Journal of Engg. Research **Vol. 3 No. (2) June 2015** pp. 79-94

ضبط المتحكمة خوارزمية لنقاط التوازن الغير واضحة والمستخدمة في نظام المكابح المانعة للانغلاق

***أ. مانيفاناه و** أ. أبوضاهر**

*قسم الهندسة الكهربائية والالكترونيات، كلية الهندسة والتكنولوجيا، تإرونلويلي، الهند

**قسم الإلكترونيات والأجهزة الهندسة، كلية الهندسة الوطنية، كوفيلباتا، الهند

الخلاصـة

أنظمة الكوابح المانعة للانغلاق (ABSs) وحدات تحكم الفرامل تهدف إلى الحفاظ على انزلاق العجلات في المستوى المطلوب خلال الكبح والتسارع. وحيث كون العوامل المسببة للانزلاق العجلات معرضة لتغييرمثل طبيعة سطح الطريق وكتلة المركبة، كانت مهمة السيطرة عليها صعبة. وفي هذا البحث، وحدة تحكم المعدلة (PID) وتسمى المتحكمة لنقاط التوازن (SPWPID) (PID) تم تصميمها للسيطرة على انزلاق العجلات. أولا، تم تطويرالخوارزميات الجينية (GA) القائمة على نظام الاستدلال الغير واضح (GAFSPWPID) لتحديد قيمة الوزن الذي يضاعف لمجموعة نقطة العمل النسبي. وعلى أساس الخطأ في الانتاج الحالي ومشتقاته، فهو يجعل تحكم أكثر تكيفا للاضطرابات الخارجية. ومن ثم، تم استبدال (GA) بخوارزمية (FA) وتم أتخاذ طريقة تقليل خطأ التكامل المربع (ISE) كهدف للحالتين. والطريقة المقترحة للخوارزمية (FAFSPWPID) (PID) تم مقارنتها مع المتحكم (SPWPID) وأيضا (GAFSPWPID)، وتم تقييم أداء تحكم المقترحة لشروط ابتدائية مختلفة وكما تم إجراء المقارنة مع وحدات تحكم المنشورة في وقت سابق. وتبين نتائج المحاكاة أن كفائة تحكم المقترح (FAFSPWPID) أفضل من نظام التتبع لمجموعة نقطة ومتكيف للاضطرابات الخارجية ومن وحدات التحكم الأخرى.

Firefly algorithm tuned fuzzy set-point weighted PID controller for antilock braking systems

A. Manivanna Boopathi* and A. Abudhahir**

**Department Electrical & Electronics Engineering, PSN College of Engineering & Technology, Tirunelveli, India*

***Department of Electronics & Instrumentation Engineering, National Engineering College, Kovilpatti, India*

**Corresponding Author: arumugamboopathy@gmail.com*

ABSTRACT

Antilock Braking Systems (ABSs) are brake controllers designed to maintain the wheel slip in desired level during braking and acceleration. Since the factors causing the wheel slip to change such as nature of road surface, vehicle mass etc are highly uncertain, the task of controlling has been a challenging one. In this paper, a modified PID controller called Set-Point Weighted PID (SPWPID) Controller has been designed to control the wheel slip. First, a Genetic Algorithm (GA) based fuzzy inference system (GAFSPWPID) is developed to determine the value of the weight that multiplies the set-point for the proportional action, based on the current output error and its derivative. It makes the controller more adaptive to external disturbances. Then, the GA is replaced by Firefly Algorithm (FA). Minimization of Integral Square Error (ISE) has been taken as objective for both cases. The performance of proposed Firefly Algorithm tuned Fuzzy Set-Point Weighted PID (FAFSPWPID) Controller is compared with SPWPID and GAFSPWPID controllers. Also, the performance of proposed controller is assessed for different initial conditions. A comparison has also been made with the controllers presented earlier in literature. Simulation results show that the proposed FAFSPWPID Controller performs better in both set-point tracking and adaptive to external disturbances than the other controllers.

Keywords: Antilock brake system; firefly algorithm; fuzzy logic; PID controller; wheel slip control.

INTRODUCTION

Antilock Braking Systems (ABSs) are primarily designed to maintain the wheel slip at an optimum value at which there will be no wheel skidding and good steerabililty during sudden braking. The system of ABS control is nonlinear because of the nonlinear nature of brake dynamics and uncertain parameters such as road surface, weight of the vehicle, tire pressure, etc and hence it is not possible to develop an accurate model of ABS. Therefore, intelligent controllers should be developed to deal with all these uncertainties. Many control strategies such as Sliding mode control (Harifi *et al.,* 2005; Unsal, & Kachroo, 1999; Choi *et al.,* 2002; Oniz, 2007; Oniz, *et al.,* 2009), intelligent techniques using Fuzzy Logic (Mauer, 1995; Radac *et al.,* 2008), Artificial Neural Networks (Layne *et al.,* 1993; Lin & Hsu, 2003), and Neuro-fuzzy control (Topalov, *et al.,* 2011) are reported earlier in literature. Genetic Algorithm is used in finding optimum values of fuzzy component (Yonggon & Stanislaw, 2002).

PID Controllers are still widely used in industrial applications due to their simplicity and robustness (Åström & Hägglund, 2004), despite advances in control strategies. In addition to providing feedback, PID controllers do have the ability to eliminate steady state error through integral action and can anticipate the future through derivative action (Åström & Hägglund, 1995). Various structures of PID controllers and their tuning rules have been given in (O'Dwyer, 2006). Amongst these, the Ziegler–Nichols tuning rule is a most popular and widely used one in PID applications. Even though it provides good load disturbance attenuation, it exhibits a large overshoot and settling time (Ziegler & Nichols, 1942). Hence, it is needed to modify the PID controller's capability without modifying its structure much. A modification in PID structure, called Set-Point weighting (Chidambaram, 2000) is found effective in reducing overshoot. Fuzzy Logic based Set-Point weight tuning of PID controllers has been reported in (Visioli, 1999).

Firefly Algorithm (FA) is one of the recent swarm intelligence methods developed by Xin-She Yang in 2010. It is based on the flashing patterns and behavior of fireflies and it is much better than most of the metaheuristic algorithms (Yang, 2010). It is a stochastic, nature-inspired, meta-heuristic algorithm that can be applied for solving the hardest optimization problems. FA and its modified versions have been widely used for solving many optimization and classification problems, as well as several engineering problems in practice (Fister *et al.,* 2013). Tuning of PID controllers using FA for minimizing ISE has been presented by (Kumanan & Nagaraj 2013).

In this paper, a Firefly Algorithm tuned Fuzzy Set-Point Weighted PID controller (FAFSPWPID) has been proposed for a laboratory ABS model. Firefly Algorithm is used to select optimum values of parameters of the Fuzzy Inference System so as to minimize the Integral Square Error (ISE). The controller is designed to regulate the wheel slip in optimum level (0.08 to 0.3). Computer simulations have been performed in MATLAB-SIMULINK, version 7.11.0 (R2010b) and the performance of the proposed controller has been compared with SPWPID, GAFSPWPID controllers and the controllers presented in Oniz, (2007) and Oniz, *et al.* (2009).

The next section describes the Inteco ABS model. The methodology of Set-Point Weighting of PID and Firefly algorithm description are given next. Further, GA and FA based FSPWPIDs are explained with the simulation results at last.

LABORATORY ANTILOCK BRAKING SYSTEM (ABS) DESCRIPTION

Even though there are variety of mathematical models been used, the Inteco laboratory ABS model is found to be widely used by the researchers. Hence the same has been considered in this work as well. The schematic diagram of Inteco ABS quarter car model is shown in Figure 1 (User's manual, 2006).

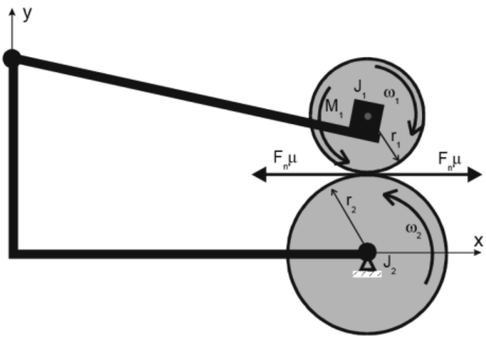

Fig. 1. Schematic diagram of Inteco ABS Quarter car model

There are two rolling wheels. The lower car-road wheel animating relative road motion and the upper car wheel permanently remaining in a rolling contact with the lower wheel. The wheel mounted to the balance lever is equipped in a tire. The car-road wheel has a smooth surface which can be covered by a given material to animate a surface of the road. The car velocity is considered as equivalent to the angular velocity of the lower wheel multiplied by the radius of this wheel and the angular velocity of the wheel as equivalent to the angular velocity of the upper wheel.

While deriving the mathematical model, only the longitudinal dynamics of the vehicle are considered and the lateral and the vertical motions are neglected. Furthermore, it is assumed that there is no interaction between the four wheels of the vehicle and hence it is termed as quarter car model. The system parameters are given in Table 1.

Table 1. Inteco ABS model parameters

Name	Description	Units
x_1, x_2	Angular velocity of upper & lower wheels	rad/s
M_1	Braking torque	Nm
r_1, r_2	Radius of upper & lower wheels	M
J_1, J_2	Moment of inertia of upper & lower wheels	Kgm^2
d_1, d_2	Viscous friction coefficients of upper & lower wheels	Kgm^2/s
F_n	Total force generated by upper wheel pressing on lower wheel	N
$\mu(\lambda)$	Friction coefficient between wheels	--
λ	Slip – relative difference of wheel velocities	--
M_{10}, M_{20}	Static friction of upper & lower wheels	Nm
M_g	Gravitational and shock absorber torques acting on the balance lever	Nm
L	distance between the contact point of the wheels and the rotational axis of the balance lever	M
ϕ	angle between the normal in the contact point and the line *L*	°

Using Newton's second law, the equations of motion of upper and lower wheels are written as;

$$\begin{aligned} J_1 \dot{x}_1 &= F_n r_1 \mu(\lambda) - d_1 x_1 - M_{10} - M_1 \\ J_2 \dot{x}_2 &= -F_n r_2 \mu(\lambda) - d_2 x_2 - M_{20} \end{aligned} \tag{1}$$

F_t is the road friction force given by Coulomb Law;

$$F_t = \mu(\lambda) F_n \tag{2}$$

F_n is calculated by the equation;

$$F_n = \frac{d_1 x_1 + M_{10} + T_B + M_g}{L(\sin\phi - \mu(\lambda)\cos\phi)} \tag{3}$$

During the normal driving conditions the rotational velocity of the wheel matches with the forward velocity of the vehicle. During braking, the applied braking force causes the wheel velocity to reduce. Hence the wheel velocity becomes lesser than the car velocity, thereby changes the slip (λ). The expression for slip in this case can be written as;

$$\lambda = \frac{r_2 x_2 - r_1 x_1}{r_2 x_2} \tag{4}$$

The dependence of wheel slip with road adhesion coefficient (μ-λ curve) is shown in Figure 2 (Topalov, *et al.*, 2011).

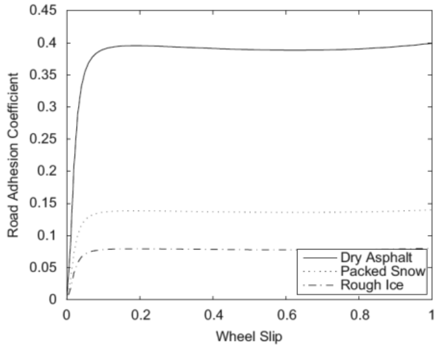

Fig. 2. Wheel Slip (λ) Vs Road Adhesion Coefficient (μ)

The mathematical representation (User's manual, 2006) of Road Adhesion Coefficient (μ) is given by,

$$\mu(\lambda) = \frac{w_4 \lambda^p}{a + \lambda^p} + w_3\lambda^3 + w_2\lambda^2 + w_1\lambda \quad (5)$$

This mathematical model has been simulated in MATLAB®-SIMULINK®. The wheel slip and stopping distance are taken out of the model as outputs and the braking force is the input to the model. The numerical values assumed for various parameters are given in Table 2.

Table 2. Numerical values for ABS model

r_1	0.0995	M_{10}	0.0032
r_2	0.099	M_{20}	0.0925
φ	65.61°	w_1	0.0424001
L	0.37	w_2	2.938E-10
J_1	0.00753	w_3	0.0350822
J_2	0.0256	w_4	0.4066269
d_1	0.0001187	a	0.0002572
d_2	0.0002147	p	2.0994527

SET-POINT WEIGHTED PID CONTROLLER

The standard form of PID controller is;

$$u(t) = K_p e(t) + K_i \int e(t)dt + K_d \frac{de(t)}{dt} \quad (6)$$

where, $e(t) = \lambda_{sp}(t) - \lambda(t)$, $\lambda(t)$ - wheel slip, $\lambda_{sp}(t)$ - reference wheel slip and K_p, K_i & K_d - proportional, integral & derivative gains.

Even though the widely used Ziegler-Nichols method of PID controller tuning results in good load disturbance attenuation, it leads to increase in overshoot and settling time. It is well known that reducing the proportional gain can get rid of this problem. An approach to scale down the set point for proportional action by a factor b<1 is referred to as Set-Point Weighting (Chidambaram, 2000). The mathematical model of Set-Point Weighted PID (SPWPID) Controller can be written as,

$$u(t) = K_p e_p(t) + K_i \int e(t)dt + K_d \frac{de(t)}{dt} \tag{7}$$

where, $e_p(t) = b\lambda_{sp}(t) - \lambda(t)$

The block diagram of SPWPID for ABS is shown in Figure 3.

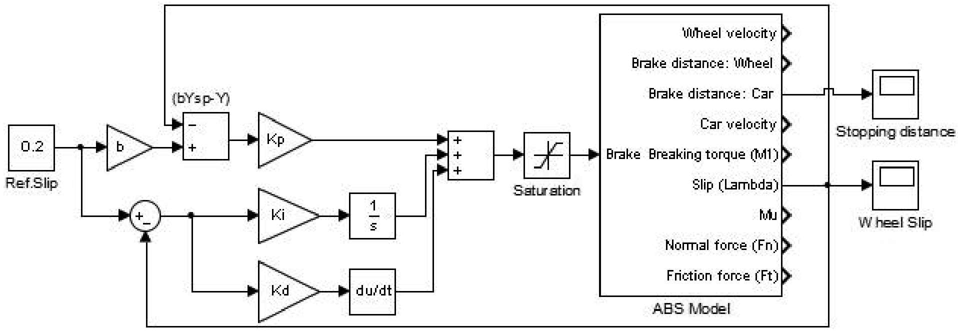

Fig. 3. Set-Point Weighted PID Controller for ABS

FIREFLY ALGORITHM (FA)

Fireflies are insects which are capable of producing a flashing light by the biochemical process called bioluminescence. Typically, the male flying fireflies produce the flashing light to attract the flightless females. In response, the females also emit continuous or flashing light. The mating partners produce distinct flash patterns encoding the information like identity and gender (Fister *et al.*, 2013). The functions of flashing lights are to communicate with mating partners, attract their prey and a protective warning mechanism.

Firefly algorithm is based on a physical formula of light intensity (H) that decreases with the increase in the square of the distance (d^2). However, as the distance from the light source increases, the brightness decreases and thereby the attractiveness also decreases. These phenomena can be associated with the objective function to be optimized.

Three idealized rules used in FA are;

- All fire flies are unisex.
- The attractiveness of each firefly is in direct proportion with the light intensity.

- The landscape of the fitness function is influenced by the light intensity of a firefly.

FA is designed based on the variation of light intensity and attractiveness of firefly. Here, intensity is the light emitted by the firefly whereas the attractiveness is the intensity of a firefly seen by other fireflies (Yang, 2010). In a standard FA, the light intensity of a firefly representing a solution is directly proportional to the fitness function value.

The light intensity (H) varies with distance (d) as;

$$H(d) = \frac{H_s}{d^2}\;; \tag{8}$$

where, H_s is the intensity at the source.

In a given medium, with an original light intensity of source (H_0) and a constant light absorption coefficient (γ), the light intensity varies with the distance (d), as given below;

$$H = H_0 e^{-\gamma d} \tag{9}$$

From equations (8) and (9), it can be approximated in Gaussian form as;

$$H(d) = H_0 e^{-\gamma d^2} \tag{10}$$

The attractiveness β of a firefly is proportional to the light intensity seen by the other fireflies. Therefore,

$$\beta = \beta_0 e^{-\gamma d^2} \tag{11}$$

where, β_0 is the attractiveness at $d=0$.

The distance between any two fireflies x_i and x_j is expressed as the Euclidean distance;

$$d_{ij} = \left\| x_i - x_j \right\| = \sqrt{\sum_{k=1}^{n} \left(x_{i,k} - x_{j,k} \right)^2} \tag{12}$$

where, $x_{i,k}$ is the k[th] component of the spatial coordinate x_i.

In a 2D case, it can be got as;

$$d_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \tag{13}$$

The movement of firefly i is attracted by another more attractive firefly j, it is given by,

$$x_i = x_i + \beta_0 e^{-\gamma d_{ij}{}^2} \left(x_j - x_i\right) + \alpha \varepsilon_i \tag{14}$$

where α is randomization parameter and ε_i is a vector of random numbers generated from Gaussian distribution.

Hence, the movement of firefly has three terms: the current position of i^{th} firefly, attraction to another one and a random walk. Therefore, the FA has three parameters, the randomization parameter (α), the attractiveness (β), and the absorption coefficient (γ) which can be adjusted to modify the performance of FA. The steps involved in Firefly Algorithm are shown in Figure 4 as pseudo code (Yang, 2010).

```
Begin
Define light absorption coefficient (γ), initial attractiveness (β0),
randomization parameter (α) and maximum generation
Objective function f(x), x = (x1, x2,.....xd)^T
Generate initial population of fireflies xi (i = 1,2,...., n)
Determine the light intensity Ii at xi by f(xi)
while (t < Maximum Generation)
for i=1: n all n fireflies
        for j=1: n all n fireflies
if (Ii< Ij), Move firefly i towards j;
end if
Vary attractiveness with distance r via exp(-γr)
Evaluate new solutions and update Ii
        end for j
end for i
Rank all fireflies and find the current best
End
```

Fig. 4. Firefly Algorithm Pseudo code

GA AND FA TUNED FUZZY SET-POINT WEIGHTED PID CONTROLLERS

The process of Set-Point Weighting leads to increase in rise time. This can be handled by the proposed GA and FA tuned Fuzzy Inference System (FIS), which determines the value of b depending on the error and its time derivative (Visioli, 1999). The Mamdani FIS is constructed with two inputs; error (e) and its derivative (de/dt). Both inputs and output of FIS are fixed in a range of [-1,1]. Hence three gains K_{in1}, K_{in2} and K_{out} are used to scale the inputs and output to this range.

Seven triangular membership functions for input and nine for the output are used as shown in Figure 5a and Figure 5b respectively.

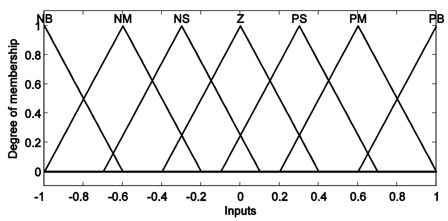

Fig. 5a. Input membership functions

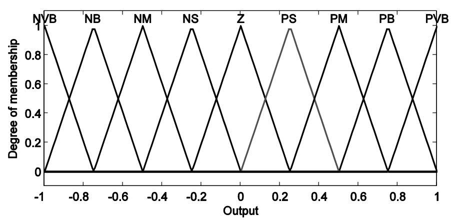

Fig. 5b. Output membership functions

The rule base using assigned linguistic variables are given in Table 3. The centroid method has been used for defuzzification.

Table 3. FIS - Rule base

e \ e_dot	**NB**	**NM**	**NS**	**ZE**	**PS**	**PM**	**PB**
NB	NVB	NVB	NB	NM	NS	NS	ZE
NM	NVB	NB	NM	NS	NS	ZE	PS
NS	NB	NM	NS	NS	ZE	PS	PS
ZE	NM	NS	NS	ZE	PS	PS	PM
PS	NS	NS	ZE	PS	PS	PM	PB
PM	NS	ZE	PS	PS	PM	PB	PVB
PB	ZE	PS	PS	PM	PB	PVB	PVB

A simple PID is used first and its parameters are tuned by trial and error method. With these fixed PID gains, it is modified to FSPWPID and then the GA and FA are used to find the optimum values of K_{in2} and K_{out} with K_{in1} arbitrarily fixed as the inverse of amplitude of the step of the set point (Visioli, 1999). Thus, the value of K_{in1} for this case is set as 5. The scheme of FSPWPID is given in Figure 6.

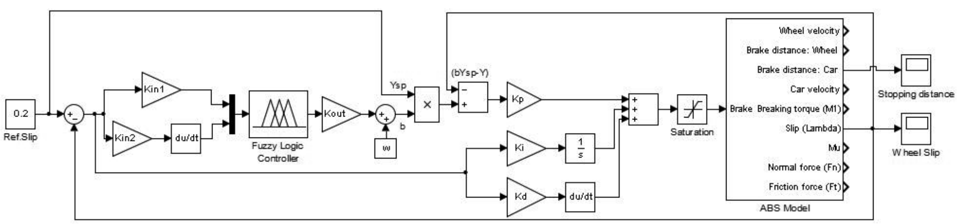

Fig. 6. FSPWPID Controller for ABS

The objective function used is to minimize ISE which is given by,

$$ISE = \int_0^\infty e(t)^2\,dt \tag{15}$$

The selected Genetic and Firefly Algorithm parameters are listed in Table 4.

Table 4. GA and FA parameters

Genetic Algorithm	
Parameter	**Value**
No. of generations	50
Population size	50
Selection	Stochastic uniform
Elite count	2
Crossover fraction	0.8
Firefly Algorithm	
No. of fireflies	20
α, β, γ	0.5, 0.2, 1
No. of iterations	50
No. of Evaluations	1000

SIMULATION RESULTS & DISCUSSIONS

The effectiveness of the developed FAFSPWPID has been investigated through computer simulations. The simulations were performed in MATLAB-SIMULINK 7.11.0 (R2010b), with a fixed step size of 0.01. A band-limited white noise is added at slip and velocity measurements of the system for getting more realistic results due to the fact that most of the practical systems are subjected to disturbances. The numerical value of noise power for slip and speed measurements are selected as 10^{-5} and 0.2 respectively (Oniz, 2007; Oniz *et al.*, 2009). A series of 25 trials have been performed for both Genetic and Firefly Algorithms with various initial vehicle velocities and set-points. The best results of these trails have been used as scaling factors of fuzzy logic and their results are presented.

Condition 1: Initial velocity of vehicle = 1720 rpm or 18 m/s and λ_{sp} = 0.2

Figure 7 depicts the set point tracking capabilities of developed controllers.

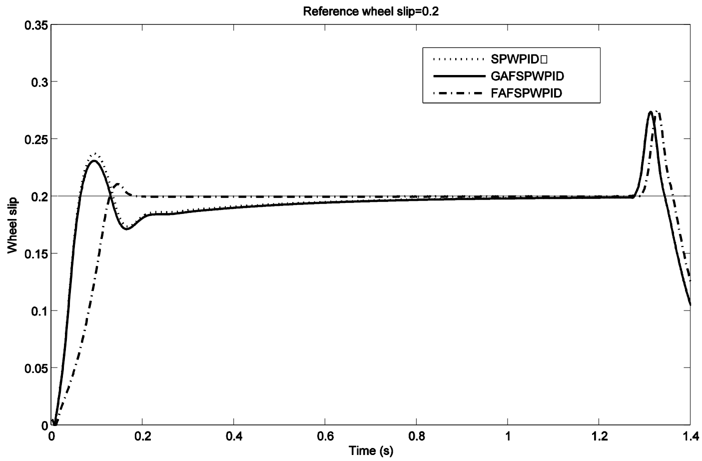

Fig. 7. Set point tracking of controllers

In Figure 7, it is found that the mere Set-Point weighting with b=0.9, leads to a response with overshoot. This means that the vehicle experiences a front and back motion when applying the brake input, which is not a desirable one. When employing fuzzy logic to find the suitable value of b and Genetic Algorithm to find the suitable values of scaling factors of fuzzy logic, the resulting GAFSPWPID exhibits a better response with relatively reduced overshoot. However, when Firefly Algorithm is used in the place of Genetic Algorithm, the resulting FAFSPWPID controller decreases the overshoot further to a negligible amount.

The stopping distance and stopping time of vehicle remain the same with all these types of controllers. The values of stopping distance and stopping time are obtained as 11.8 meters and 1.4 seconds respectively, as shown in Figure 8. There is a smooth braking torque produced by the controller as shown in Figure 9.

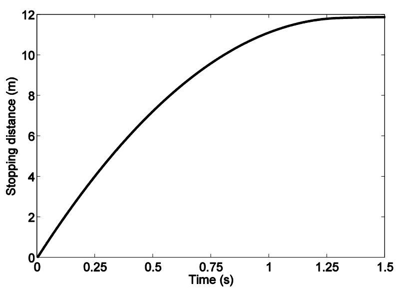

Fig. 8. Stopping distance

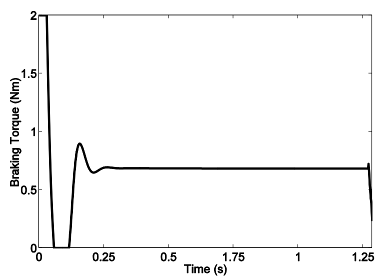

Fig. 9. Braking torque

The values of ISE of various developed controllers are presented in Table 5. The ISE for FAFSPWPID is 20.5901, which is the minimum among that of all other controllers. There is a reduction in ISE from 20.7015 to 20.5901, which is 11.14% reduction, when making use of Firefly algorithm in the place of Genetic algorithm. Hence, the FA performs much better than GA.

Table 5. Performance measures for Reference slip=0.2

Control scheme	ISE
SPWPID	20.9691
GAFSPWPID	20.7015
FAFSPWPID	20.5901

To assess the performance of the proposed controller, different values of set-points and different initial velocities have been considered as stated in conditions 2, 3 and 4. The results are presented in Figures 10 – 16. These results also show that the controller using FA performs better than the same with GA.

Condition 2: Initial velocity of vehicle = 2290 rpm or 24 m/s and λ_{sp} =0.2

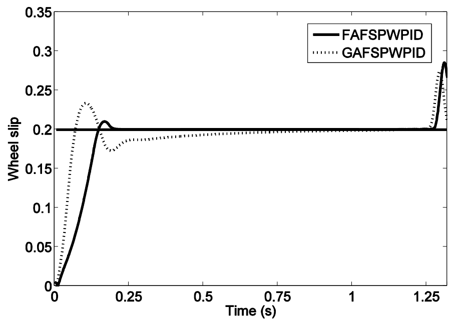

Fig. 10. Wheel slip tracking of controllers

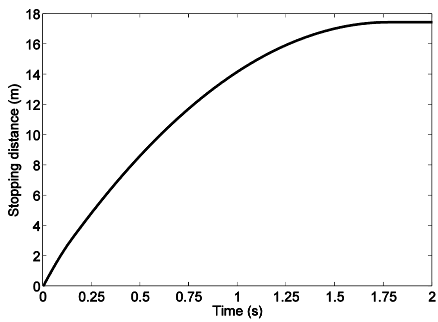

Fig. 11. Stopping distance

Condition 3: Initial velocity of vehicle = 1720 rpm or 18 m/s and λ_{sp} =0.3

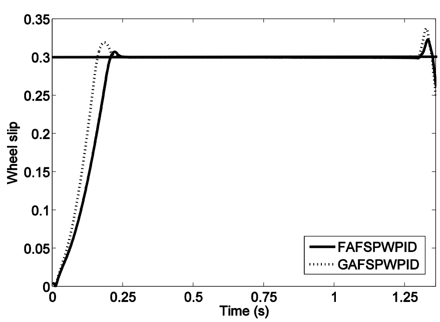

Fig. 12. Wheel slip tracking of controllers

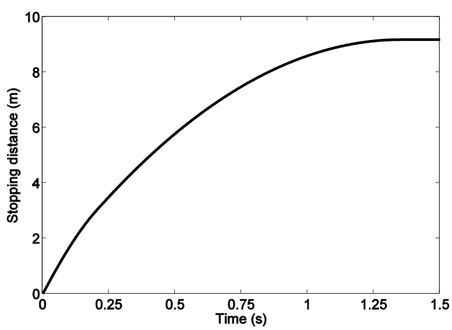

Fig. 13. Stopping distance

Condition 4: Initial velocity of vehicle = 1720 rpm or 18 m/s and λ_{sp} =0.6

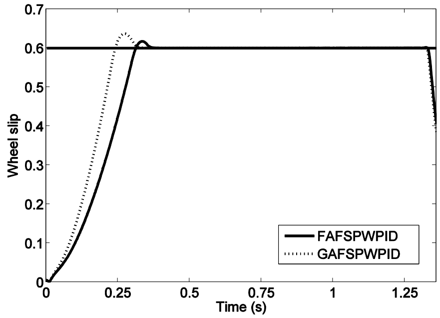

Fig. 14. Wheel slip tracking of controllers

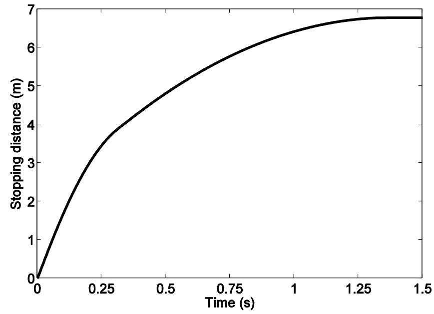

Fig. 15. Stopping distance

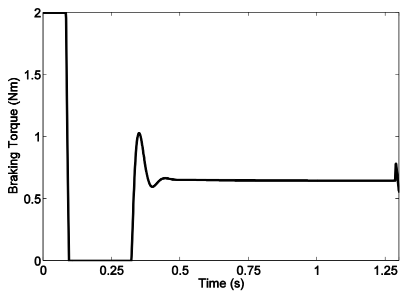

Fig. 16. Braking torque

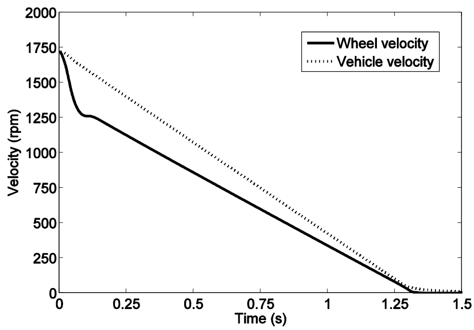

Fig. 17. Velocity profile

When the braking torque is applied by the controller, the velocity of wheel gradually reduces and hence the vehicle velocity also reduces. Finally, the vehicle comes to rest only after the wheel coming to rest. As seen in Equation 4 and Figure 17, the value of wheel slip increases towards unity during the wheel velocity being zero for a short time after which the vehicle velocity also becomes zero. This situation leads to a drastic jump in wheel slip when the time is around 1.3 seconds in Figure 7, Figure 10 and Figure 12.

Comparison with existing results and methods:

The comparison of responses of controllers presented in (Oniz, 2007) and proposed controllers, is presented in Table 6. It clearly indicates that the proposed controllers are more adaptive than the others for the disturbances and produce responses with negligible fluctuations around the set-point.

Table 6. Set point tracking of controllers

Controllers		Controlled Wheel Slip (Desired Slip=0.2)		
		Min	Max	% Deviation at steady state
Oniz (2007) and Oniz *et al.* (2009)	SMC	0.196	0.209	2 to -4.5%
	GSMC	0.198	0.204	1 to -2 %
Proposed Controllers	SPWPID	--	0.199	0.40%
	GAFSPWPID	--	0.199	0.35%
	FAFSPWPID	--	0.199	0.35%

CONCLUSION

A modified PID controller called Set-Point Weighted PID controller has been designed to control the wheel slip of Antilock Braking Systems. Effect of weighting the set point to the proportional action has been compensated by Fuzzy Logic whose inputs are scaled down to a defined range using scaling factors which are determined by the Firefly Algorithm. The same control scheme is also tuned by Genetic Algorithm and the obtained results have been compared. The comparison through simulations prove that the FA tuned Fuzzy Set-Point Weighted PID Controller (FAFSPWPID) for minimizing ISE is superior to the other developed controllers and the controllers found in literature. It is also found that the proposed controller is more adaptive to external disturbances and for different initial conditions and set-points.

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Submitted: 5-8-2014

Revised: 3-12-2014

Accepted: 2-2-2015