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Neural Network Based Feedback Linearisation Slip Control of an Anti-Lock Braking System

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***Abstract*— This paper presents the design of a neural network-based feedback linearisation (NARMA-L2) slip controller for an anti-lock braking system (ABS). The dynamics of the electro-mechanical based braking system are incorporated in the ABS model and thus a slip controller is developed to minimise the braking distance. The proposed controller is compared with an optimally-tuned PID controller. Simulation results demonstrate the superiority of the NN-based controller over the generic PID-based controller.**

I. Introduction

Anti-lock Braking Systems (ABS) have been in use in wheeled vehicles for numerous decades with the specific aim of wheels avoiding locking during braking and thereby improve braking performance. As research into reducing braking times and distances under various road conditions has developed, a number of approaches have been suggested, most notably the slip control during deceleration [1], [2]. Slip control primarily allows for the maximising of the braking friction coefficient, hence primarily providing the maximum braking force and achieving minimum braking times and/or distances [3].

A review of the approaches for the design of ABS indicates that the research is easily classified based on the control methodology used [4], [5], braking actuators employed [6], [7], braking conditions handled [2] and inclusion or exclusion of various pertinent modelling simplifications [8] among other criteria. Yet, on the whole slip control is targeted because it enables the handling of the wide range of road conditions, actuators, initial travelling speeds, targeted braking times and distances among other various braking performance criteria.

Optimal control based controllers have been used in the control of ABS. Foremost optimal control theory has been used to prove the need for slip control of ABS and in so doing the enforcing of maximum friction at an optimal value of the slip [9]. In the same work a formal proof is provided for the maximum friction at optimal slip using optimal control theory [9]. Optimal control can very well handle nonlinearities such as the slip and the aerodynamic drag, yet the control law is adversely open loop. An alternative approach that has been taken is to use a feedback control law, typically in state feedback form. This approach has been shown to handle various road terrains modelled as vector random inputs and disturbances and this has been demonstrated to be one of the strengths of linear optimal robust control. Yet the major drawback is the need of linearising the ABS system model. While a linear optimal controller can be designed to be robust, yet the braking road terrains have a number of factors that cannot be easily linearised or handled as disturbance constraints. Further singularities often occur especially for the common linear braking inputs and the optimal solution in such challenging cases is still work in progress.

In [10] a simple yet effective rudimentary gain-scheduling approach is proposed whose controller gains are a function of the initial braking speed, yet the results of this approach are very poor when road surfaces change. In [4] an improvement of this approach is proposed with much better results, however, the model uses linear modelling approaches where a number of key system parameters such as aerodynamic drag are highly nonlinear. Consequently, this approach does not yield superior results especially for high initial speeds and also at very small deceleration speeds. As an improvement on this method in [2], [4], a method is proposed that avoids controller-scheduling as speed changes, by using a combination of linear parameter varying (LPV) methods and linear matrix inequalities (LMI). In so doing admissible robust control is achieved yet the main drawback in this implementation of LPV/LMI methods lies in the critical real-time estimation of longitudinal vehicle speed [2].

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In ABS design three key braking actuating systems are often used namely hydraulic system, electric motor or a combination of these two i.e electro-mechanical systems. The design choice being often influenced by the high attainable braking forces of hydraulic brakes [11] versus their poor speed of response hence inferior control [7]. Electrical brakes are a lot more flexible and can be made to operate much faster yet the braking forces attainable are not as high given the space and volume limitations of braking systems. Electromechanical brakes are therefore generally used to gain both better speed of response and also achieve high braking forces [2], [3].

The intelligent control approach (i.e., neural network (NN) and/or fuzzy logic) to ABS control is an area of intensive research [5], [12], [13], [14]. Hunt et al. [15] conducted a survey focusing on the use of NN for modelling, identification, and control of nonlinear systems. NN have found wide applications in the field of control because of the following reasons: its ability to approximate arbitrary nonlinear mapping, its highly parallel structure allows parallel implementation, thereby making it more fault-tolerant than conventional schemes, its ability to learn and adapt on-line, its good application for multivariable systems. Hagan and Demuth [16] presented a review of various neuro-controller techniques, such as: adaptive inverse controllers, nonlinear internal model controllers, model reference controllers, adaptive critic controllers and stable direct adaptive controllers.

Lin and Hsu [5] developed a hybrid control system (combination of sliding mode control (SMC) and a recurrent neural network (RNN) observer) for ABS. PID control has been applied in various comparative tests mainly because it combines robust control, ease of tuning, very good performance albeit not superior performance [17] [18]. A PID controller is therefore used as a basis to benchmark the neural-network controller performance to show superiority or unsuitability of the neural network based controller for ABS slip control.

In this paper, NARMA-L2 (feedback linearization)-based controller has been proposed for the slip control of an ABS. The novelty of this paper lies in the application of this controller to such systems specifically to significantly improve braking system real-time performance parameters and also reducing the control inputs throughout the braking process. Firstly, the wheel dynamics, braking system and slip curves are modelled after which the slip control methodology is introduced. PID slip control and tuning is then explained along with neural-network based slip controller training and control. Various simulation results are analysed before concluding the paper.

II. Modeling

A. Physical Model

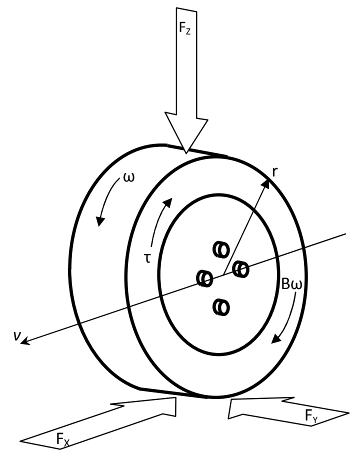

Fig. 1. Quarter car braking model

The quarter car wheel and braking system is shown in Fig. 1. At any point in time the car has a forward longitudinal velocity, $v(t)$, and each of the wheels has an angular velocity, $\omega(t)$. As the brakes are applied each wheel will have a component of the car's total weight F_z exerted on it. It is assumed that the weight is equally distributed on the four wheels of the vehicle. Further it is assumed that all the four wheels contribute equally to the car's total braking force.

B. Mathematical Model

The car while travelling has brakes applied at an initial time $t = t_0$ and comes to a stop at a final time $t = t_f$. As the brakes are applied the car's longitudinal velocity v is initially $v(t_0)$ and at $t = t_f$ it will have come to zero i.e. $v(t_f) = 0$.

Application of Newton's law to the quarter car wheel and braking system shown in Fig.1 gives the governing equations of motion. The vehicle translational dynamics is:

$$M\dot{v} = -\mu(\lambda)F_z - C_x v^2 \tag{1}$$

where M is the car's total mass, μ is the longitudinal friction coefficient, F_z is the total normal force acting on all wheels of the vehicle, and C_x is the vehicle aerodynamic friction coefficient. For slip control as explained later μ is a function of the slip ratio λ as detailed later in Fig.2. The wheel rotational dynamics is:

$$I\dot{\omega} = \mu(\lambda)F_z r - B\omega - \tau_b \quad (2)$$

where I is the moment of inertia of the wheel, r is the wheel radius, B is the wheel bearing friction coefficient, and τ_b is the braking torque. An electro-mechanical set of brakes is used to apply a braking torque, τ_b, on the disk/drum brakes. The electro-mechanical system is modelled as a first order system with time constant τ, with braking gain K_b and controlling braking pressure v_b

$$\dot{\tau_b} = (-\tau_b + K_b v_b)/\tau \quad (3)$$

The normal force, F_z, is given by:

$$F_z = Mg \quad (4)$$

where g is the acceleration due to gravity. By definition the slip ratio λ is:

$$\lambda = \frac{v - r\omega}{v} \quad (5)$$

Typical relationship between μ and λ is given in Fig. 2, which for an asphalt road surface is modelled by the approximate equation [8]:

$$\mu(\lambda) = 2\mu_0 \frac{\lambda_0 \lambda}{\lambda_0^2 + \lambda^2} \quad (6)$$

Different road surfaces are modelled with different μ_0. Since the peak friction coefficient μ_0 is obtained when λ has the value λ_0, i.e. $\mu_0 = \mu(\lambda_0)$ hence the goal of slip control is to maintain the braking slip value always close or equal to its optimal value λ_0.

III. Control Implementation

From Eqs. (1)-(6) we obtain the non-linear state equations.

$$\begin{aligned} \dot{\omega} &= \mu(\lambda)F_z r/I - B\omega/I - \tau_b/I \\ \dot{v} &= -\mu(\lambda)F_z/M - C_x v^2/M \\ \dot{\tau_b} &= (-\tau_b + K_b v_b)/\tau \end{aligned} \quad (7)$$

where the states are $x_1 = \omega$, $x_2 = v$ and $x_3 = \tau_b$, $u = v_b$ is the control input, and $y = \lambda$ is the controlled output. The system model can thus be defined in the state-space form as:

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, u) \quad \mathbf{y} = \mathbf{g}(\mathbf{x}) \quad (8)$$

A. Slip Control

The primary qualitative objective of the slip controller is to bring a car travelling with an initial speed v_0 down to stop in a shortest possible while using admissible control ($v_{b_{min}} \leq v_b \leq v_{b_{max}}$). In doing so the slip value should rise to its optimum value of 0.9 as fast as possible and maintain this value through the deceleration process with minimal deviation from the set reference value

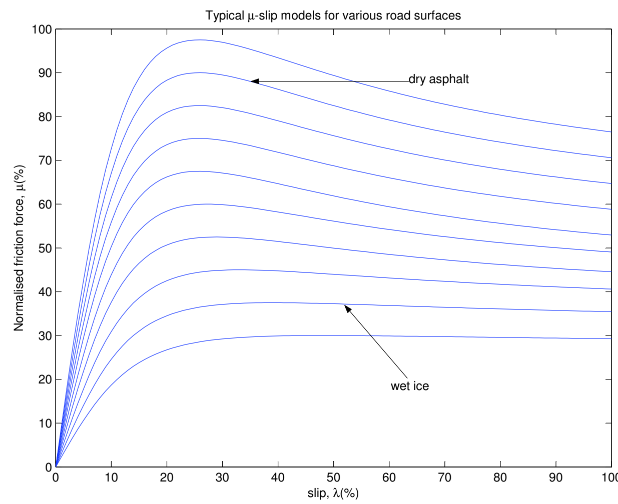

Fig. 2. Typical tire longitudinal friction μ-λ curves

of 0.9 until the car stops. The braking system should also use admissible braking forces, i.e. have limited control input through the braking process including initial transient response, steady state control and at the end-point of the braking process.

Fig. 3 shows the comparison results for locked wheel braking and ideal slip control. The ideal slip control is obtained by assuming an ideal actuator with zero time delays in its response. A similar actuator is also assumed for the locked wheel braking case. As can be observed from these results optimal braking gives far better results of about half the braking time and half the braking distance.

For this quarter car model [3] the maximum braking pressure is $1800Pa$ while the optimal slip value as obtained from the dry-asphalt graph on Fig.2 is $\lambda_0 = 0.25$ with $\mu_0 = 0.9$. The ideal braking time and distance is to be identified and used as a basis for evaluating the various controller performances.

B. PID Control and Tuning

The structure of the PID controller is given as [20]:

$$U(s) = \left(K_P \frac{1 + T_D s}{1 + \alpha T_D s} \frac{1 + T_I s}{T_I s} \right) E(s) \quad (9)$$

where $E(s) = Y_{ref}(s) - Y(s)$ is the error signal between the reference signal $Y_{ref}(s)$ and the actual output signal $Y(s)$, $U(s)$ is the plant input signal, K_P is the proportional gain, T_D is the derivative time constant,

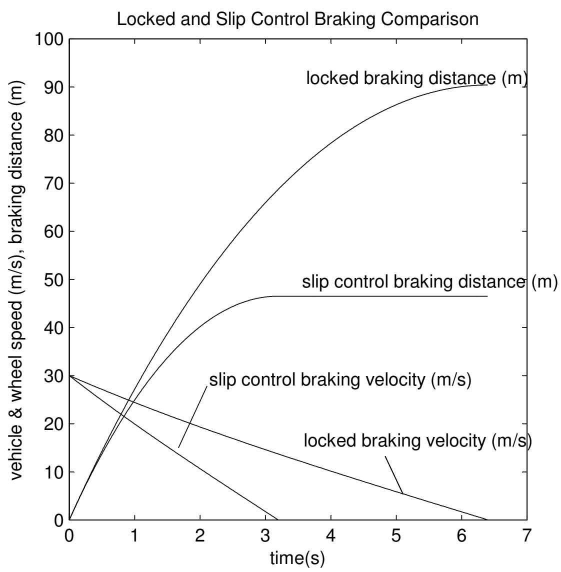

Fig. 3. locked and slip control braking for ABS.

T_I is the integral time constant and α is the lag factor in the derivative component of the PID controller. Ziegler-Nichols tuning rule is used with a 0.25 decay ratio to obtain the PID controller gains and fine tuning is achieved by ensuring that reasonable control inputs are generated. This is because typically PID controllers can easily generate too high control inputs which would lead to saturation.

C. Neural Network Based Control

Two steps are generally involved in most neural networks architectures used for control: system identification and control design.

The ABS plant is first identified from a set of input-output data pairs collected from a numerical experiment. There are four steps in the identification process namely: Experimentation, Model Structure Selection, Model Estimation, and Model Validation.

A non-saturating random input spanning the entire operating range of the ABS system is used in the model simulations to generate the experimental data. Results of the ABS model (Eqs. (7) or Eqs.(8)) simulations are collected in the form:

$$Z^N = f\left\{[u(k), y(k)]\,; k = 1, \ldots, N\right\} \tag{10}$$

where $u(k)$ is the system input, $y(k)$ is the system output, k is the sampling instant number, and N is the total number of samples. We chose the sampling time in accordance with the fastest dynamic of the system.

The Nonlinear Autoregressive Moving Average (NARMA) model is used to represent the ABS system after experimentation [21] and [23]:

$$\begin{aligned} y(k+d) \;\; = \;\; & F\,[y(k), y(k-1), \ldots, y(k-na+1), \\ & u(k), u(k-1), \ldots, u(k-nb+1)] \end{aligned} \tag{11}$$

where F is a nonlinear function, na is the number of past outputs, nb is the number of past inputs, and d is the system delay. The network is trained during identification to approximate the nonlinear function F. In principle the NARMA-L2 controller transforms nonlinear system dynamics into linear dynamics, by cancelling the nonlinearities. The choice of feedback linearization for the neurocontroller imposes the following model structure (companion) form [22] and [23]:

$$\begin{aligned} y(k+d) \;\; = \;\; & f\,[y(k), y(k-1), \ldots, y(k-na+1), \\ & u(k), u(k-1), \ldots, u(k-nb+1)] \\ & +g\,[y(k), y(k-1), \ldots, y(k-na+1), \\ & u(k), u(k-1), \ldots, u(k-nb+1)]\,u(k) \end{aligned} \tag{12}$$

where f and g are two nonlinear functions and the next controller input $u(k)$ is not contained in the nonlinearity. Two separate MLP neural networks are trained offline to approximate the nonlinear functions $f[\cdot]$ and $g[\cdot]$ in the NARMA-L2 neural controller.

The following identical specifications were used for both NN: the number of hidden layers - one, the number of neurons in the hidden layer - 5, the activation functions - tangent hyperbolic for the neurons in the hidden layer and linear in the output layer, training algorithm - Levenberg-Marquandt (due to its rapid convergence properties and robustness), the model order - number of past output, na = 2, number of past input, nb = 2, and the time lag, d = 1, the sampling time - Ts = 0.01, and the total number of sample - 320.

NARMA-L2 controller which has the form:

$$\begin{aligned} u(k) \;\; = \;\; & \{y_r(k+d) - f\,[y(k), \ldots, y(k-n+1), \\ & u(k-1), u(k-1), \ldots, u(k-n+1)]\} \\ & \times g\,[y(k), \ldots, y(k-n+1), u(k-1), \\ & \ldots, u(k-n+1)]^{-1} \end{aligned} \tag{13}$$

is more efficient than the exact cancellation of the nonlinearities. The model order is $n = na = nb = 2$. Using Eq. (13) directly can cause realization problems, because one must determine the control input $u(k)$ based on the output at the same time, $y(k)$. So, instead, we used the model:

$$
\begin{aligned}
y(k+d) &= f\left[y(k), y(k-1), \ldots, y(k-n+1),\right. \\
&\quad \left. u(k), u(k-1), \ldots, u(k-n+1)\right] \\
&\quad + g\left[y(k), y(k-1), \ldots, y(k-n+1),\right. \\
&\quad u(k), \ldots, u(k-1), \\
&\quad \left. u(k-n+1)\right] u(k+1) \qquad (14)
\end{aligned}
$$

where $d \geq 2$. Rearranging the neural network plant model [22] and [23] gives the controller simply as:

$$
\begin{aligned}
u(k+1) &= \{y_r(k+d) - f\left[y(k), \ldots, y(k-n+1),\right. \\
&\quad \left. u(k), \ldots, u(k-n+1)\right]\} \times g\left[y(k), \ldots,\right. \\
&\quad y(k-n+1), u(k), \ldots, \\
&\quad \left. u(k-n+1)\right]^{-1} \qquad (15)
\end{aligned}
$$

The block diagram of the NARMAL2 controller is shown in Fig. 4.

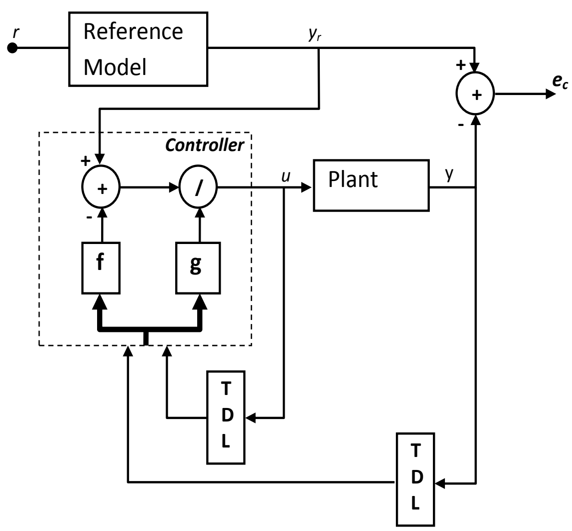

Fig. 4. NARMA-L2 (Feedback Linearisation) Controller

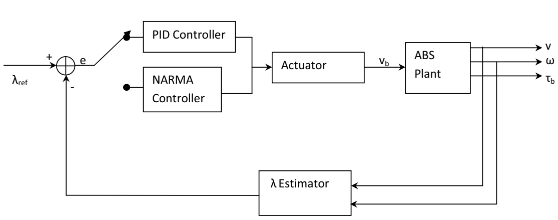

Fig. 5. NARMA and PID Feedback System

TABLE I

PARAMETERS OF THE QUARTER-CAR MODEL USED FOR SIMULATION.

Parameters	Parameters	Parameters
B = 0.08 kgm^2/s	C_x = 0.856 kg/m	I = 1.6 kgm^2
K_b = 0.8	M = 440 kg	r = 0.3 m
τ = 0.003 s	μ_0 = 0.9	λ_0 = 0.25
K_P = 1	T_D = 8 s	α = 0.1
T_I = 14.9 s	$v_{b_{min}}$ = 0 Pa	$v_{b_{max}}$ = 1800 Pa

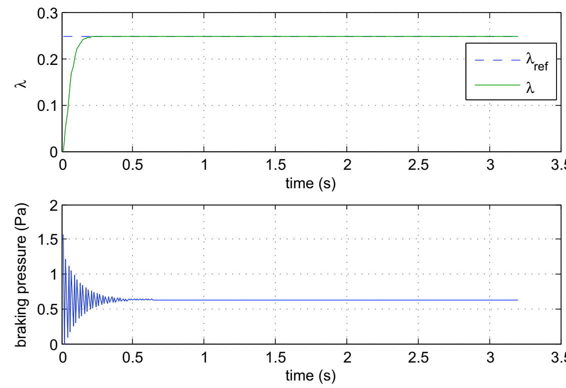

Fig. 6. Time response of NARMA-L2 controlled ABS.

IV. RESULTS AND DISCUSSION

The parameters used in the simulation tests are given in Table I. Fig.6 presents the ABS model output constrained by the neurocontroller to follow the desired reference slip ratio. It can be seen from Figs. 6 and 7 that the slip rises from zero to its optimal value of 0.2 and is maintained at this value through out the duration of the braking period. Hence, both NARMA-L2 and PID controllers are good candidates for slip control. The main goal of maintaining the slip at its optimal value albeit with a small initial error while the slip rises to its optimal value of 0.2 is achieved. Both controllers consequently have μ time responses that quickly rise to the optimal value of 0.9 and maintain this μ value constant while braking.

The vehicle translational dynamics Eq. (1) shows that if μ is maintained at its optimal value of 0.9, then Eq. (1) models velocity reducing from its initial value of 30 ms^{-1} and influenced only by the constant parameters F_z, M and C_x. Therefore, this gives the ideal braking profile with a braking time of 3.2 s as shown in Fig.8. Hence, the goal of the controllers is to reduce the linearised wheel angular velocity ω from its initial value of 100 rad/s toward 0 rad/s such that a slip value of 0.25 is maintained giving a μ value of 0.9.

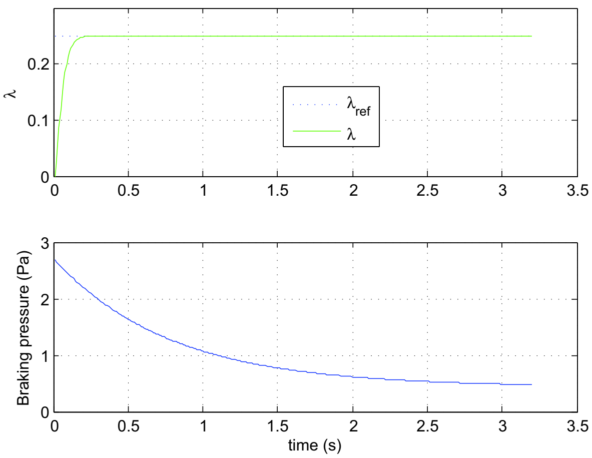

Fig. 7. Time response of PID controlled ABS.

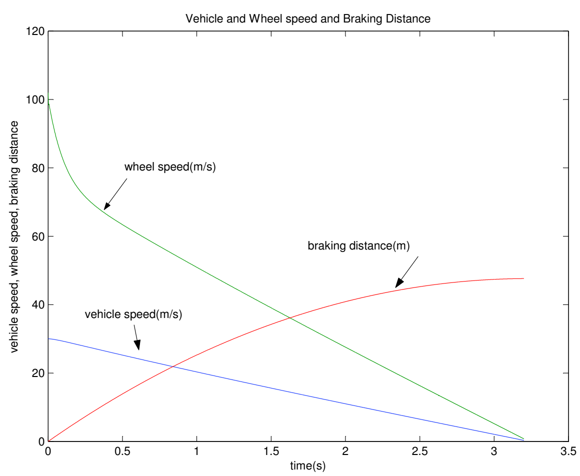

Fig. 8. Time response of braking speeds and distance.

Both controllers brought the car almost to rest in 3.2 s (from initial velocity of 30 ms^{-1} to final velocity of 0.3 ms^{-1}. It is customary to stop the ABS when very low speeds have been achieved; as ABS is not normally applied until the car stops. It is acceptable to apply ABS braking up to about 0.5 ms^{-1}. This is because the controller gains for very low speeds normally increase to extremely high values, but given that the car will have come to almost rest this is acceptable behaviour and the wheels are normally allowed to lock and bring the car to rest.

The main difference in the performance is therefore not in the μ and λ responses as these are equally optimally achieved, but in the control input required to achieve the control of the ω that maintains the optimal slip values. But there is a marked difference in the control input (braking pressure) for the NARMA-L2 controller (Fig. 6) and the PID controller (Fig. 7). The NARMA-L2 controller achieved the same reference slip tracking as the PID controller but with much less control effort, braking pressure. The NARMA-L2 controller requires a braking pressure that rises to a peak of about 1.5 Pa and quickly settles down to a very small value of about 0.65 Pa. On the other hand, the PID controller generates an almost double peak braking pressure of about 2.8 Pa slowly decaying to a steady value of about 0.5 Pa. The PID controller peak value is much higher so are the general PID controller braking pressures compared to the NARMA-L2 controllers braking pressures. Thus, the NARMA-L2 based slip controller implementation for the ABS produced more superior results.

V. Conclusion

The paper has presented a versatile and effective NARMA-L2-based slip controller for an ABS. This is illustrated by considering the commonly used quarter-car model of the wheel and a minimum braking distance objective (i. e., maximum longitudinal friction coefficient obtainable at optimal slip ratio, $\mu_{max} = f(\lambda_0)$).

NARMA-L2 is characterized by simple and realistic implementation capability to solve complex ABS control problems; low memory and computation time requirements; high flexibility and generally valid for all classes of ABS models. The minimum braking distance objective is attained with high precision without violating the constraints on the control input. Performance comparison of the proposed control approach with a PID controller demonstrates the superiority of the former over the latter. It has been found that NARMA-L2 controller is able to regulate the slip ratio without saturating the actuator. The ABS model and/or the control objectives can be changed to adequately describe different road surface conditions; the NN control will learn to model and control this new situation.

Ongoing future work includes comparison of NARMA-L2 with other NN control architectures such as MPC (model predictive control) and MRC (model reference control); and also the inclusion of actuator dynamics and effects of suspension systems in the ABS mathematical model. It is also intended in the future to design and construct a test rig for experimental validation. This will involve real-time implementation issues for actual ABS sensors and control actuator.

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