CEAI, Vol.16, No.1 pp. 31-39, 2014 Printed in Romania

Biogeography-Based Optimization of PID Tuning Parameters for the Vibration Control of Active Suspension System

R. Kalaivani*, P. Lakshmi**

**DEEE, CEG, Anna University, Guindy, Chennai -25*
India (e-mail: kalaivanisudhagar@gmail.com, lakshmi_ p_2000@yahoo.com).

Abstract: This paper compares the Biogeography-Based Optimization (BBO) and Particle Swam Optimization (PSO) algorithms for the tuning of Proportional Integral Derivative (PID) controller parameters and concludes BBO works well compared to other in reducing the body acceleration of Vehicle Active Suspension System (VASS). Biogeography a mushrooming nature enthused global optimization procedure, which is based on the study of the geographical distribution of biological organisms and a swarm intelligence technique are used to find the optimal parameters of the PID controller to improve the performance of VASS. Simulations of passive system, active system with PID controller with and without optimization are performed with dual bump, sinusoidal and random kind of road disturbances using MATLAB/SIMULINK. The simulation results indicate the improvement of results with the BBO algorithm.

*Keywords***:** vehicle suspension, vibration, PID controller, Biogeography-Based Optimization, Particle Swam Optimization.

1. INTRODUCTION

The automobile industries promote the research on vibration control in order to guarantee the driving and travelling comfort to the passengers. Otherwise the vibration will lead to unwanted noise in the vehicle, damage to the fittings attached to the car and cause severe health problems such as increase in heart rate, spinal problems etc to the passengers. The suspension system of an automobile plays a vital role in vehicle handling and ride comfort. Handling of vehicle depends on the force acting between the road surface and the wheels. Ride comfort is related to vehicle motion sensed by the passenger. In order to improve the handling and ride comfort performance, instead of conventional static spring and damper system, semi-active and active systems are being developed. A semi-active suspension involves the use of dampers with variable gain. An active suspension involves the passive components augmented by actuators that supply additional forces. Alternatively, an active suspension system possesses the ability to reduce the acceleration of sprung mass continuously as well as to minimize suspension deflection which results in the improvement of tyre grip with the road surface (Seok_il Son, 1996; Hrovat D., 1997). Increased competition in the automotive market has forced industries to research on the control strategies of Vehicle Active Suspension System (VASS).

In the past, many researchers discussed about a number of control approaches theoretically, simulated using simulation software, experimentally verified and proposed for the control of active suspension system. The survey of optimal control technique applications to the design of active suspensions are listed in (Hrovart D., 1993) and the emphasis is on Linear-Quadratic (LQ) optimal control. A methodology to design a controller with a model which includes the passenger dynamics is presented in (Esmailzadeh E. and Taghirad H. D., 1996). The comparison of Linear Matrix Inequality (LMI) based controller and optimal Proportional Integral Derivative (PID) controller by (Abdalla MO et al., 2007) proved the sprung mass displacement response improvement by LMI controller with only the suspension stroke as the feedback.

PID controller for single Degree of Freedom (DOF), two DOF Quarter Car (QC) and half car model are discussed in (Abdalla MO et *al.,* 2007; Rajeswari K. and Lakshmi P., 2011; Demir O. *et al.,* 2012) respectively. Design of robust PI controller which is used to obtain optimal control is discussed in (Yeroglu C. and Tan N. 2008). The conclusion made by (Dan Simon, 2008), stimulated the idea of using Biogeography-Based Optimization (BBO) for the optimization of PID parameters.

(Panchal V. K. *et al.,* 2009) focused on classification of the satellite image of a particular land cover using the theory of BBO and concluded that with this highly accurate land cover features can be extracted effectively. (Urvinder Singh *et al.,* 2010) used BBO to optimize the element length and spacing for Yagi-Uda antenna and the performance is evaluated with a method of moment’s code NEC2. (Aniruddha Bhattacharya and Pranab Kumar Chattopadhyay, 2010) presented BBO algorithm to solve both convex and non-convex Economic Load Dispatch (ELD) problems of thermal plants and suggested that it is the promising alternative approach for solving the ELD problems in practical power system. (Dan Simon, 2011) used Markov theory for partial immigration based BBO to derive a dynamic system model. (Abhishek Sinha *et al.,* 2011) given a better insight into the dynamics of migration in actual biogeography systems and also helped in the understanding of the search mechanism of BBO on multimodal fitness landscapes. (Jamuna K. and Swarup K. S. 2012) projected a multi-objective BBO algorithm to design optimal placement of phasor measurement units which makes the power system network completely observable and performed the simultaneous optimization of the two conflicting objectives such as minimization and maximization of two different parameters. (Aniruddha Bhattacharya and Pranab Kumar Chattopadhyay, 2012) highlighted the effectiveness of BBO over Genetic Algorithm (GA) and Particle Swam Optimization (PSO) for an ELD problem. (Haiping Maa *et al.,* 2013) tested the performance of BBO for real-world optimization problems with some benchmark functions. (Lohokare M. R. *et al.,* 2013) presented an improved accuracy yielding algorithm in which the performance of BBO is accelerated with the help of a modified mutation and clear duplicate operators. Also discussed the suitability of BBO for real time applications.

Tuning the PID controller parameters is a challenging task for the controller designers to achieve certain goals. Hence a choice is taken to optimize the tuning parameters of PID controller applied to VASS with BBO as it has the characteristics of information sharing among the solutions. To check the suitability of this optimization technique, another optimization method PSO which is developed by (Kennedy J. and Eberhart R. C., 1995) is used because it can generate a high quality solution with more unwavering convergence characteristics with less calculation time than other stochastic methods. Also it is attractive because there are only a few parameters to adjust. Compared to most of other evolutionary algorithms, in BBO and PSO each solution stay survive to the end of optimization procedure which enhances the capability of global search. The chance of the population convergence to the optimum is also more for BBO compared to GA. (Voratas Kachitvichyanukul, 2012) highlighted the features PSO compared to GA.

In (Zwe-Lee Gaing, 2004), the author proposed PSO-PID controller for AVR system and shown that it is more efficient than the GA-PID controller. (Rajeswari K. and Lakshmi P. 2010b) optimized a Fuzzy Logic Controller (FLC) used in VASS with two optimization algorithms GA and PSO and concluded that PSO tuned FLC based active suspension system exhibits an improved ride comfort and good road holding ability. (Shen-Lung Tung *et al.,* 2011) proposed an active suspension mechanism for three DOF twin-shaft vehicles of front axle suspension with bounded uncertainties using exponential decay control and PSO techniques. (Juing-Shian Chiou *et al.,* 2012) presented a design method for determining the optimal fuzzy PID controller parameters of active automobile suspension system using PSO. (Oscar Castillo and Patricia Melin, 2012a) considered the application of GA, PSO and Ant Colony Optimization (ACO) as three different paradigms that help in the design of optimal type-2 fuzzy controllers and concluded that both PSO and ACO are able to outperform GA. Wu Q H and Liao H L (2013) used PSO for comparison with newly presented algorithm, Function Optimization by Learning Automata (FOLA), to solve complex function optimization problems.

In this paper, an attempt is made to optimize the controller parameters with two different optimization techniques namely PSO and BBO and the comparison is made with the outputs of linear system model which is considered for the simulation study.

Organization of the paper is as follows. QC model dynamics of an active suspension system is briefly explained in section 2. Discussion of PID control scheme is presented in section 3. PSO and PSO based PID (PSOPID) are discussed in sections 4. In section 5, BBO and BBO based PID (BBOPID) are discussed. In section 6, the simulation results are presented and discussed. The final section concludes the paper.

2. ACTIVE SUSPENSION – QUARTER CAR MODEL

A two DOF QC model of VASS is shown in Fig. 1. It represents the automotive system at each wheel i.e. the motion of the axle and the vehicle body at any one of the four wheels of the vehicle. QC model used in (Rajeswari K. and Lakshmi P., 2010a) is considered because it is simple and one can observe the basic features of the VASS such as sprung mass displacement, body acceleration, suspension deflection and tyre deflection.

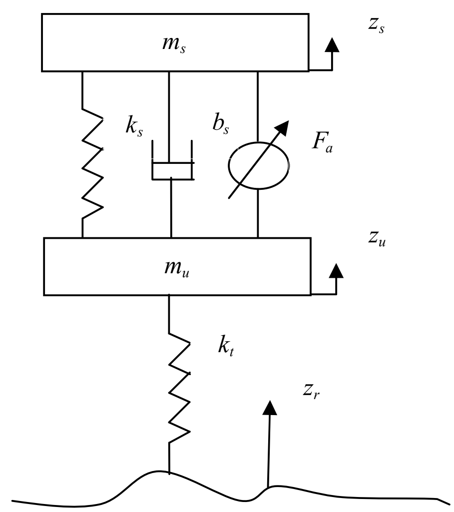


Fig. 1. Two DOF QC model.

The suspension model consists of a spring k_s, a damper b_s and an actuator of active force F_a. For a passive suspension, F_a can be set to zero. The sprung mass m_s represents the QC equivalent of the vehicle body mass. An unsprung mass m_u represents the equivalent mass due to axle and tyre. The vertical stiffness of the tyre is represented by the spring k_t . The variables z_s, z_u and z_r represents the vertical displacements from static equilibrium of sprung mass, unsprung mass and the road respectively. Equations of motion of two DOF QC model of VASS are given in (1). It is assumed that the suspension spring stiffness and tyre stiffness are linear in their operating ranges and that the tyre does not leave the ground. The state space representation of QC model is given in (2).

$$m_s\ddot{z}_s + b_s(\dot{z}_s - \dot{z}_u) + k_s(z_s - z_u) = F_a$$

$$m_u\ddot{z}_u - b_s(\dot{z}_s - \dot{z}_u) - k_s(z_s - z_u) - k_t(z_r - z_u) = -F_a \tag{1}$$

$$\begin{bmatrix}\dot{X}_1\\ \dot{X}_2\\ \dot{X}_3\\ \dot{X}_4\end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0\\ \frac{-k_s}{m_s} & \frac{-b_s}{m_s} & \frac{k_s}{m_s} & \frac{b_s}{m_s}\\ 0 & 0 & 0 & 1\\ \frac{k_s}{m_u} & \frac{b_s}{m_u} & \frac{-k_s-k_t}{m_u} & \frac{-b_s}{m_u}\end{bmatrix}\begin{bmatrix}X_1\\ X_2\\ X_3\\ X_4\end{bmatrix} + \begin{bmatrix}0\\ \frac{1}{m_s}\\ 0\\ \frac{-1}{m_u}\end{bmatrix}F_a + \begin{bmatrix}0\\ 0\\ 0\\ \frac{k_t}{m_u}\end{bmatrix}z_r \tag{2}$$

$$\dot{X} = AX + BF_a + Fz_r \tag{3}$$

where $X_1 = z_s, X_2 = \dot{z}_s, X_3 = z_u, X_4 = \dot{z}_u$

The natural frequency of unsprung mass is

$$\omega_0 = \sqrt{\frac{k_s + k_t}{m_u}} \tag{4}$$

3. PID CONTROL STRUCTURE

PID controller (Rajeswari K. and Lakshmi P. 2011) which is a combination of proportional, integral and derivative controller can improve the total performance of the system. In other words, both the transient and steady state response can be improved.

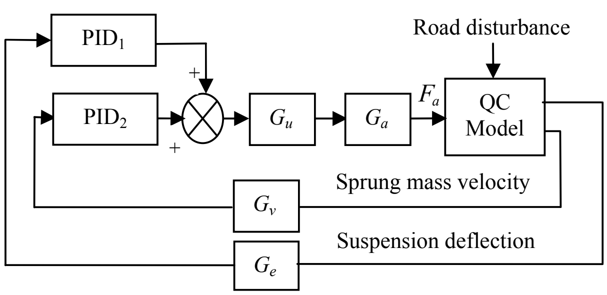


Fig. 2. The block diagram representation of control scheme of VASS using PID controller.

$$U_c = k_p e(t) + k_i \int e(t)dt + k_d \frac{de}{dt} \tag{5}$$

where U_c is the controller output

k_p Proportional gain

k_i Integral gain

k_d Differential gain

$e(t)$ Input to the controller

$\int e(t)dt$ Time integral of the input signal

$\frac{de}{dt}$ Time derivative of the input signal

To reduce the effect of road disturbance input (Fig. 2), two QC suspension parameters such as suspension deflection ($z_s - z_u$) and sprung mass velocity ($\dot{z}_s$) are feedback to the controllers (Jyh-Chyang Renn, and Tsung-Han Wu 2007). The feedback gains are G_e and G_v respectively. The output control signals are amplified by a gain G_u and then given as the input to the actuator. In this work the nonlinear dynamics of actuator is not considered and the gain of the linear actuator is taken as G_a. The actuator force F_a which is the additional input to the system is proportional to the controller output to have better comfort. PID Controllers are tuned by three methods -robust response tuning, PSO tuning and BBO tuning. First, autotuning has been carried out for both PID_1 and PID_2 to give robust performance using the MATLAB simulation software. Next, for optimized tuning, the RMS value of body acceleration ($\ddot{z}_s$) is taken as the performance index. The objective is to find tuning parameters of PID_1 ((k_{p1}, k_{i1} & k_{d1}) and PID_2 (k_{p2}, k_{i2} & k_{d2}) to minimize the cumulative RMS value of body acceleration signal ($\ddot{z}_s$). In other words,

$$\text{Minimize } J(K) = \sqrt{\frac{1}{T}\int_0^T \|\ddot{z}_s\|^2 dt} \tag{6}$$

where T is the total time period

4. PARTICLE SWAM OPTIMIZATION

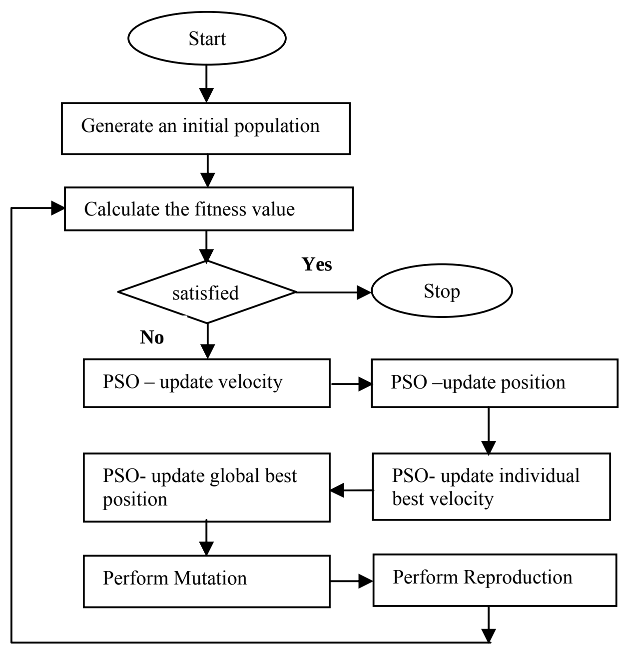


Fig. 3. The Flow Chart for PSO Optimization.

A population based stochastic optimization technique PSO which is developed because of the insight of group actions of bird flocking or fish schooling is having immense curiosity among the optimizing techniques In PSO, the optimization procedure starts with the initialization of the population of random solutions as in GA and searches for optima by updating generations (Oscar Castillo and Patricia Melin, 2012b). Compared to other evolutionary algorithms, in PSO the individual solutions called particles, fly through the problem space by following the current optimum particles with the change of its velocity and position. Each and every particle keeps the pathway of its coordinates in the problem space, which are associated with the best solution it has achieved so far in each generation. In every iteration, each particle is updated by two "best" values *Pbest* and *Gbest*. Out of which the *Pbest* is the best solution (fitness) it has achieved so far and the *Gbest* is the best solution obtained so far by any particle in the population. Each particle knows *Pbest* and *Gbest*. Each particle tries to modify its position using the current velocity and the distance from *Pbest* and *Gbest*. The modified velocity and position of each particle can be calculated using equations given below.

$$v_{i,g}^{k+1} = w * v_{i,g}^{k} + c_1 * rand_1 * (Pbest_{i,g} - x_{i,g}^{k}) + c_2 * rand_2 * (Gbest_g - x_{i,g}^{k}) \quad (7)$$

$$x_{i,g}^{k+1} = x_{i,g}^{k} + v_{i,g}^{k+1} \quad (8)$$

$$i = 1, 2, \ldots n$$

$$g = 1, 2, \ldots m$$

where n - Number of particles in a group

m - Number of members in a particle

c_1, c_2 - Weight factors

$v_{i,g}^{k}$ - Velocity of the particle i in k^{th} iteration

$x_{i,g}^{k}$ - Position of particle i in k^{th} iteration

$rand_1, rand_2$ - Random numbers between 0 and 1

$Pbest_{i,g}$ - *Pbest* of particle i

$Gbest_g$ - *Gbest* of the group

Proper selection of inertia weight parameter w by (9) provides a balance between global and local explorations.

$$w = w_{max} - ((w_{max} - w_{min}) * \frac{t}{t_{max}}) \quad (9)$$

where w_{max} and w_{min} are the upper and lower bounds for w .

t - Current iteration number

t_{max} - Maximum number of iterations

The flowchart for optimization steps of PSO algorithm (Juing-Shian Chiou et al. (2012)) is shown in Fig. 3.

4.1. PSOPID controller

In this paper, PSO algorithm is used to find the PID parameters (Zwe-Lee Gaing, 2004) of both the PID controllers [$k_{p1}, k_{i1}, k_{d1}, k_{p2}, k_{i2}, k_{d2}$] which represents an individual K. Hence there are six members in a paricle (m). Since the number of individuals in a group is n, the population dimension is n x 6. The fitness function f is the performance index $J(K)$.

$$f = J(K) \quad (10)$$

For each variables to be tuned the velocity is updated as in (7), the position is updated as in (8) The optimization steps explained in section 4 are followed by maintaining the values with in the lower and upper bounds.

5. BIOGEOGRAPHY-BASED OPTIMIZATION

Another population based BBO technique has been developed based on the theory of Biogeography (Yeroglu C. and Tan N., 2008) which describes how species voyage from one habitat to other, how new species come up and how species become vanished. A habitat is a geographically isolated island from other habitats. Each habitat has its individual features which are specified by the Habitat Suitability Index (*HSI)* variables. A habitat with high *HSI* is well suited for species living. The migration of a species among habitats takes place when the high *HSI* habitats have more species or habitat has low *HSI*. This process is known as emigration. Another process called immigration takes place when the species move towards the habitat with high *HSI* having few species. The emigration and immigration of species from a habitat are called migration. The emigration rate (μ) and immigration rate (λ) vary with the number of species available in the habitat. With no species the immigration rate touches the upper limit and with maximum number of species it is zero where as the emigration rate increases with increase in the number of species. The change in *HSI* due to natural disaster is taken into account with the mutation operation.

The optimization steps of BBO algorithm (Jamuna K. and Swarup K. S., 2012) are described as follows:

1. Initialize the optimization problem and the BBO parameters.
2. Initialize randomly the habitat variables.
3. Perform BBO migration operation as in definition 7 and mutation operation as in definition 8 (Yeroglu C. and Tan N., 2008) and compute the *HSI*.
4. The emigration and immigration rates of each solution are useful in probabilistically sharing the information between the habitats. Each solution can be modified with the habitat modification probability to yield good solution. Recompute *HSI* and modify the habitats.
5. Check the stopping criteria. If not achieved, repeat from step3.

BBO does not involve the reproduction of solution as in GA. In each generation, the fitness of every solution (habitat) is used to find the migration rates.

5.1. BBOPID controller

As discussed in section 4.1, to find the individual K, instead of PSO, BBO is introduced. With the initial random choice of the individual K, depending on the emigration rate and immigration rates decided by the *HSI* allows the survival of a habitat in the search space. Good solutions can be achieved by increasing the diversity of population by mutation operation. Mapping of *HSI* to the maximum number of species S_{max}, calculation of the emigration rate and immigration rate using equations 11 and 12 are done.

$$\lambda = I(1 - \frac{d}{S_{max}}) \tag{11}$$

$$\mu = \frac{E \times d}{S_{max}} \tag{12}$$

where d is the number of species at the instant of time. Final values of individual K are taken by checking the fitness function.

6. SIMULATION

The parameters of the quarter car model taken from Rajeswari K and Lakshmi P (2010a) are listed below.

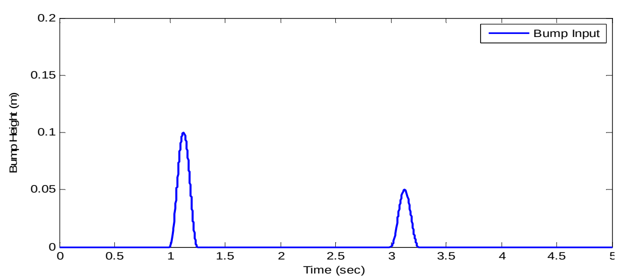
Sprung mass (m_s) = 290 kg

Unsprung mass (m_u) = 59 kg

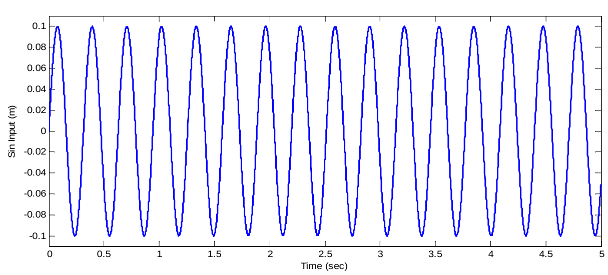
Damper coefficient (b_s) = 1,000 Ns/m

Suspension stiffness (k_s) = 16,812 N/m

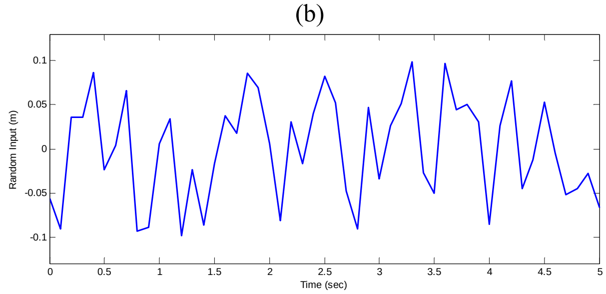
Tyre stiffness (k_t) = 190,000 N/m



(a)



(b)



(c)

Fig. 4. Road Input profile (a) Dual Bump Input (b) Sinusoidal Input (c) Random input .

International Organization for Standardization gives the classification of road roughness using Power Spectral Density values. In this work three kinds of the road disturbance are considered – initially a dual bump and for robustness checking a sinusoidal and random input. Mathematical representation of the dual bump input with 10cm and 5cm amplitude can be stated as

$$z_r(t) = \begin{cases} \dfrac{a_1(-cos(8\pi t))}{2} & if\ 1.0 \le t \le 1.25 \\ \dfrac{a_2(-cos(8\pi t))}{2} & if\ 3.0 \le t \le 3.25 \\ 0 & otherwise \end{cases} \tag{13}$$

where a_1 and a_2 denotes the two bump amplitudes.

The following parameters are initialized for PSO.

Population size : 100
Number of variables to be tuned : 6
Initial population : Random selection
Initial velocity : 0
Mutation rate : 0.5
Number of iterations : 100
Weight factors (c_1, c_2) : 0.5, 0.5
Minimum and maximum parameter values of decision variable (K) : Table 1

The following parameters are initialized for BBO.
Population size : 100
The maximum species count (S_{max}) : 50
Migration probability : 1
Mutation probability : 0.05
Selectiveness parameter δ : 2
Max migration rate I : 1
Max emigration rate E : 1
Step size used for numerical integration : 1
Minimum and maximum parameter values of decision variable (K) : Table 1
Lower bound and Upper bound for immigration probability per gene : [0.01, 1]

Table 1. Range of the controller tuning parameters.

Tuning Parameter	Lower Bound	Upper Bound
k_{p1}	0	0.1
k_{i1}	0	10
k_{d1}	0	0.5
k_{p2}	0	10
k_{i2}	0	1
k_{d2}	0	1

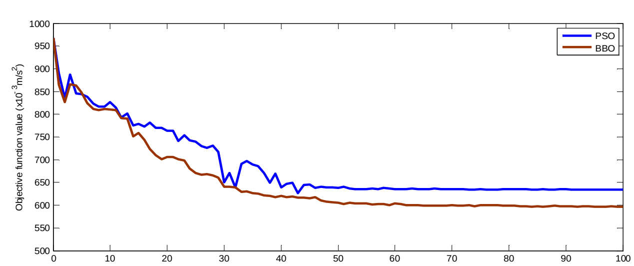


Fig. 5. Statistics of search process.

The optimization results were computed by averaging 50 minimization runs and the convergence characteristics of each technique are shown in Fig. 5. Each run yielded the global minimum results. From the convergence plot, BBO algorithm is found to be superior to PSO algorithm discussed. Also the dynamic behaviours and convergence characteristics of the algorithms can be analyzed with the statistical indices mean (M) and standard deviation (σ) which are given by

$$M = \frac{\sum_{i=1}^{n} f(K_i)}{n} \tag{14}$$

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(f(K_i) - M)^2} \tag{15}$$

where $f(K_i)$ the fitness value of the individual K_i and n is the population size.

The BBO algorithm results better fitness value and mean value compared PSO algorithm (Table 2).

Table 2. Comparison of computational efficiency of PSO and BBO algorithms.

Algorithm	Maximum	Minimum	Range	M	σ
PSO	968	626.9	341.1	686.9	78.04
BBO	968	596.9	371.1	652.6	84.37

The robust response tuning, PSO and BBO optimized values of PID tuning parameters which are obtained are appended to Table 3.

Table 3. The Optimized PID tuning parameters with PSO and BBO.

Controller / PID Parameter	Robust response tuning	PSOPID	BBOPID
kp_1	0.0103	0.0329	0.0475
ki_1	0.415	4.8769	4.8
kd_1	0.0022	6.34×10^{-4}	0.1450
kp_2	0.3801	6.1419	6.7500
ki_2	0.56	0.8545	0.8750
kd_2	0.0044	0.0342	0.0375

The mathematical model of vehicle suspension system (1) with the PSOPID and BBOPID controllers discussed in sections 4 and 5 are simulated with all the mentioned road input profiles (Fig. 4).

The simulation results of passive system, system with PID, PSOPID and BBOPID controllers are shown in Fig. 6, 7 and 8. (a) - (d). Also the RMS values of the time responses of the system are tabulated in Tables 4-6.

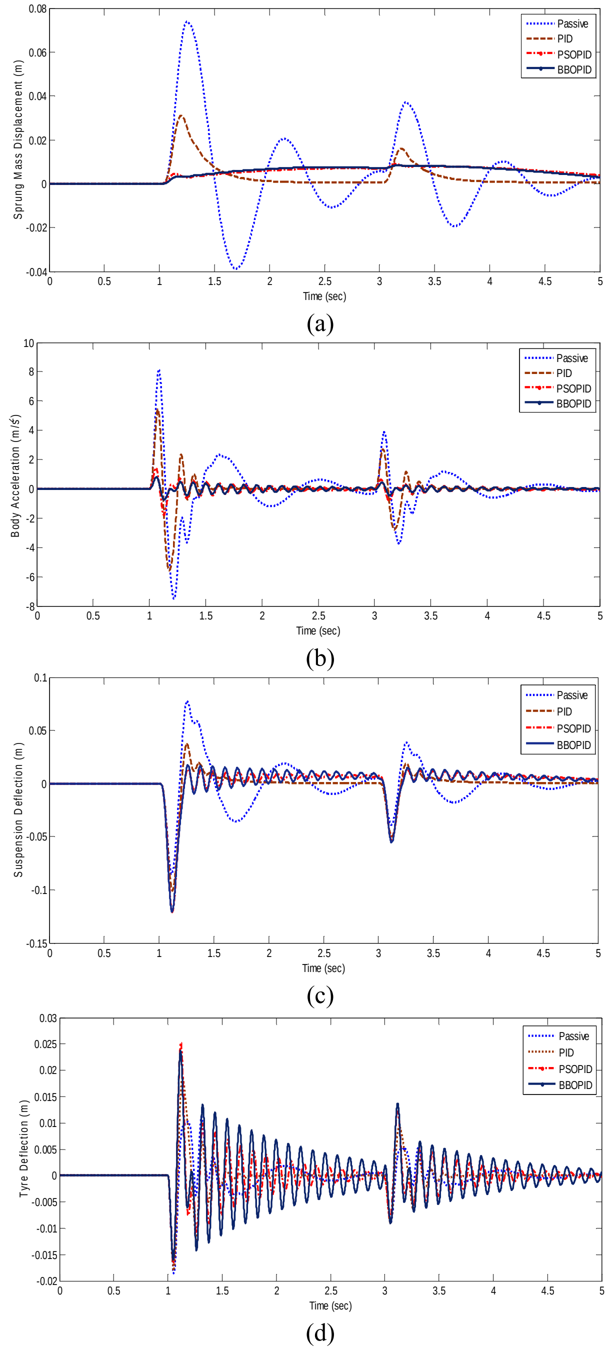
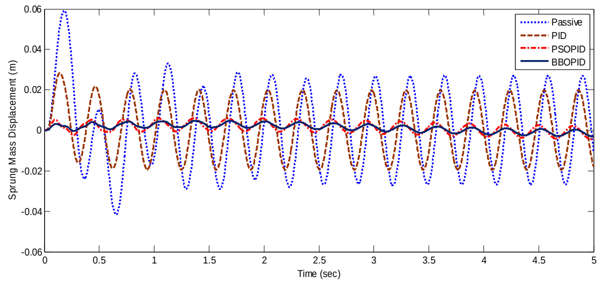
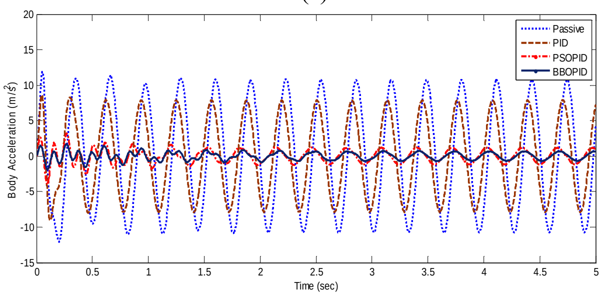


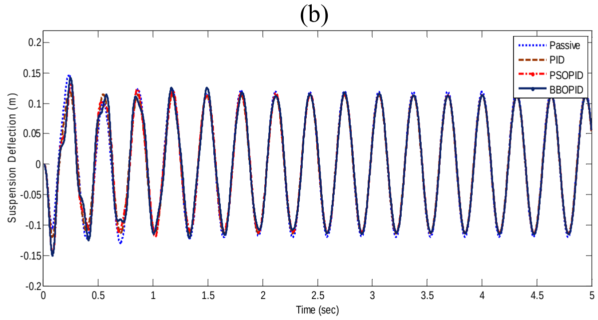
Fig. 6. Time responses with dual bump input (a) Sprung mass displacement (b) Body acceleration (c) Suspension deflection and (d) Tyre displacement.



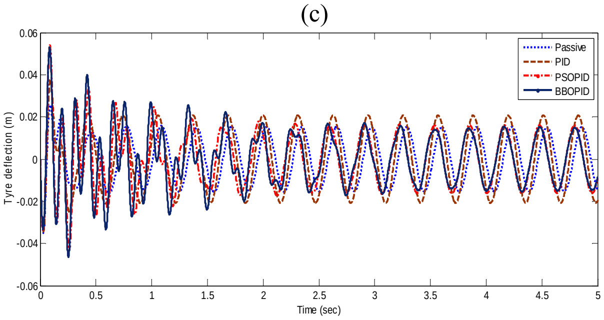
(a)



(b)



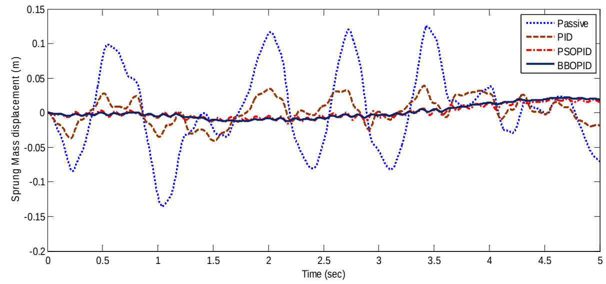
(c)



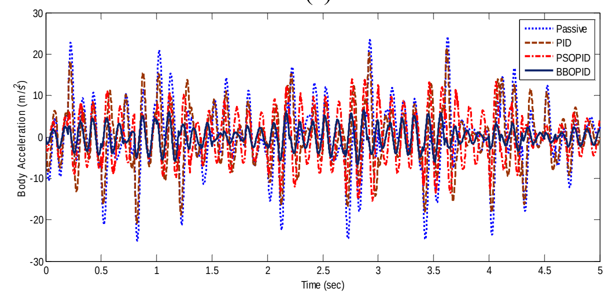
(d)

Fig. 7. Time responses with sinusoidal input (a) Sprung mass displacement (b) Body acceleration (c) Suspension deflection and (d) Tyre displacement.

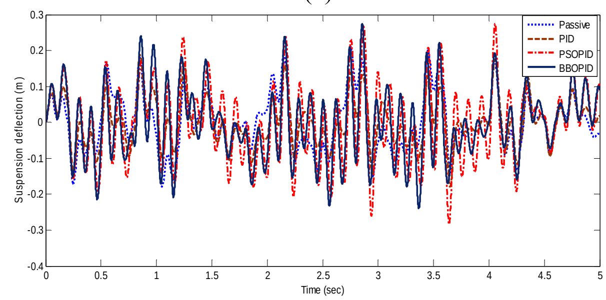
It is clear from Fig. 6, 7, 8. (a) and Fig. 6, 7, 8. (b) that the vehicle body acceleration and sprung mass displacement are considerably reduced by the proposed BBOPID controller. It guarantees the travelling comfort to the passengers. Both the designed PSOPID and BBOPID have robust performance which is true from Fig. 7, 8. (b). Also Fig. 6, 7, 8. (c) shows that the suspension deflection by both the controllers is nearly the same. Fig. 6, 7, 8. (d) illustrates the road holding ability maintained by both the controllers. Tyre displacement of active systems is higher than that of the passive suspension system.



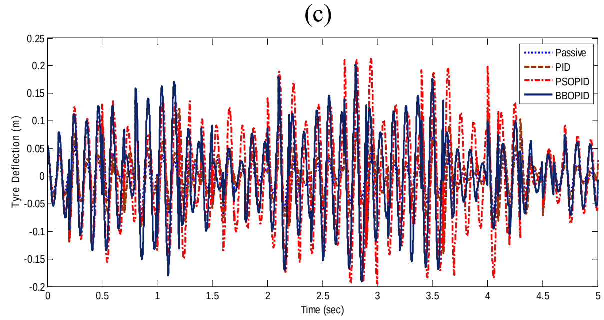
(a)



(b)

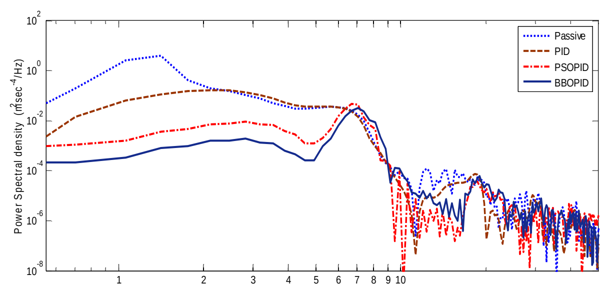


(c)



(d)

Fig. 8. Time responses with random input (a) Sprung mass displacement (b) Body acceleration (c) Suspension deflection and (d) Tyre displacement.



(a)

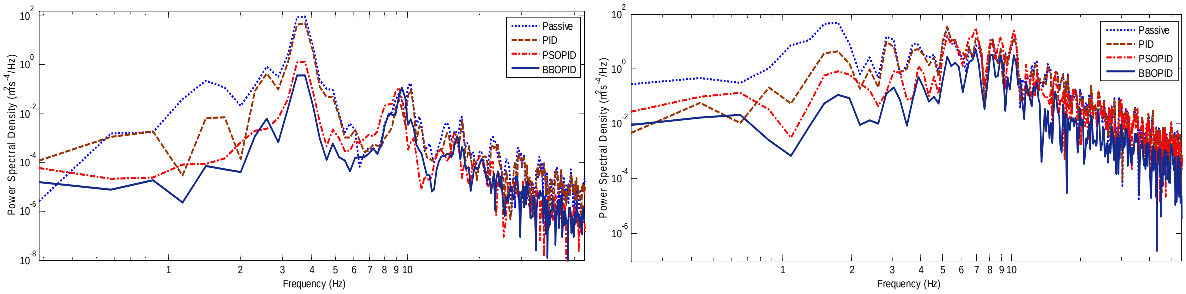


Fig. 9. PSD of Body acceleration comparison of Passive, PID and BBOPID with a) Dual bump b) Sinusoidal c) Random inputs.

Table 4. RMS values of the time responses of quarter car model with dual bump input.

System	Sprung Mass Displacement $x10^{-3}$ (m)	Body Acceleration $x10^{-3}(m/s^2)$	Suspension Deflection $x10^{-3}$(m)	Tyre Displacement (m)
Passive	19.67	1567	20.09	0.002864
PID	6.578	968.2	14.64	0.00314
PSOPID	5.774	634.2	17.2	0.004572
BBOPID	5.661	596.9	16.86	0.003773

Table 5. RMS values of the time responses of quarter car model with sinusoidal input.

System	Sprung Mass Displacement $x10^{-3}$ (m)	Body Acceleration $x10^{-3}(m/s^2)$	Suspension Deflection $x10^{-3}$(m)	Tyre Displacement (m)
Passive	20.82	7617	84.61	0.01122
PID	14.07	5576	80.4	0.01509
PSOPID	2.292	2426	81.22	0.01404
BBOPID	2.934	2273	80.66	0.01381

Table 6. RMS values of the time responses of quarter car model with random input.

System	Sprung Mass Displacement $x10^{-3}$ (m)	Body Acceleration $x10^{-3}(m/s^2)$	Suspension Deflection $x10^{-3}$(m)	Tyre Displacement (m)
Passive	59.61	8429	80.68	0.03355
PID	19.19	7359	65.31	0.03812
PSOPID	10.39	3742	97.95	0.07377
BBOPID	9.395	3261	105.3	0.08585

The RMS values of the time responses of the four outputs with different inputs are listed in Table 4, 5 and 6. It is clear that the VASS using BBOPID controller is useful for betterment of ride and travelling comfort with reduced body acceleration over PID controller and passive system. In the evaluation of vehicle ride quality, the Power Spectral Density (PSD) for the body acceleration as a function of frequency is of prime interest and is plotted for passive and system with PID and BBOPID controller for three different types of road inputs (Fig. 9). It is clear from the PSD plot that in the human sensitive frequency range 4-8 Hz, compared to PID and PSOPID, BBOPID reduces the vertical vibrations to a great extent and improves the comfort of travelling.

8. CONCLUSIONS

In this paper the PSO and BBO optimization of PID tuning parameters has been discussed for application in QC model with linear actuator. Repeated runs of both the optimization techniques have been carried out 50 times and the simulations are carried out with most fitted values. Among the two optimization techniques, the BBO gives better performance. With BBOPID controller, the results are improved compared to passive system, conventional PID and PSOPID controllers for the control of VASS. BBOPID reduces the body acceleration considerably and ensures the travelling comfort to the passengers. The controllers discussed are easy to implement and with reference to the PSD of body acceleration, it is clear that all the controllers provides better vibration control compared to the passive system. BBOPID gives better PSD and proves its effectiveness for the control of vibration in comparison with the other two controllers discussed. In future, the BBO can be hybridized to increase the convergence speed.

REFERENCES

Abdalla, MO., Al Shabatat, N., and Al Qaisi, M. (2007). Linear matrix inequality based control of vehicle active suspension system. *Vehicle System Dynamics*, 47, 121-134.

Abhishek Sinha, Swagatam Das, and Panigrahi, B. K. (2011). A Linear State-Space Analysis of the Migration Model in an Island Biogeography System. *IEEE Transactions on Systems, Man, and Cybernetics—Part A: Systems and Humans*, 41, 331-337

Aniruddha Bhattacharya and Pranab Kumar Chattopadhyay, (2010). Biogeography-Based Optimization for Different Economic Load Dispatch Problems. *IEEE Transactions on Power Systems*, 25, 1064-1077.

Aniruddha Bhattacharya and Pranab Kumar Chattopadhyay, (2012). Closure to Discussion of "Hybrid Differential Evolution with Biogeography-Based Optimization for Solution of Economic Load Dispatch". *IEEE Transactions on Power Systems*, 27, 575.

Dan Simon, (2008). Biogeography based optimization. *IEEE Transactions on Evolutionary Computation*, 12, 702-713.

Dan Simon, (2011). A dynamic system model of biogeography-based optimization. *Applied Soft Computing* 11, 5652–5661.

Demir, O., Keskin and Cetlin, S. (2012). Modelling and control of a nonlinear half vehicle suspension system; A hybrid fuzzy logic approach. *Nonlinear Dynamics*, 67, 2139-2151.

Esmailzadeh, E., and Taghirad, H.D. (1996). Active Vehicle Suspensions with Optimal State feedback Control. *J. Mech. Sci.*, 200, 1-18.

Haiping Maa, Dan Simon, Minrui Fei and Zhikun Xie. (2013) Variations of biogeography-based optimization and Markov analysis. *Information Sciences,* 220, 492–506

Hrovart, D. (1993). Applications of optimal control to Dynamic advanced automotive suspension design. *ASME Journal of Dynamic Systems, Measurement and Control*, (Special issue commemorating 50 years of the DSC division) 115, 328-342.

Hrovat, D. (1997). Survey of advanced suspension developments and related optimal control applications. *Automatica*, 33, 171-181.

Jamuna, K., and Swarup, K.S. (2012). Multi-objective biogeography based optimization for optimal PMU placement. *Applied Soft Computing,* 12, 1503-1510.

Juing-Shian Chiou, Shun-Hung Tsai, and Ming-Tang Liu. (2012). A PSO-based adaptive fuzzy PID-controllers. *Simulation Modelling Practice and Theory*, 26, 49–59.

Jyh-Chyang Renn, and Tsung-Han Wu. (2007). Modeling and control of a new 1/4T servo-hydraulic vehicle active suspension system. *J. of Marine Science and Technology*, 5, 265-272.

Kennedy, J., Eberhart, R.C. (1995). Particle swarm optimization. *Proceedings IEEE International Conference on Neural Networks*, IV, 1942–1948.

Lohokare, M.R., Pattnaik, S.S., Panigrahi, B.K., and Sanjoy Das. (2013). Accelerated biogeography-based optimization with neighborhood search for optimization. *Applied Soft Computing*, In press, Unpublished, available on line.

Oscar Castillo and Patricia Melin. (2012a). A review on the design and optimization of interval type-2 fuzzy controllers, *Applied Soft Computing*, 12, 1267–1278.

Oscar Castillo, and Patricia Melin. (2012b). Optimization of type-2 fuzzy systems based on bio-inspired methods:A concise review. *Information Sciences*, 205, 1–19.

Panchal, V.K., Parminder Singh, Navdeep Kaur, and Harish Kundra. (2009). Biogeography based Satellite Image Classification. *International Journal of Computer Science and Information Security*, 6, 269-274.

Rajeswari, K., and Lakshmi, P. (2010a). Simulation of suspension system with intelligent active force control. *International Conference on Advances in Recent Technologies in Communication and Computing*, 271-277.

Rajeswari, K., and Lakshmi, P. (2010b). PSO optimized Fuzzy Logic Controller for Active Suspension System. *International Conference on Advances in Recent Technologies in Communication and Computing*, 278-283.

Rajeswari, K., and Lakshmi, P. (2011). Vibration control of mechanical suspension system. *Int. J. Instrumentation Technology*, 1, 60-71.

Seok_il Son. (1996). Fuzzy Logic Controller for an Automotive Active suspension system. *Master's Thesis, Syracuse University*.

Shen-Lung Tung, Yau-Tarng Juang, Wei-Hsun Lee, Wern-Yarng Shieh and Wei-Ying Wua. (2011). Optimization of the exponential stabilization problem in active suspension system using PSO. *Expert Systems with Applications* 38, 14044–14051

Urvinder Singh, Harish Kumar, and Tara Singh Kamal. (2010). Design of Yagi-Uda Antenna Using Biogeography Based Optimization**.** *IEEE Transactions on Antennas And Propagation*, 58, 3375- 3379.

Voratas Kachitvichyanukul (2012). Comparison of Three Evolutionary Algorithms: GA, PSO, and DE. *Industrial Engineering & Management Systems,* 11, 215-223.

Wu, Q.H., and Liao, H.L. (2013). Function optimisation by learning automata. *Information Sciences*, 220 , 379–398.

Yeroglu, C., and Tan, N. (2008). Design of robust PI controller for vehicle suspension system. *Journal of Electrical Engineering & Technology,* 3, 135-142.

Zwe-Lee Gaing. (2004). A particle swarm optimization approach for optimum design of PID controller in AVR system. *IEEE Transactions on Energy Conversion*, 19, 384-391.