Design of an automatic brake control system using artificial neural network

Eneh I.I. and Okafor P.U.
Department of Electrical/Electronic Engineering Enugu State University of Science and Technology Nigeria.

Abstract - An automatic brake control system using artificial neural network was designed to reduce acceleration from a predetermined speed once it detects an obstacle 250m ahead. Two inputs and one output parameters; position, velocity and brake, were designed using Fuzzy logic toolbox, to develop the car brake controller while Simulink based on back propagation training algorithm was used to train the network. After extensive training, the fuzzy controller was replaced by the neural network controller in the drive system simulation.

Keywords: antilock brake system (ABS), brake, fuzzy logic and neural network.

1.0 INTRODUCTION

There is no gainsaying that automobile vehicles would not have made sense without effective and real time response brake system. The effects of road accidents on lives and properties cannot be overemphasized.so any vehicle without an effective brake system is prone to accident and apparently disastrous effect follows. The purpose of automated car braking system is to develop an automated control system that would maintain a safe driving distance from obstacles while driving. This research work proposes a car braking system that will be controlled by the artificial neural networks to curb road accidents and effectively assure safety and stress free driving.

In many road accident cases, a major cause of the accident is the driver distraction and failure to react in time. Advanced system of auxiliary functions has been developed to help avoid such accident and minimize the effects of collision in effect. This was achieved by reducing the total stopping distance through works done by researchers in the past. Lately some of the works were used in many car brake system developments deploying electronic brake control system which has led to significant safety in driving. [1] Applied a predictive approach to design a non- linear model-based controller for the wheel slip. The integral feedback technique is also employed to increase the robustness of the designed controller. Therefore, the control law is developed by minimizing the difference between the predicted and desired responses of the wheel slip and it's integral. Also [2] proposed a static-state feedback control algorithm for anti-lock brake system (ABS) control. The robustness of the controller against model uncertainties such as tire longitudinal force and road adhesion coefficient has been guaranteed through the satisfaction of a set of linear matrix inequalities.

On the other hand, [3] developed a new continuous wheel slip ABS algorithm. In the ABS algorithm, rule-based control of wheel velocity is reduced to the minimum. Rear wheels cycles independently through pressure apply, hold, and dump modes, but the cycling is done by continuous feedback control. While cycling rear wheel speeds, the wheel peak slips that maximize tire-to-road friction are estimated. [4] Described a quarter-vehicle and an ABS in MATLAB-SIMULINK known as the SWIFT-tire model. This has relevance in modeling the tire characteristics and the dynamic behavior on a flat as well as an uneven road. From the performance of ABS with variation of weight, friction coefficient of road, road inclination etc. a self-tuning PID control scheme to overcome these effects via fuzzy GA is developed; with a control objective to minimize stopping distance while keeping slip ratio of the tires within the desired range [5]. An adaptive NN- based controller for ABS. The proposed controller is designed to tackle the drawbacks of feedback linearization controller for ABS has been proposed by [6].

A neuro-fuzzy adaptive control approach for nonlinear system with model uncertainties in antilock braking systems was proposed by [7]. The control scheme consists of PD controller and an inverse reference model of the response of controlled system. Its output is used as an error signal by an online algorithm to update the parameters of a neuro-fuzzy feedback controller. Decoupling feature can be used in frictional disk brake mechanism derived through kinematic analysis of ABS to specify reference braking torque [8]. While [9] illustrated the fuzzy model reference learning control (FMRLC), braking effectiveness when there is transition between icy and wet road surfaces. [10] Have used the fuzzy controller to control the hydraulic modulator and hence the brake pressure. The performance of controller and hydraulic modulator are assessed by the hardware in loop (HIL) experiments.

These studies deployed electronic brake control system and was based on a precise mathematical model of the vehicle. But the fact remains that, the behaviors of the drivers are mostly based on the experience, not the exact mathematical computation. Ordinary cruise control systems for passenger cars are becoming obsolete because of the increasing traffic density rarely makes it possible to drive at a pre-selected speed. However, in order to achieve high customer acceptance, applying artificial neural network to intelligent

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cruise control seems to be an appropriate way to achieve human behavior, because driver's experience can be transformed easily into rules is a way out to curb accident, lost of lives and properties on our roads.

2.0 EXPERIMENTAL DESIGN

In order to design this project, a system modeling is necessary to provide method for the control system. By this, a descriptive model of the system as a hypothesis of how the system could work is built. For both controllers, the car will be modeled according to the Newton's second law of motion, F=ma.

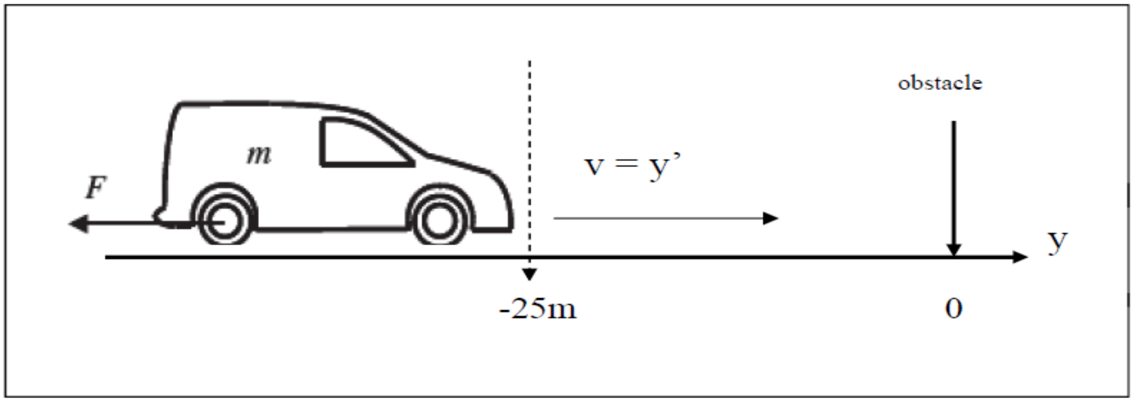

Fig 1: Model of a Car

To model the car, the engine dynamic, skidding, slip and friction of the car is not taken into consideration. Therefore, using Newton's second law of motion, the force F causes acceleration:

$F = ma$ (1)

Acceleration is the derivative of velocity y'. y' is the derivative of the position, y. Thus, a equals to y''. Therefore, the differential equation models the motion of the car as:

$F = my''$ (2)

Assuming the mass of the car is 1500kg, the initial position which the car will be controlled to stop is 250m and the initial velocity is 10ms-1. The following constants were identified:

$m = 1500kg$

$y(0) = -250m$

$y'(0) = 10ms^{-1}$

Considering that once the speed is zero, the car will not move anymore. The variable force, F is thus negative or zero, since the brake is the only means of control.

$v = 80km/h = 22.22ms^{-1}$

$y = 27.3m$

Knowing that kinetic energy is converted to work:

$Ke = ½ mv2$ (3) $W = Fs$

Therefore;

$\frac{1}{2} mv^2 = Fy$ (4)

$\frac{1}{2}(1500kg)(22.22ms^{-1})^2$

$F = \frac{my^2}{2y}$ (5)

$= \frac{(1500kg)(22.22ms^{-1})^2}{2(273)m}$

$= 13600N$

The automatic brake system limits the magnitude of the brake force to 13600N. The control signal is thus subject to the constraints

$-13\,600 \le F \le 0$

3.0 DEVELOPING THE CONTROLLER WITH FUZZY LOGIC TOOLBOX

Fuzzy logic toolbox from MATLAB is used to develop a controller for fuzzy logic using the Fuzzy Inference System (FIS); the FIS editor, membership function editor and rule editor. Meanwhile, rule viewer and surface viewer are used to display the output of the controller designed.

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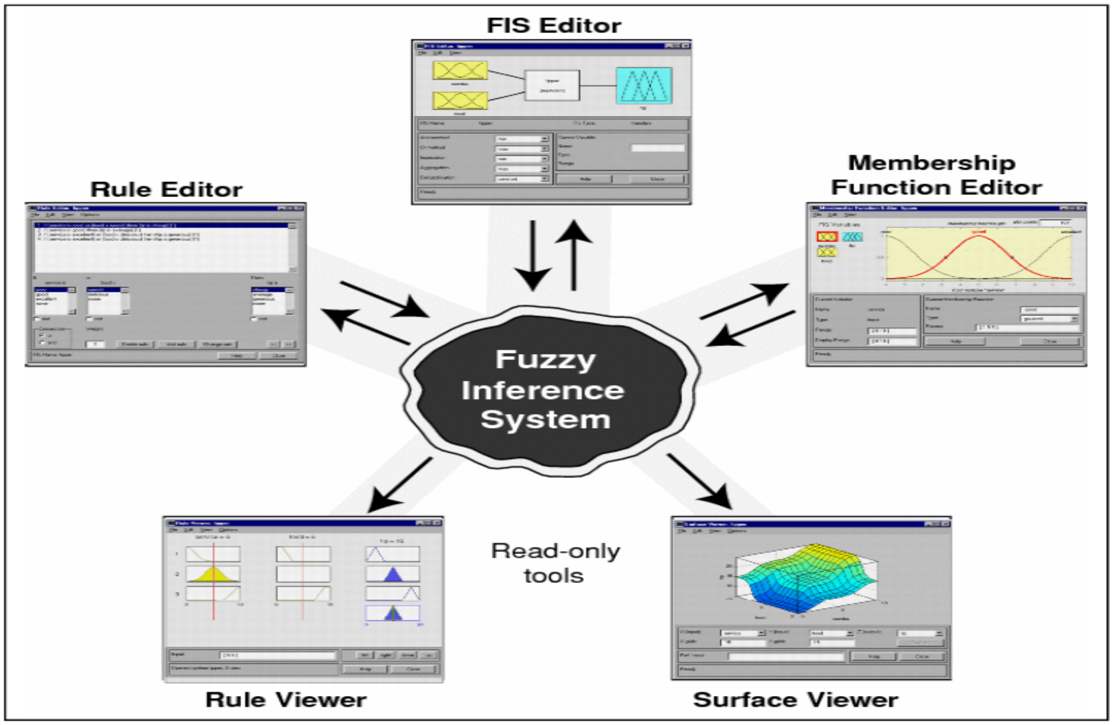

Fig 2: Fuzzy Inference Systems (FIS)

Afterwards, once the controller is complete, it is integrated with MATLAB simulink. This is done to simulate the controller of the car brake towards the car model itself. Thus, the performance of the car brake system is evaluated. Using the fuzzy logic toolbox, the first things to be done is at the FIS Editor shown in figure 3. The FIS Editor handles the high-level issues for the system. It displays general information about a fuzzy inference system.

4.0 SYSTEM PARAMETERS

For the car brake controller design, there are two inputs and one output that are designed through the toolbox. The inputs are position and velocity. The output is the brake. The position represents the distance of the car from the obstacle detected. Velocity is measured from the velocity of the car towards the obstacle and brake represents the force of the car brake needed to stop the car. Defuzzication method used for this controller is mean of maximum (mom) method. In this work, the controller is the first input which is the position that uses two membership functions: I. Short II. Long.

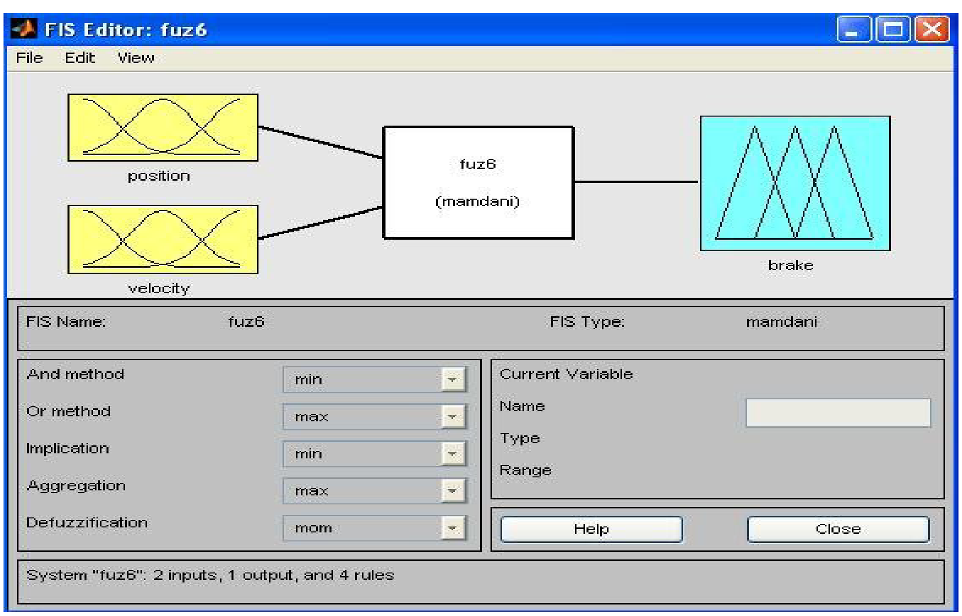

Fig 3: FIS Editor

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Parameters of neural network model - below in table 1, is the artificial neural network model parameters required to serve as an input to the new system.

TABLE 1: PARAMETERS OF NEURAL NETWORK MODEL

Input	ω_m, T_e
Output	f_{op}, V_{op}
Maximum input value	$\omega_{max} = 1$(p.u.) $T_{max} = 1.5$(p.u.)
Minimum input value	$\omega_{min} = 0$(p.u.) $T_{min} = 0$(p.u.)
Maximum output value	$f_{max} = 1$(p.u) $V_{max} = 1$(p.u.)
Minimum output value	$f_{min} = 0$(p.u) $V_{min} = 0$(p.u.)
Functions	Tansigmoidal + Linear
Hidden nodes	8
Number of samples	7104
Epochs	76
Mean square error	$1\text{x}10^{-4}$

5.0 DATA MEASUREMENT TECHNIQUES

The values of Brake are obtained by substituting different values of vehicle position and velocity, into neural network model are given in Table 2 and 3 respectively. The range of the vehicle position is from -250M to 250M.

The table 2 below shows the effect of artificial neural network on the brake considering the vehicle position from the object (obstacle). The data was simulated using the range of -250 to 250 with velocity at a constant of 0.5.

TABLE 2: SIMULATED DATA FROM THE NEURAL NETWORK MODEL.

Vehicle Position	Velocity	Brake
-250	0.5	0.612
-230	0.5	0.612
-210	0.5	0.611
-190	0.5	0.611
-170	0.5	0.61
-150	0.5	0.609
-130	0.5	0.608
-110	0.5	0.606
-100	0.5	0.605
-80	0.5	0.603
-60	0.5	0.601
-40	0.5	0.598
-20	0.5	0.598
0	0.5	0.591
20	0.5	0.587
40	0.5	0.582
60	0.5	0.577
80	0.5	0.572
100	0.5	0.566
120	0.5	0.56
140	0.5	0.554
150	0.5	0.552
170	0.5	0.546

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190	0.5	0.54
210	0.5	0.535
230	0.5	0.529
250	0.5	0.524

Table 3 below shows the effect of artificial neural network on the brake considering the velocity of the vehicle. The data was simulated using the range of 0 to 1 with vehicle position at a constant of 50.

TABLE 3: SIMULATED DATA FROM THE NEURAL NETWORK MODEL

Vehicle Position	Velocity	Brake
50	0	0.532
50	0.1	0.52
50	0.2	0.5
50	0.3	0.5
50	0.4	0.559
50	0.5	0.599
50	0.6	0.559
50	0.7	0.559
50	0.8	0.559
50	0.9	0.559
50	1	0.559

6.0 EXPERIMENTAL RESULT

Considering the two input parameters; the vehicle position and velocity from figures 4 and 5, observation was that the simulated result of vehicle position versus applied brake and vehicle velocity versus applied brake, that vehicle position from the object can determine the amount of pressure that should be applied to decelerate the car to stop. Also it was observed that the velocity of the vehicle can determine the amount of pressure needed to stop the car. Results from the simulation, proved that the artificial neural network model developed helped to control the brake automatically by calculating the vehicle distance from the object and the velocity of the vehicle as well.

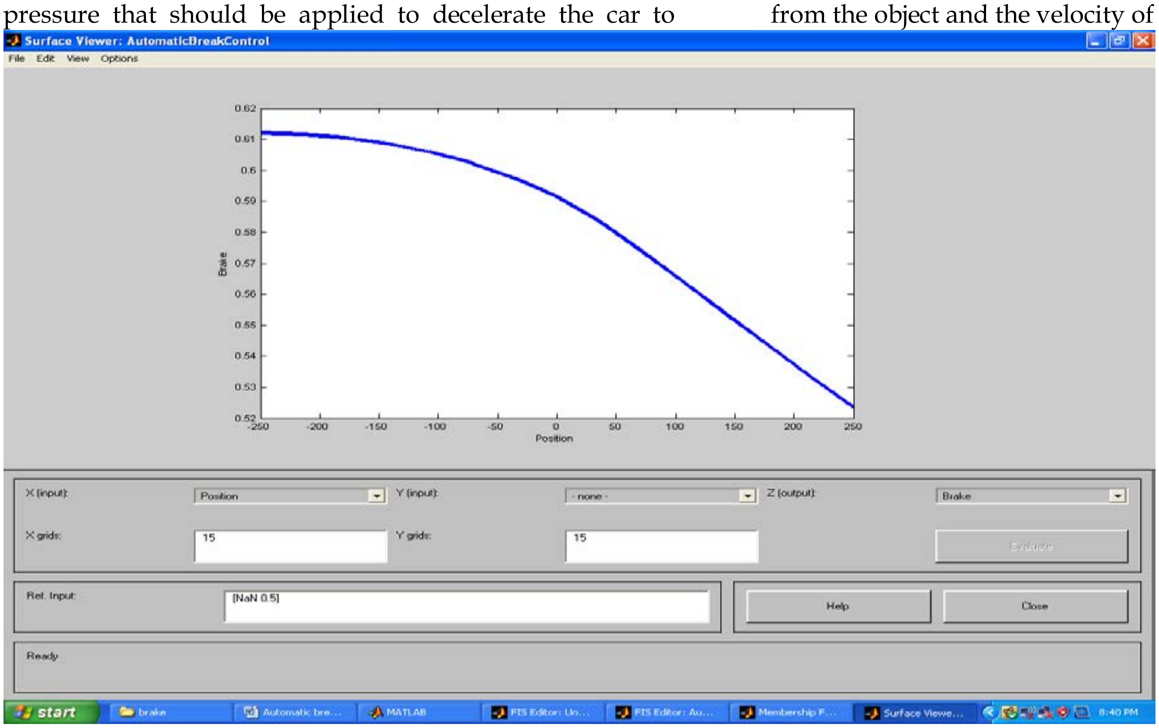

Fig 4: Simulation of vehicle position vs. brake applied

From the graph, it shows that the nearer the vehicle is to the object, the more active the automatic break control system using artificial neural network
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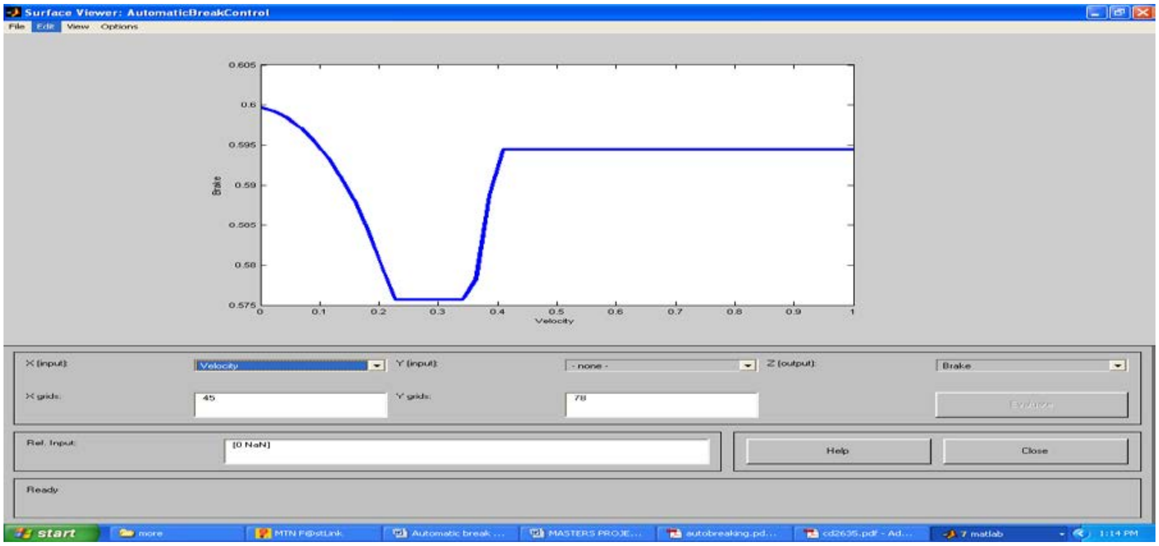

Fig 5: Simulation of vehicle Velocity vs. brake applied

It can be deduced from the graph that when the velocity is between 0.2 and 0.3, the brake is less active but maintains a uniform mode at other points.
Figure 6 below shows a graph of membership function plot for velocity. From the simulation, it is clear that the nearer the car is to the object, the more active the brake is. This is not obtainable in ordinary situation where the break system is not controlled by any model. Also, the velocity of the car affects the brake system as the higher the velocity, the more active positioned, the brake system becomes.

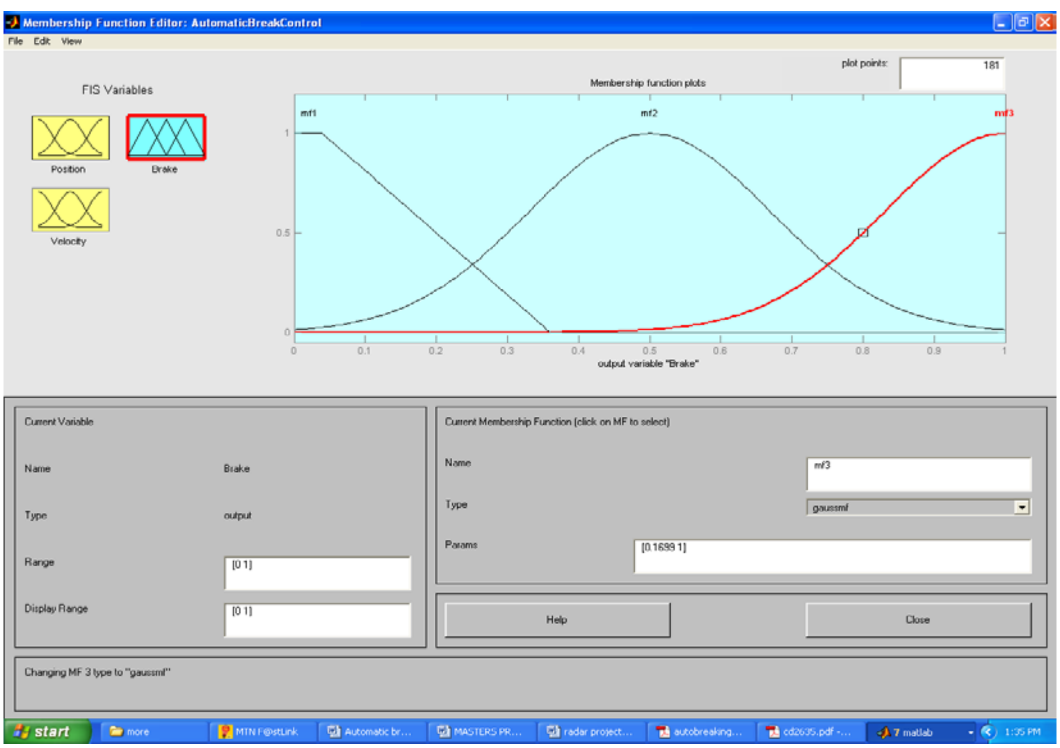

Fig 6: Membership function plot.

7.0 CONCLUSION

During system validation, several simulated data was used to test the system under relative velocities, and initial 250m separation distances conditions, the sensor read the velocity of the object directly in front of it and the position of the vehicle from the object. Validation confirms that the automatic brake control system brought the vehicle at rest within the desired safety. Situations where stopping the vehicle without collision was possible, the system consistently applied sufficient and appropriate brake pressure to stop the vehicle in time. Other cases where an accident was physically unavoidable, the control system still reacted immediately and applied a significant amount of brake pressure, minimizing the vehicle velocity at impact perhaps, reducing the significance of the collision.

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