ANN Based Controller for Anti-locking Braking System

Kommabathula Prakash Babu

Abstract*—*Braking has great impact on the stability of a moving vehicle, as it has to dissipate all the energy that has been stored (kinematic energy) through brake pads (in another forms i.e. heat and sound energy). Stability of the system is more likely to flop as it has to transform and deplete the energy in flash of time, leads to loss in control over desired path followed by drift. Slip (μ) is the key factor to measure stability of this system explicitly, which is defined in terms of vehicle speed (Vs) and wheel speed (Ws). Using Artificial Neural Network (ANN) as a tool to control Anti-lock braking system (ABS) to attain optimal brake pressure thereby minimizing the stopping distance, jerk's and ultimately system stability. Validation of result were carried out by using MAT-LAB and compared with Hysteresis controller. Simulated results proved that the system performance is improved.

Index Terms*—*Anti-lock braking system (ABS), Artificial Neural Network (ANN), Slip, Vehicle Stability.

I. INTRODUCTION

Transportation plays a crucial role for development of a nation. Among all road ways play major role for interconnecting [1], [2] as they were more flexible. Since, first accident (1970) [3] safety has been considered as a most important factor in automotives with a motivation "It is more important to able to stop a car than to start it"[4]. Braking system has gone through a long evolution to reach this stage, which not only decelerate the vehicle but also assist the driver in difficult manoeuvres and dangerous situations.

Early brake systems were designed to operate on the rear wheels only, which not only caused serious stability problems under heavy braking but also poor braking efficiency [5]. From late 1934 existing mechanical breaking systems were gradually replaced by hydraulic braking system [4].

First Anti-lock braking (ABS) was designed in the 1950s [6]and in the same year aircraft industry succeeded in developing an experimental system to prevent wheel skidding [7]. Since 1978, cars manufacturer unit start using ABS [8],[9], because of its predominance performance over existing braking system [10], as it adds gravity to the following factors which explicitly measure safety:

i. Stopping Distances (d_s),
ii. Stability, and
iii. Steerable during Braking.

*A. Stopping Distance (ds):*It is function of the mass of the vehicle (m_o), initial velocity (V_o), and braking force(f_b). d_s need to be minimized by applying the affordable f_b.

On every surface, greater (or) lesser there exists a peak in frictional coefficient as function of slip [11]. ABS continuously computes the slip and track's peak frictional coefficient value by optimizing f_b for attain maximum fictional force to minimize d_s.

*B. Stability:*Although decelerating and stopping the vehicle is the fundamental purpose of braking system [12], maximum friction force may not be desirable in all cases. For example if the vehicle is on a road with different friction coefficients, applying maximum braking force on both sides (all tires) will result in a YAW moment (torque develop due to uneven braking forces), ABS has potential to compensate (YAW) and brings the system to equilibrium [13].

*C. Steerable during Braking:*The stability control systems are linked with the ABS,know to be Electronic Stability Program (ESP). Stability control systems apply brake at any wheel to correct over (or) under steer. The control unit receives signals from the typical sensors (yaw, lateral acceleration (G-force) and a steering angle).

The system uses the angle of the steering wheel and the speed of the four wheels to calculate the path chosen by the driver and then compare with lateral G-force and yaw moment to measure where the vehicle is going.

Under steer is the condition in which the vehicle is slow to respond for steering changes and over steering occurs when the rear wheels try to swing causing the car to spin. If the system is under steered brake at the inside rear wheel were applied. During over steered the outside front brake is applied [14] [13].

II. CONTROLLER DESIGN

A. Predictive Control: The model predictive control method is based on the receding horizon technique. The neural network model predicts the plant response over a specified time period. The predictions are used by a numerical optimization program to determine the control signal that minimizes the following performance criterion over the specified horizon.

$$J = \sum_{i=N_1}^{N_2} \left(Y_r(t+j) - Y_m(t+j)\right)^2 + \rho \sum_{i=1}^{N_u} \left(U'Y_r(t+j-1) - U'Y_m(t+j-2)\right)^2$$

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N1, N2, and Nu define the horizons over which the tracking error and the control increments are evaluated, Ú is the tentative control signal, Yr is the desired response, and Ym is the network model response. The value determines the contribution that the sum of the squares of the control increments has on the performance index.

*B. System Identification:*The first stage of model predictive control is to train NN to learn the forward dynamics of the plant. The predicted error between the actual plant output and the NN output is used as a neural network training signal.

Two-layer network with sigmoid transfer functions in hidden layer and the linear transfer functions in output layer are universal approximations. The default transfer function for the hidden layers is tan-sig and for output layers is purelin. In function approximation problems, the Levenberge Marquardt (LM) algorithm will have the fastest convergence and it was chosen for network training. This network will be trained offline in batch mode, using data collected from the operation of the plant.

*C. Neural Network Predictive Controller (NNPC):*The NNPC is neural network toolbox software uses a simulink model of a nonlinear plant to predict the future performance of the plant. The controller then calculates the control input that will optimize plant performance over a specified future time horizon.

Assign N_2= 5, N_u= 2, Control Weight Factor = 0.1, search parameter = 0.2, Minimization Routin = 'csrchgol' and number of iteration per sample = 5 in NNPC. After assigning all the parameters, proceed to plant identification.

Assign size of hidden layer = 5, Sampling interval = 0.1, Number of delayed at plant input and output = 3(as model has 3 integrating elements), training samples =3000(for better understanding of model), Min and Max plant inputs = [-1, 1], Minimum interval value = 0.06667 s (1/15, where 15 is delay included in plant for more practicality in the modal), limit output data [0, 0.2](Expected value of slip 0.2 µ) and then browse plant model.

*2.C.1Generation of Training Data:*The program generates training data by applying a series of random input to the simulink plant model, for given sampling interval. The potential training data is as shown in Fig.1.

Data must be accepted only if plant output is continuously varying (0.0 – 0.24 µ), otherwise reject the data, check the parameters and regenerate the training data. After training the network, response of the plant model is displayed, we can notice that plant output is varying in triangular patterns of identical nature (indicates that the controller was able to control the slip independent of speed and brake time) then parameters will update into NNPC once we click OK button.

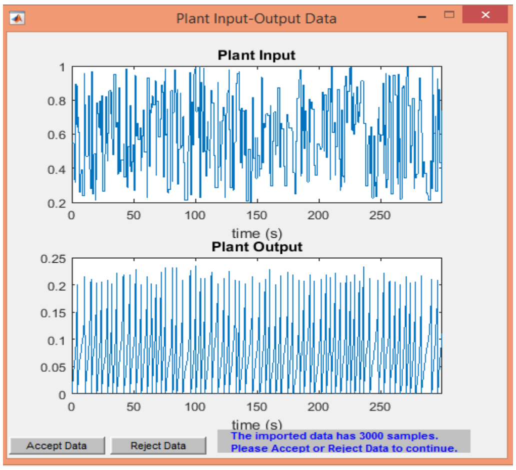

Figure 1: Plant input-output data.

III. RESULTS & DISCUSSION

In this section, computer simulated dynamic responses of proposed NNPC is investigated and compared. The sampling time is 0.1s for all the simulations. All figures shows below are simulation results of quarter vehicle model [15] with initial longitudinal velocity of V_0=100 km.h^{-1} and m = 200 kg (Can be any initial velocity and mass) maneuvering on a straight line (i.e. no steering is applied during brake time). Considering slip as reference with an assumption that friction coefficient is constant throughout the braking.

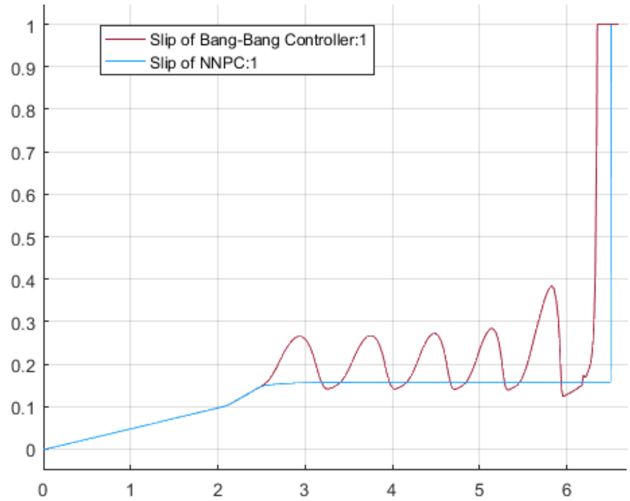

Figure 2: Comparing Slip of Hysteresis Controller and NNPC

From Fig 2, it can be observed that for first 2.451s slip of Hysteresis controller and NNPC valued the same (0.1529 µ), after that Hysteresis controller starts swinging in between 0.14 – 0.24 µ (80% deviation) with frequency ~ 1.4 Hz, whereas in case of NNPC it had never shoots over, which means the probability of system skids is zero.

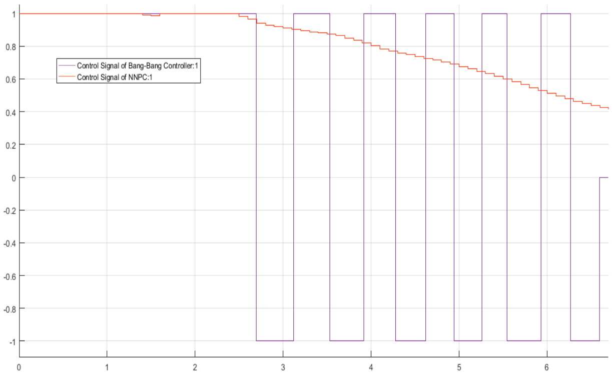

Figure 3: Comparing Control Signal

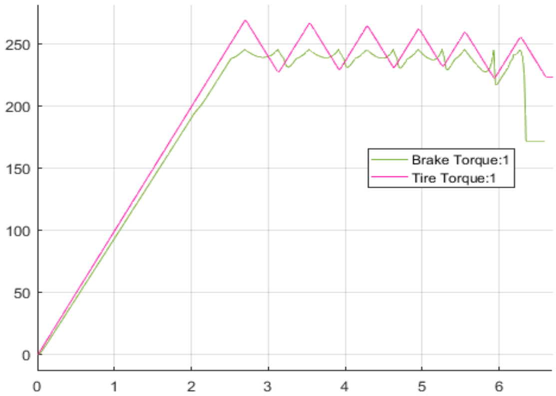

Figure 4: Braking toque and Tire Torque Vs Time of Hysteresis controller.

Fig 3 gives information about controlling signal applied to the braking system. Both controllers are at maximum braking pressure up to 2.451 s, then controlling signal of NNPC start following certain pattern by avoiding sudden change, which not only helps system to maintain maximum friction throughout braking time but also help in improving lifetime of the system, whereas Hysteresis controller keep jumping from one extreme to other, which deteriorate the system (brake life).

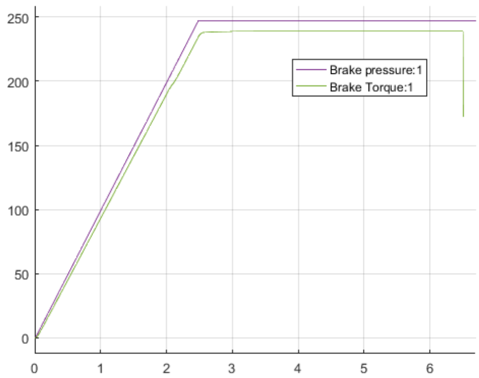

Figure 5: Braking toque and Tire Torque Vs Time of NNPC.

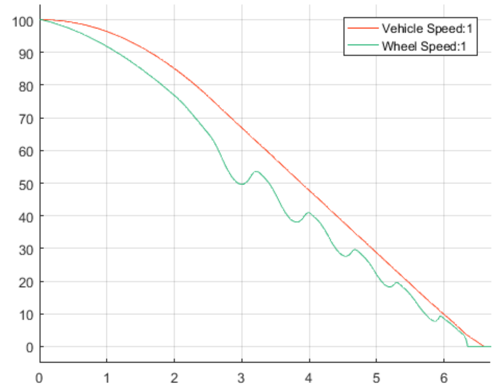

Figure 6: Velocity of vehicle and wheel of Hysteresis controller.

Fig 4 and Fig 5 are plotted by taking Tire Torque (N.m) and Braking Torque (N.m) on Y-axis and time (s) on X-axis of Hysteresis controller and NNPC respectively. From the graphs it can be observed that NNPC maintain consistency with maximum braking torque (245.25 N.m) for a given break pressure, whereas torque of Hysteresis controller varies continuously causing vibrations and inconvenience to the passenger which not only detonates the break life but also increase the risk ofbrake failure.

Fig 6 and Fig 7 are the graphs plotted by taking Vehicle Velocity ($km.h^{-1}$)and Wheel Velocity ($km.h^{-1}$)on Y-axis and Time (s) on X-axis of Hysteresis controller and NNPC respectively. From the observation it can be concluded that NNPC undergoes smooth deceleration at maximum phase with constant rate, whereas Hysteresis controller failed to achieve so.

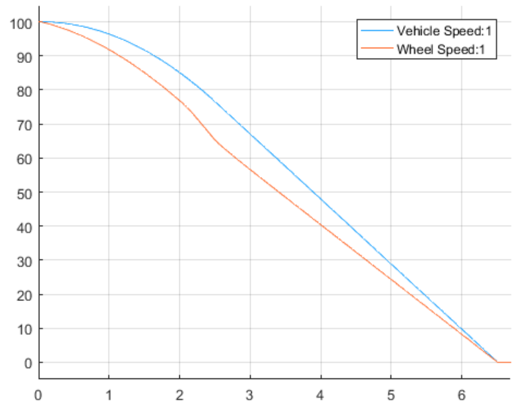

Figure 7: Velocity of vehicle and wheel of NNPC controller.

IV. CONCLUSIONS

ANN based controller is designed for ABS by taking slip as manipulated variable to optimize the controlled variables (stopping distance, deceleration and braking time); For more realistic in the results equipment saturation and non-linearity are included in the simulink model. Obtained results are compared with the existing controller. The proposed controller is smarter in response as it attain maximum deceleration without jerks, which gives better control on the vehicle in panic/emergency braking, which was never achieved by the reference controller. Once NNPC is trained, the same NN can be used for vehicle at any initial velocity and mass which is comparable with reference system.

V. FUTURE SCOPE

This work is under assumption that no steering is applied during brakes, it can be extended to the case where steering can apply. Cementing regenerative braking to the ANN based ABS for maximizing harvested energy. Using smart tires to incorporate influencing factors like varying friction, dynamics in the radius of tire which will make system more practically appreciable [16].

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