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Towards Distance Induced Automatic Braking System for Vehicular Agents using Neural Network and Proportional Integral Derivative Controller

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Abstract: Human fault and recklessness of drivers especially in developing countries are mainly responsible for numerous road traffic accidents recorded in those countries. Many of these road accidents have led to injuries and loss of lives. Technological advancement has led to the development of autonomous braking system to aid drivers in avoiding collision with another car or obstacle. This has been further advanced with the development of driverless vehicles. In this article, Proportional Integral Derivative (PID) and an Artificial Intelligence (AI) based on Neural Network (NN) model for Automatic Braking System (ABS) is proposed. The inputs to the network are the distance from vehicle to an obstruction and the velocity while the force applied on the brake to bring the vehicle to a halt without hitting the obstruction is the output. The simulation results for the two techniques show that the vehicle was able to stop at a good and acceptable distance before the obstacle and at minimal time. It is therefore reasonable to state that the PID and especially NN based ABS are excellent at providing robust and safe braking and can be implemented to good effect.

Keywords- ABS, Artificial Intelligent, Automation, Driverless vehicle, Neural Network, PID

I. INTRODUCTION

Automatic braking system (ABS) combines sensors and brake control to help high speed vehicle avoid or reduce the impact of collision. Although most are designed to reduce the impact of collision by slowing the speed before it collides with an obstacle. Either avoidance or reduced impact can go long way to save lives and reduce the amount of property damage due to accident. In 2018, World Health Organisation (WHO) reported that over 1.35million death and 50million injuries were recorded from road accidents. Another report ranked road accidents as the eighth primary cause of death and will likely rank fifth in near future [1 - 3]. In Nigeria, 15,090 deaths from 3,075 road accidents were recorded between 2006 and 2014 and the trend seems to be increasing and currently ranked the third most cause of death in Nigeria [4, 5]. United Nations (UN) set a decade (from 2011 to 2020) goal to even out road traffic fatalities [6].

Autonomous and driverless vehicles are gradually being introduced to highway networks. Some autonomous braking systems provide assistance to a driver or takes full responsibility of braking the vehicle without the help of the driver. The ABS relies on sensor which can use laser, radar or video data. The sensor is used to determine if there is an obstacle on the road, what distance they are from the vehicle, their level of mobility and, if the speed is greater than the speed of the vehicle. The nature of the information collected from the sensor triggers the ABS and determines the braking force applied to avoid the collision or reduce the impact [7 - 11].

Braking systems are essential for the safe operation of an automobile. Without the ability to slow and stop vehicles, accidents would occur at every stoplight. The way brakes are built has evolved, but the modern braking system comprises service brakes, parking brakes, and emergency brakes. It is known that different intelligent systems installed in a vehicle can help drivers to avoid or mitigate accidents. The development of the vehicle intelligent systems and accordingly intelligent vehicle safety system is an attempt to move towards a new paradigm, where possibilities for traffic accidents could be drastically reduced or eliminated. These intelligent systems can assist the driver in the driving/braking functions thus preventing accidents [12, 13].

Many road accidents are caused by the drivers' failure to respond on time in a situation that could lead to an accident. The ABS is an advanced auxiliary system capable of avoiding such a situation and in the worst case reduce the impact of collision if avoidance is impossible due to close proximity with the obstacle [14 – 16]. A vehicle with the ability to brake automatically can be improved with an intelligent Neural Network. Recently the Nigeria Federal Road Safety Commission (FRSC) introduced the speed limit with a deadline of October 1, 2016 for commercial buses to reduce accidents on Nigeria roads. The road safety agency has introduced some driving regulations (level of alcohol intake, no call etc) to ensure drivers are not distracted. Generally, the manual method of car brake system without ABS can only brake if the driver pushes the brake pedal.

Therefore, to address this problem, an intelligent and smart autonomous car braking system was developed using Artificial Neutral Networks (ANN) controller and PID. The available NN toolbox in MATLAB was used to develop the system.

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The braking force will depend on the measured distance and speed using an ultrasonic sensor and speedometer respectively. The braking force varies as the distance and speed change once the ABS is activated using the pre-set threshold distance for the system. Finally, a comparative analysis of PID and NN system was carried out.

II. Review of Related Literature

Proposed in [17] is an antilock braking system using an Adaptive Neuro-Fuzzy Inference System (ANFIS). This is a system where the change in output is not in proportionality with changes in the input variables and the ANFIS was able to model the uncertainties in the system. The control system comprised of a Proportional Derivative (PD) controller and an Inverse Reference Model (IRM) of the outcome of the controlled system. The error signal which is a derivative of the difference between the actual and the predicted position of the car is used to adapt the variables of the ANFIS feedback controller. These resulted in a very impressive and intelligent braking system. The use of disengaging attributes in frictional disk brake system developed from the kinematic study of ABS to identify reference braking torque is proposed in [18]. The car actuator modelling an ABS design was described. The Fuzzy Model Reference Learning Control (FMRLC) was applied in [19] to develop ABS. Also studied are the efficiencies of the braking when the car is in transition on a wet and icy road surface. The fuzzy controller to run the hydraulic modulator and thus the brake pressure was proposed in [20]. The performance of the controller and hydraulic modulator were measured by hardware in loop testing and was good.

A novel technique for the design of Sliding Mode Controller (SMC) was proposed in [21]. The optimal value of the wheel slip changes with the change in the vehicle speed. Gray predictor is applied to predict the future output of the system. A static-state feedback control algorithm for automatic braking system control was proposed in [22]. The controller showed robustness against model uncertainties such as tire longitudinal force and road adhesion coefficient has been assured through the approval of a set of linear matrix inequalities. Equally addressed is the robustness of the controller against actuator time delays besides the controller gains tuning method. Further tuning strategies have been given through a general robustness analysis, where especially the design conflict imposed by noise rejection and actuator time delay has been addressed. In [23], a new continuous wheel slip automatic braking system algorithm was developed. The techniques use the estimated reference velocity to track and control the front wheel continuously. The rule control of wheel velocity is reduced to the minimum using the algorithm and improved performance of the braking system. An artificial Neural Network approach proposed in [24] is used to brake vehicles autonomously to prevent skidding due to sharp turns and sudden obstacle detection. The vehicle's stability was improved by distributing brake force to individual wheels in the vehicles.

III. Design Methodology

This model aims to design a NN controller for an automatic braking system that leads to improved vehicle braking response prediction. Detailed explanations of approaches adopted in developing the controllers are explained ranging from data collections to model development.

A. *Car Brake System Modelling*

In this article, the car engine braking dynamics, skidding, slip, road condition and tire friction are disregarded to ease computation and implementation. Therefore, the relationship between the force F and the acceleration using Newton's second law of motion is depicted in Fig.1 and given in equation 1.

$$F = ma \tag{1}$$

The derivative of velocity v' is acceleration a, velocity v is derived from the derivative of distance y'. Hence, acceleration (a) is equals to y''. Thus, a car can be modelled using the differential equation shown in equation 2[12].

$$F = my'' \tag{2}$$

The following constants are used assuming a vehicle of a mass 1500kg is controlled to initiate braking at 25m from an obstacle and at an initial velocity of 10m/s.

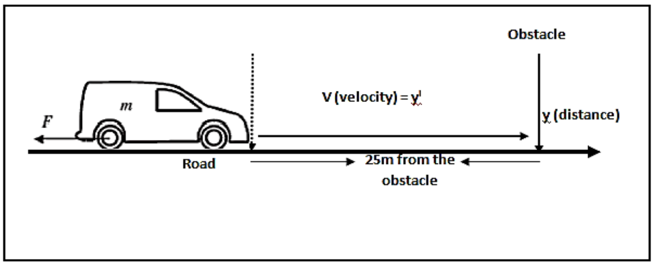

Fig. 1. Model of a car

For the vehicle to stop, the velocity must be brought to zero. Therefore, the force, F is negative or zero which is used to controls the brake actuator. As specified in [12], a vehicle at a velocity of 80km/h (22.22m/s) will take the velocity to zero at a distance of 27.3m. If kinetic energy is the energy to do work, the kinetic energy must be equals to work done.

$$Ke = {}^{1}\!/_{2}\, mv^2 \tag{3}$$

$$W = Fy \tag{4}$$

Therefore;

$$Ke = W, \qquad {}^{1}\!/_{2}\, mv^2 = Fy \tag{5}$$

$$F = \frac{mv^2}{2y} \tag{6}$$

Based on equation 6, it can be assumed that 13600N is the maximum brake force of the automatic brake system and the control signal is limited to -13600N $\leq$ F $\geq$ 0N. Importantly, equation 6 is used to generate the data for the two controllers.

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TABLE I. THE ABS PARAMETERS

Parameters	Value
Mass of the car, m	1500kg
Initial Velocity, v	10m/s
Distance to initiate brake, y	-25m
Braking force, F	13600N

B. *PID controller design model*

The PID controller for ABS is designed in Fig.2 and simulated to observe the performance and compare it with the proposed NN controller. The PID is the most used control algorithm [25]. The summation of the P-term which is proportional to the error, the I-term which is proportional to the integral of the error, and the D-term which is proportional to the derivative of the error result in the control variables. The parameters for the controller are proportional K, integral time Ti, and derivative time Td. These parameters are related with the control variable u(t) and control error e(t) as shown in equation 7

$$u(t) = K\left(e(t) + \frac{1}{T_i}\int_0^t e(\tau)d\tau + T_d\frac{de(t)}{dt}\right) \quad (7)$$

$$e = \lambda_{Ref} - \lambda_P \quad (8)$$

The feedback is to ensure that the process variable is close to the reference point despite the variation and disturbances at the process characteristics. Here the reference point is the velocity of the vehicle which is set at 0m/s. This value as shown in equation 8 is compared with the current velocity at each time sample and the error used to vary the controller variable.

In the proportional controller used for this study, the input to the PID controller is the control error and the output is the control signal. The proportional controller was chosen because the characteristic of the controller is proportional to the control error unlike the on-off controller that over react to any small change in control error [25].

The control variable/signal is the brake force. The proportional controller must be given a limits, say umax and umin of the control signal. The linear range of this limit was specified by giving the slope of the characteristic or by giving the range where the characteristic is linear (proportional band Pb) which is centred on the reference point. The proportional band and the controller gain (K) are related as given in the equation 9

$$u_{max} - u_{min} = KP_b \quad (9)$$

Assuming umax – umin is 100%, it then implies that

$$K = \frac{100}{P_b} \quad (10)$$

The proportional control equation is;

$$u(t) = Ke(t) + u_b \quad (11)$$

From equation 11, the control signal is proportional to the control error plus the bias or reset variable ub. The control signal assumes the bias value when the control error is zero. The bias which is most of the time fixed to the average of the range/limit can sometimes be manually adjusted so that the stationary control error is zero at a given reference point. Therefore, assuming a steady-state with the control signal u0 and a constant error e0, the control signal proportional and integral (PI) controller is given by

$$u_0 = K\left(e_0 + \frac{e_0}{T_i}t\right) \quad (12)$$

$$e_0 \neq 0$$

The derivative action improves the stability of the control loop as a result of the process dynamics which result from a delay in process output from a change in the control variable. A controller with only proportional and derivative action may be seen as proportional to the predicted process output. The equation of a proportional and derivative (PD) controller is

$$u(t) = K\left(e(t) + T_d\frac{de(t)}{dt}\right) \quad (13)$$

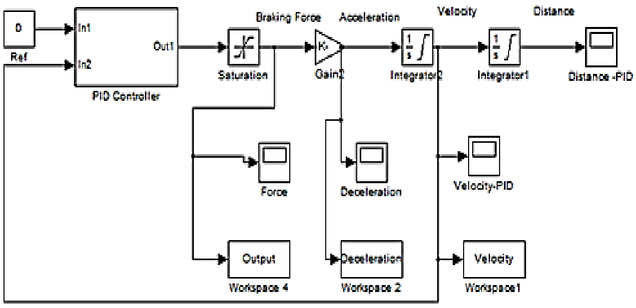

Fig. 2. PID controller for ABS

The PID controller directly worked with the tuning constant parameters such as Ki and Kd instead of using the derivative time constant Td and integral time constant Ti. The used parameter values are shown in Table 2. The parameters Kp , Kd and Ki was estimated optimally so that the closed loop system has to give desired response [26, 27].

TABLE II. PID CONTROLLER PARAMETERS

Controller Parameters	**Value**
Kp	2
Kd	3000
Ki	30

C. *NN Controller Design*

In the ABS system using NN controller, there are two inputs –distance and velocity and one output (brake force) for the system. ANN is a very important technique recently used for automatic breaking system due to its robustness in handling indistinct data and accuracy of estimation. The Multilayered Perceptron (MLP) neural network architecture was adopted for this design because of its ease and ability to predict results correctly. Optimum weights in the network are achieved using Levenberg-Marquardt optimization Algorithm (LMA). The LMA is a backpropagation algorithm chosen instead of resilient (trainrp) or scaled conjugate gradient (trainscg) because of its excellent performance in function approximation problems on small networks with few weights. LMAs were designed for least square problems, achieve convergence faster at minimum means square errors. The network is trained with two features of the ABS, velocity and distance, and predicts a possible force at its output.

The vast potential of NN control is built on a strong mathematical establishment that consists of adaptable and tacit mathematical tools [28]. This is the reason NN is used as one of the key elements in the design of controller for the ABS. In the modeling stage, a neural network to control the ABS was developed. Many research works have proven that ANN provides good function approximation for non-linear function [28, 29].

An MLP neural network of one hidden layer with four neurons was designed. This was trained using data gotten from equation 6, where many distant, velocity and force data were collected. The MPL was trained using the data to correctly predict the amount of force to be exerted by the ABS. Subsequently, the trained network was saved and used for mapping real measured input data (distant and velocity) onto a network output (braking force).

D. Multi-Layer Perceptron (MLP) Network

The input vectors are simultaneously supplied to the NN system in no particular time order. The input and output of the n-th layer of the neurons are defined by equations 14 and 15 respectively [30, 31].

$$a_k = \sum_j w_{jk} y_j + b_k \tag{14}$$

$$y_k = F\left(\sum_j w_{jk} y_j + b_k\right) = F(a_k) \tag{15}$$

In the equation 15, F represents the nonlinear activation function called "sigmoid", wjk are the weights of the links between input nodes (j) and neurons (k) in the next layer (hidden layers h_k), y_j are the input elements and y_k is the neuron's output from the hidden layer.

Though NN abilities have improved since its inception it has the inherent problem of lack of equation that can guide a user in determining the perfect architecture and number of neurons in the hidden layers of the network. As a result, several network architectures and numbers of neurons were tried through training and evaluation, and the 2,4,1 architecture in Fig 3. Two input nodes (because of the two features – velocity and distance) connected via weights to neurons in the hidden layer which were fully connected to a single neuron at the output layer. This structure was found suitable for the problem because it yielded less control error.

LMA optimises the weights and biases of the network by constantly adjusting the weights to reduce the mean square error (MSE) between the desired and the predicted output of the NN by using the matrix equation. The change in weight can be expressed as in equations 16 and 17 [32].

$$\Delta W = (J^T J + \mu I)^{-1} J^T e \tag{16}$$

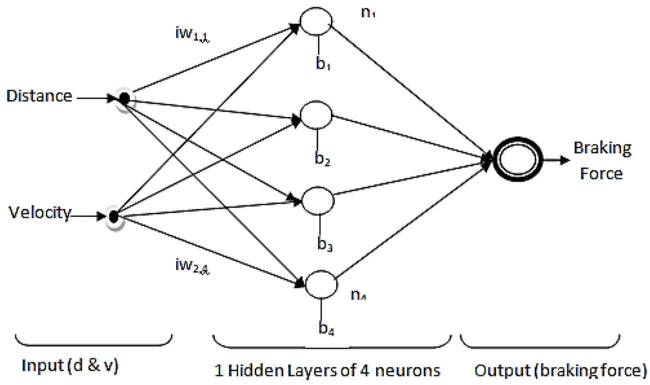

Fig. 3. Multi-Layered Perceptron architecture

$$J = \frac{\partial e_{n,m}}{\partial w_N} = \frac{\partial e_{501,1}}{\partial w_8} \tag{17}$$

Where the parameters, e, μ, W and J represent respectively the error vector, scalar parameter, matrix of networks weights and, Jacobian matrix derived from the error components relating to the network weights. Also where, N is number of hidden weights. In this model a total of 12 weights were used, 2 inputs nodes are connected to 4 neurons in the hidden layer through (2 × 4=8) weights. In the connection between hidden layer and output layer, N is 4(4 × 1) resulting in a total of 8+4 = 12 weights in the network. n is number of input observation (501), and m is the number of output nodes (1). Each value of the weight is updated during back propagation computation as shown in equation 18

$$W_{n+1} = W_n + \Delta W = W_n + (J^T J + \mu I)^{-1} J^T e \tag{18}$$

Where, ΔW is the change in weight, W_n is the previous weight and W_{n+1} is the new weight for the subsequent iteration or the absolute weight of the NN model. The mean square error for each epoch can be calculated as in equation 19.

$$MSE = e = \frac{1}{N}\sum_{k=1}^{N}(t(k) - y(k))^2 \tag{19}$$

Where; MSE is the mean square error, N is the number of output nodes,'t' is the target output and 'y' is the network output. In this model N is 1.

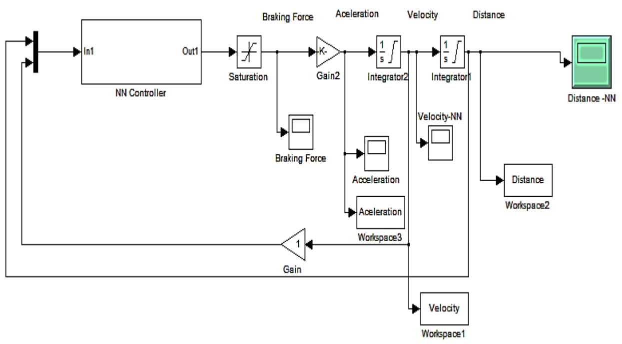

Figure 4. The block diagram of ABS using NN

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IV. Model Simulation and Result Analysis

The simulation and result analysis of the proposed NN controller for ABS using generated data are presented in this section. The main objective was to ensure the car stopped at a distance before the obstacle to avoid a collision. The criteria for performance evaluation include the stopping distance and the time at which the velocity of the car reached zero. Also considered are the braking deceleration, how smooth the velocity of the car is while braking and the performance of the proposed system against the traditional ABS controller using PID technique.

A. *Simulation results for PID controller*

The PID controller was simulated and the following results were obtained as displayed in Figs 5 and 6 for distance and velocity-time graph respectively.

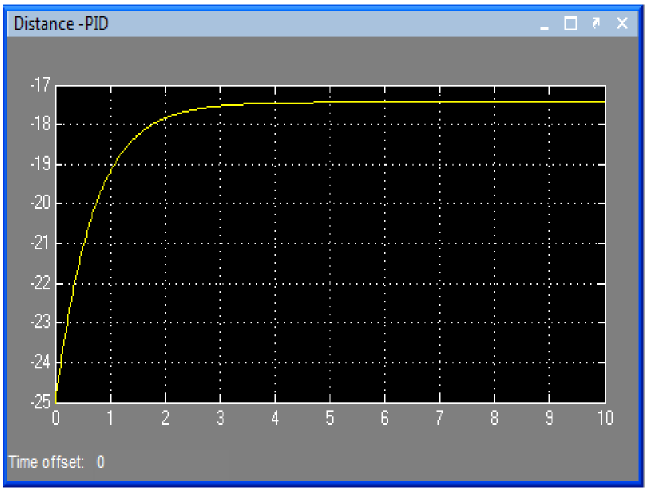

Fig. 5. Distance versus time graph for PID controller

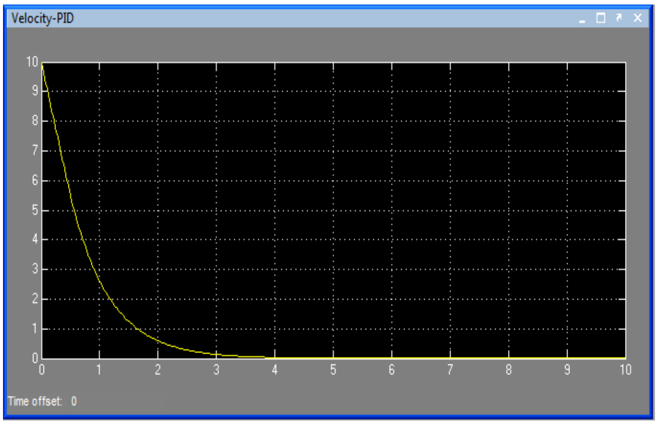

Fig. 6. Velocity versus time graph for PID controller

The well-known PID has been used to improve the performance of the ABS. The simulation results show that the PID controller model is sufficient to predict vehicle braking responses accurately. The developed ABS based on PID achieved a stopping distance of 17.5m from the obstacle as shown in Fig. 5. The results also demonstrate in Figs 5 and 6 that the use of a PID controller brought the velocity to zero at a minimal time of 3.8seconds.

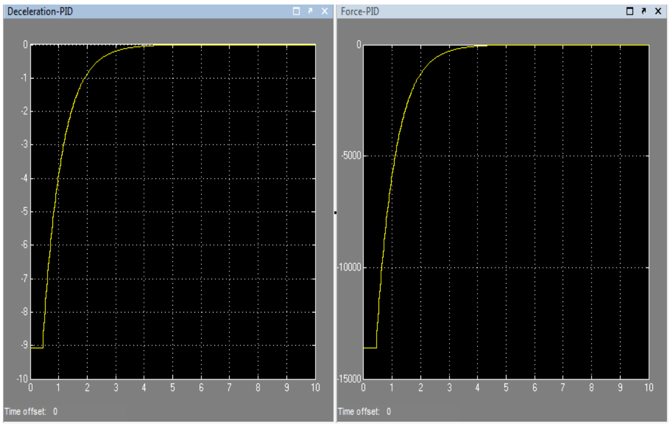

Fig. 7. Braking force & deceleration versus time graph for PID controller.

A look at the Fig. 7 shows that the ABS started to break the vehicle immediately the ABS was initiated with 13600N braking force until 0.5s with the initial deceleration of $9m/s^{2,}$ and the breaking force started to decline gradually along with the deceleration until the vehicle stopped at 3.8s.

The PID controller though is very simple to design it has its limitation. It is not robust enough to be considered good for practical implementation. As result, the neural network is considered best because of its robustness.

B. *Simulation results of NN controller*

ANN as an approximation algorithm was used in this research as MLP networks shown in Fig 3. Five hundred and one (501) sample data were generated from equation 6. The generated dataset (input and desired output) for the network were subdivided in the ratio of 70:15:15 for training, validation and testing respectively. The dataset comprised of three attributes, velocity, distance and force. There were 501 observations of these features used to conduct supervised learning on the MLP network. The Fig 8 shows that the network becomes completely trained after 1000 epoch, when the validation and test error show no significant improvement. This was to prevent any form of overfitting where the network gets to memorize the training data and suffer from poor generalization.

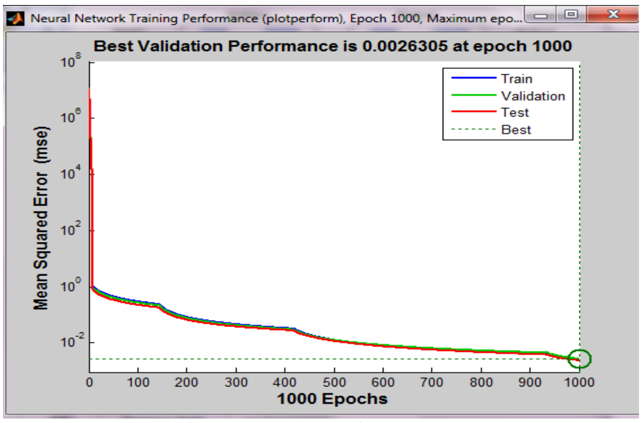

Fig. 8. Performance analysis of the network response

It can be observed from the curve that there are steeper curves between epoch 0 and 410, this means a rapid descent to find the optimum weights by the training algorithm and quick arrival at optimum values and very low MSE. At the beginning of the training session the MSE was large but reduced rapidly as the training advanced which demonstrate the NN learning progress. Also the error of the test set and the validation set has comparable uniqueness and continue to decrease steadily until the 1000th epoch where there is no significant improvement and the training comes to an end to avoid overfitting.

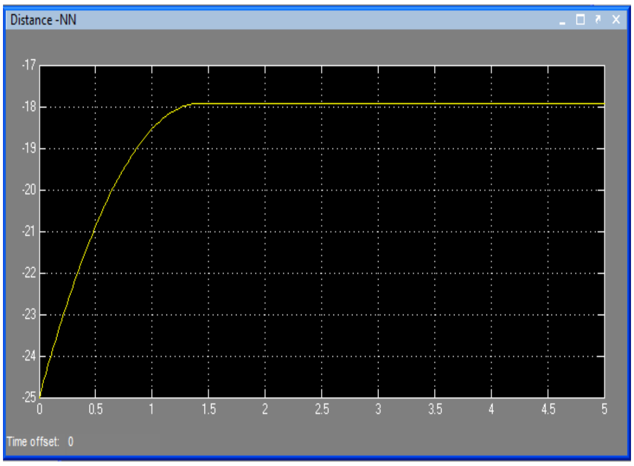

Figure 9. Distance versus time graph for NN controller

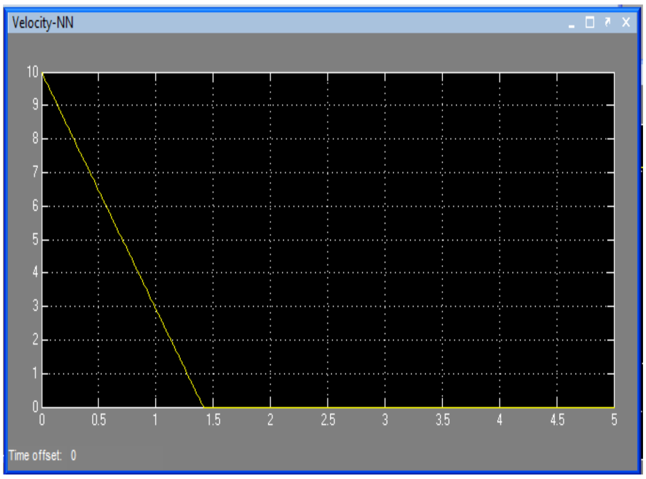

Figure 10. Velocity versus time graph for NN controller

Fig 9 shows that the vehicle began to sense an obstacle at 25m and brakes gradually to stop at roughly less than 18m from the obstacle. Fig 10 also shows the initial velocity of the car when it started braking is 10m/s. The velocity gradually reduced to 0m/s due to the applied brake force on the vehicle, taken only 1.4s and 7m to stop the vehicle. The simulation results show that the system is effective and efficient in stopping the vehicle with a minimal time and a relatively short distance.

C. Comparative analysis of the two models

The statistical parameters for performance evaluation of the proposed model and PID model are shown in Table 3. The NN system proved to be a more efficient system than PID. The result from Table 3 shows that the NN system was able to achieve a higher value of braking deceleration and stopped the vehicle at a shorter distance and faster rate compared to the PID system. Figs 9 and 10 of the simulation results show that the NN curve settled down smoothly and did not experience jerk at high braking conditions as seen in the PID velocity curve. It also stopped at shorter time of 1.4 seconds and compared to PID at 3.8 seconds. Therefore, one can conclude that NN provides a better controller for the automatic braking system.

Table 3. Statistical results for the two models

Parameters	PID Results	NNResults
Stopping time (s)	3.8	1.4
Stopping Distance (m)	17.5	18
Braking Deceleration (m/S^2)	-9	-7.1

V. Conclusions

Bang-bang or PID controller had been the main technique in the electronic control unit of automatic braking system for vehicles. This paper proposed the use of a neural network to design a controller for ABS. The system proved to be more reliable and robust compared to the PID controller. The result shows that the system was able to achieve higher a value of braking deceleration and stopped at a shorter distance compared to the existing system. The neural network controller was able to stop the vehicle faster than the PID. In addition, safety was guaranteed and collision averted due to faster and smooth braking action. Both controllers have shown good performance and are recommended for ABS system.

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