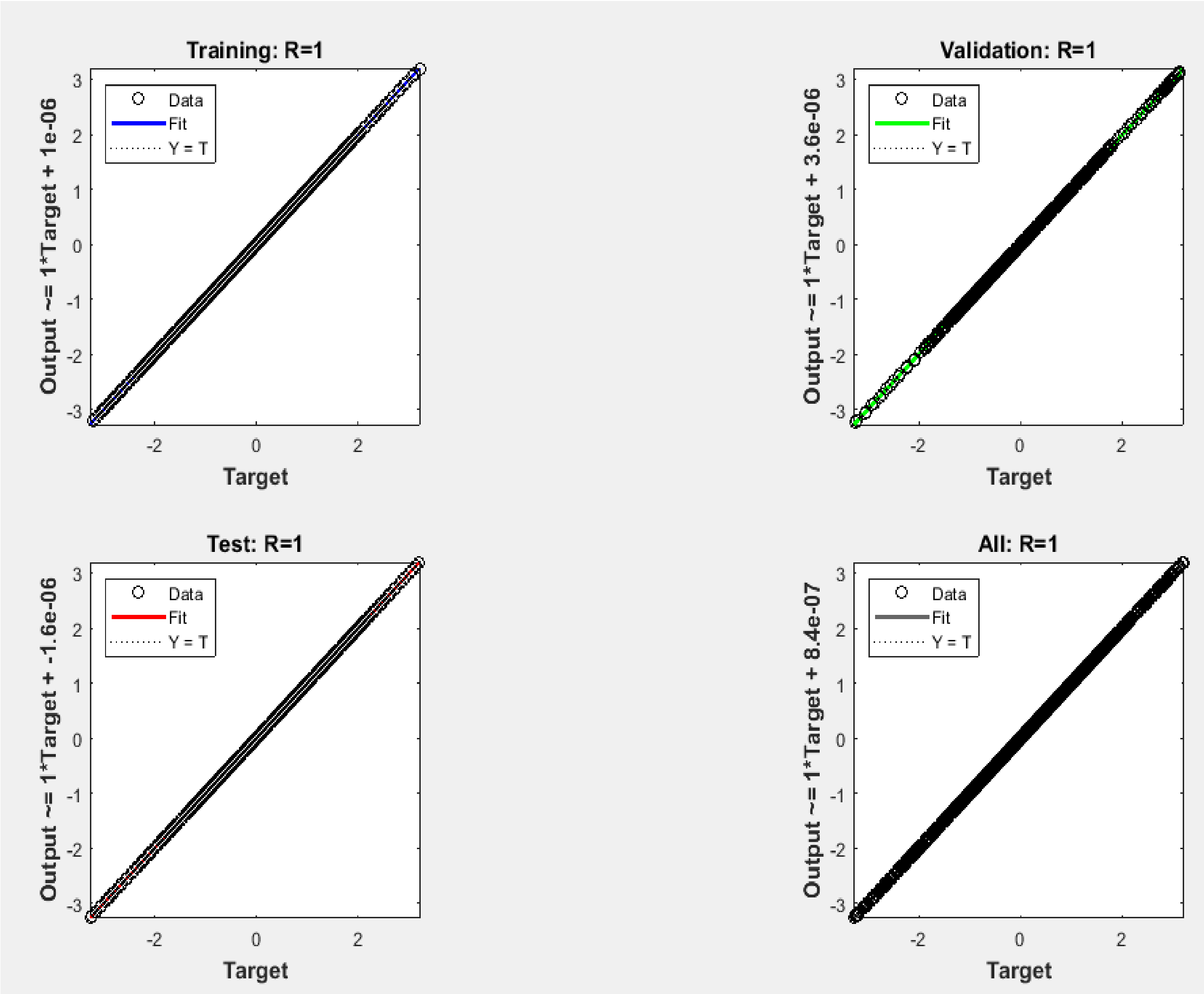


Figure 9: NN regression performance

The figure 9 presented the regression performance of the training process. The result showed that the average regression of the training, test and validation process of the algorithm is 1. This regression implied good training performance as it also showed that over fitting do not occur during the training process. The control response of the algorithm to vehicle dynamics is presented in the figure 10, showing how the controller was able to control the vehicle dynamics to steady state.

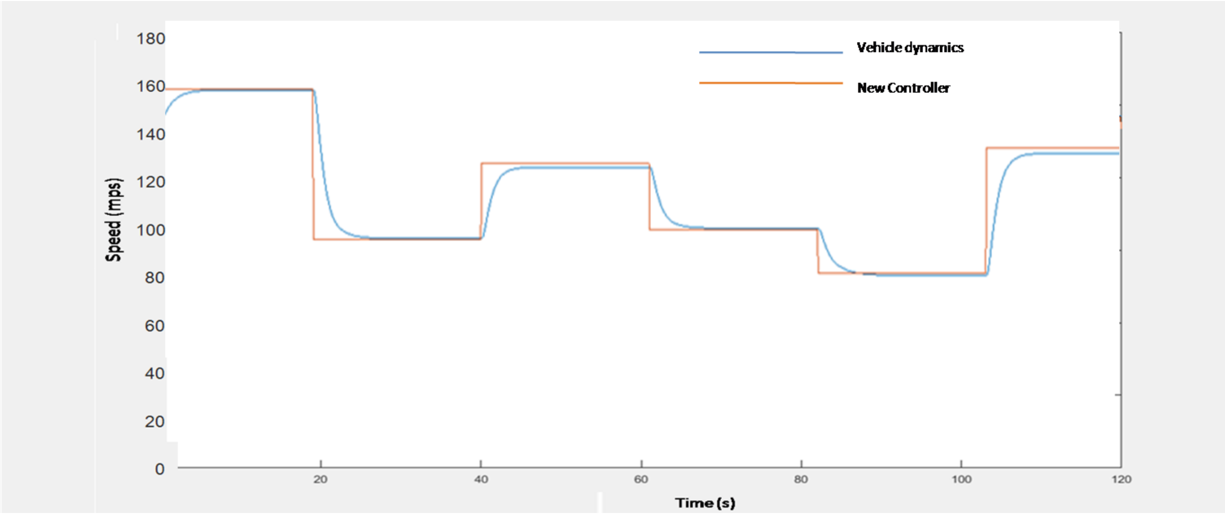


Figure 10: controller performance

From the figure 10 it was observed that the algorithm was able to control the vehicle dynamics to a steady state position based on the reference model originated from the training process. The step response which was used to measure the response time of the algorithm to the system nonlinearity was presented in the figure 11;

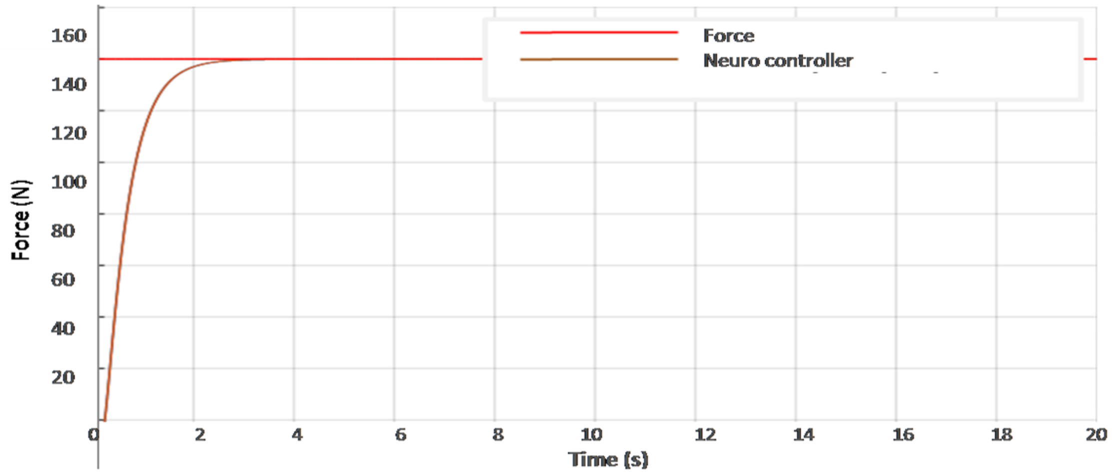


Figure 11: response time of the new system

From the result in the figure 11, the vehicle was controlled by the ABS at 2.25s. This result implied that with the neural network based control system, the vehicle during nonlinear state was stabilized at 2.25s. The brake control system having tested with simulated and discovered a better response performance for the vehicle stability, was integrated on the testbed and evaluated as in table 4;

Table 4: Performance of the new controller on a vehicle

Time (hr)	Vehicle Speed (km/hr)	Control time (s)	Vehicle behavior
1	40	1.80	Speed ok, dynamics ok
2	45	1.87	Speed ok, dynamics ok
3	50	1.89	Speed ok, dynamics ok
4	55	1.95	Speed ok, dynamics ok
5	60	2.02	Speed ok, dynamics ok
6	65	2.08	Speed ok, dynamics ok
7	70	2.12	Speed ok, dynamics ok
8	75	2.19	Speed ok, dynamics ok
9	80	2.22	Speed High , dynamics not ok
10	85	2.29	Speed High , dynamics not ok
11	90	2.34	Speed High , dynamics not ok
12	95	2.52	Speed very High , dynamics not ok
13	96	2.62	Speed very High , dynamics not ok
14	97	2.71	Speed very High , dynamics not ok
15	98	2.79	Speed very High , dynamics not ok
16	99	2.85	Slip very high, dynamics not good
17	99	2.91	Slip very high, dynamics not good
18	100	2.97	Slip very high, dynamics not good
Average		2.45	

The table 4 presented the vehicle behaviors when integrated with the developed neural network based brake control system and tested at varying speed. The result showed that the average response time achieved is 2.45s. The system was then compared with the characterized testbed and the result presented in the table 5;

Table 5: Comparative analysis of the control performance

Time (hr)	Vehicle Speed (km/hr)	ANN time (s)	Fuzzy time (s)
1	40	1.80	3.90
2	45	1.87	3.95
3	50	1.89	4.02
4	55	1.95	4.15
5	60	2.02	4.26
6	65	2.08	4.35
7	70	2.12	4.40
8	75	2.19	4.56
9	80	2.22	4.72
10	85	2.29	4.83
11	90	2.34	5.01
12	95	2.52	5.12
13	96	2.62	5.22
14	97	2.71	5.31
15	98	2.79	5.37
16	99	2.85	5.45

17	99	2.91	5.71
18	100	2.97	5.83

The table 5 presented a comparative performance of the ANN brake control system and the fuzzy based brake control system and the result is presented using graph in figure 12;

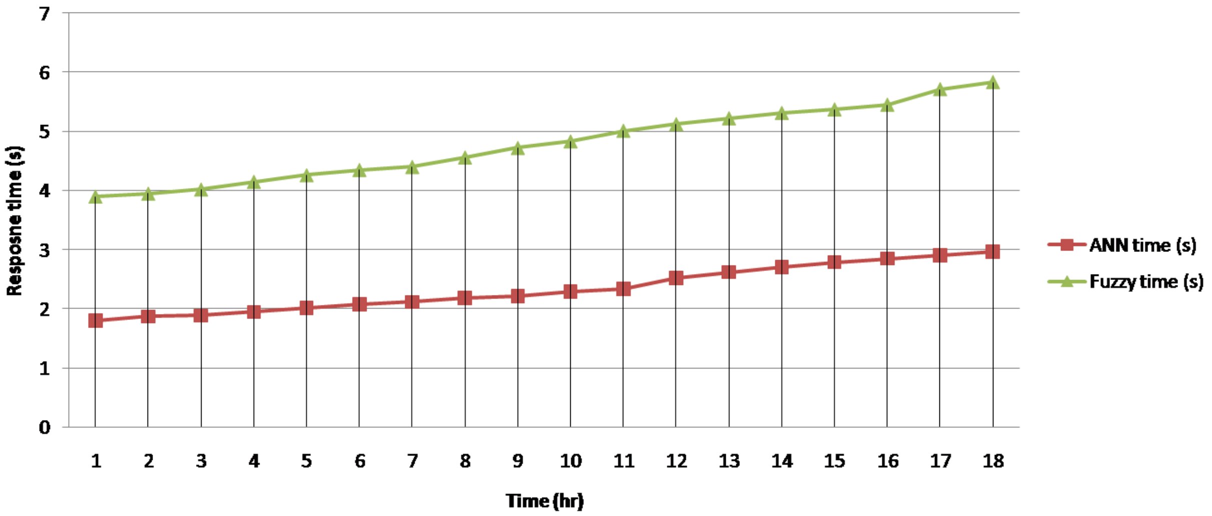


Figure 12: Comparative response performance

The result in figure 12 showed that comparative performance of the characterized fuzzy with an average step response of 4.78s and the neural network control brake response which is 2.45s. The percentage improvement is 48.7% which is very good.

CONTRIBUTION TO KNOWLEDGE

This paper developed an improved intelligent brake control system using artificial neural network.

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