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IMPROVED GENETIC ALGORITHM FOR ENHANCING THE COMFORTNESS OF A PASSENGER CAR

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ABSTRACT

This paper mainly focusing the significance of effective and most powerful optimization technique Real coded Genetic Algorithm (RGA) for vehicle system over Binary coded Genetic Algorithm (BGA). Normal Fuzzy Logic Controller (FLC) can act intelligently to improve the comfort of passengers inside a car. For multi input controllers, the choice of scaling factors of the FLC requires more effort and knowledge where most of the FLC designers struggle. In this paper the FLC scaling factors have been identified with two different but similar optimization techniques – BGA and RGA. For the optimization, the RMS value of car Body Acceleration (BA) is taken as the Performance Index (PI). The simulation work has done in MATLAB/SIMULINK environment by considering the dual bump as the road disturbance input. The effectiveness of the RGA tuned FLC (RGAFLC) is proved in comparison with the BGA tuned FLC (BGAFLC) for the passenger car.

Key words: *Fuzzy Logic Controller, Binary coded Genetic Algorithm (BGA), Real coded Genetic Algorithm (RGA), Simulation*

INTRODUCTION

The suspension system of a vehicle plays a major role in providing the ride comfort to the occupants. Now a day, active suspension system which posses-ses the ability of electronic monitoring and control is of great interest among the researchers in various aspects (Weichao Sun et al., 2012, Jiongkang Lin et al., 2013 and Weichao Sun et al., 2013). The design of controller for the suspension system is the chall-enging task to give in and effect control signals.

Jiangtao Cao (2008) have listed different adaptive, intelligent and optimal control methodologies applic-able to suspension system. The normal Fuzzy Logic Controller (FLC) can intelligently serve for control of suspension system (Rao, 1997, Huang et al., 2000). FLCs emulate the decision-making process that humans exhibit and are capable of controlling the processes that are too complex for Proportional Integral Derivative (PID) controllers. The performa-nce enhancement of FLC can be carried out with proper selection of rule base and scaling factors (Hongyi Li et al., 2013). Tuning of FLCs with well known stochastic optimization technique Genetic Algorithm (GA) either Binary coded or Real coded (BGA/RGA) and other optimization techniques (Yeh, et al., 1994, Huang, et al., 2004, Pingkang Li et al., 2006, Ramakrishnan et al., 2017 and Herrera et al., 1998). Because of rapid initial converging ability of GA, they have been applied with remarkable out-come in various fields including image processing. The RGA differs from BGA in the implementation of recombination operation (Homaifar, et al., 1995). Magdalena, et al., (2004) used RGA for fuzzy swit-ching grey prediction PID controller to minimize the Integral Time Squared Error (ITSE) of a twin rotor Multi Input Multi Output (MIMO) system. In this paper an attempt is made to test the effectiveness of RGA over BGA for a Quarter Car (QC) suspension system (Kalaivani et al., 2014, Kalyanmoy 1995 and Rajeshwari et al., 2010).

The paper is organized as follows. Section III describes the control concepts. Section IV dealt with the simulation results and discussions. Finally, Section V concludes the paper.

PASSENGER CAR: For the theoretical analysis, design and test of suspension systems, the QC models are usually used as they are simple and can capture merely many features of the full car model.

QC model Ali Jamshidi., et al., (2013) represents one wheel of a car and its associated parameters such as sprung mass m_s, unsprung mass m_u, tyre stiffness k_t, suspension stiffness k_s, suspension damping coeffici-ent c_s and an actuator force F_a (Fig. 1). It is assumed that the tyre always in contact with the road and the system parameters are linear in the operating region. The input we taken start in road is assume as y_s, the sprung mass, unsprung mass and tyre displacements are denoted as y_s, y_u and y_t respectively.

$$m_s\ddot{y}_s + c_s(\dot{y}_s - \dot{y}_u) + k_s(y_s - y_u) = F_a$$

$$m_u\ddot{y}_u - c_s(\dot{y}_s - \dot{y}_u) - k_s(y_s - y_u) - k_t(y_t - y_u) = -F_a \quad (1)$$

CONTROLLERS: It is very essential to improve the travelling comfort to the passengers irrespective of the road condition. For the QC system, the Suspen-sion Deflection (SD) which is the relative displace-ment between the sprung mass and unsprung mass and Sprung mass Velocity (SV) are feedback to the intelligent FLC Mouleeswaran Senthil kumar (2007). The controller will produce the control force F_a to reduce the effect of road disturbance which is a dual bump in this study. For the optimization of scaling factors of FLC using GA that is developed by John Holland and his co-workers in University of Michigan in the beginning of 60’s is a stochastic global search technique that combines the concepts natural selection and natural genetics, the cumulative RMS value of Body Acceleration (BA) signal ($\ddot{y}_s$), which is defined as follows is taken as the fitness function.

$$J = \sqrt{\frac{1}{T}\int_0^T \left\|\ddot{y}_s\right\|^2 dt} \qquad (2)$$

where T is the total time period.

A. Quarter Car Model

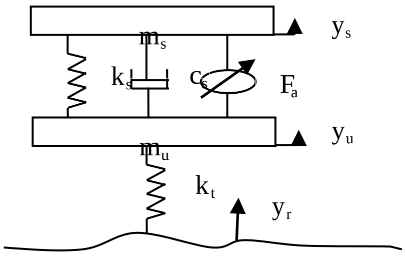
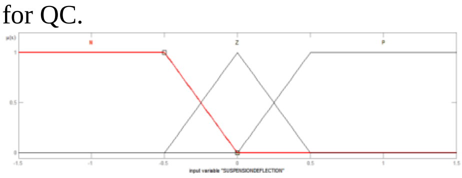


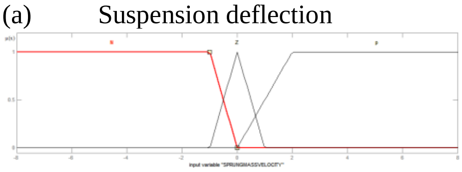
Fig. 1. Quarter car model

GA is inspired from the Darwin's theory of "Survival of fittest". The normal operators are involved in GA is crossover related to mutual information. Based upon the types of these operators GA is classified into Binary coded GA, Real coded GA, and Micro GA etc. GA can be effectively used for optimization of FLC (Pingkang Li et al., 2006). This paper concentrates on BGA and RGA for finding the optimized scaling factors of FLC.

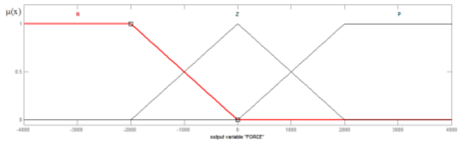
A. ***Fuzzy Logic Controller****:* Fuzzy logic refers to logic of estimation. Bineet Mishra et al., (2009) produces the control action with that estimation. This intelligent design approach using a set of conditional statements can work well because it does not require any accurate mathematical model of the system to be controlled. The universe of discourse is divided into three sections using the linguistic variables Negative (N), Zero (Z) and Positive (P) for all the input and output variables. The triangular membership function (Fig. 2) is chosen and using the linguistic variables, a set of fuzzy rules (3x3) are developed and are shown in Table I. As equally arranged membership functions may not perform well, the distribution of the membership functions of each fuzzy variable of the FLCs can be determined by the scaling factor. G_{sd}, G_{sv} and G_{out} are the two inputs and one output scaling factors of FLC used for QC.



(a) Suspension deflection



(b) Sprung mass Velocity



(c) Force

Fig. 2. Membership functions

TABLE I RULE BASE

SD \ SV	N	Z	P
N	P	P	Z
Z	P	Z	N
P	Z	N	N

B. ***Genetic Algorithm based Optimization of Fuzzy Logic Controllers:*** Three scaling factors such as G_{sd}, G_{sv} and G_{out} have been tuned with the two methods of GA viz. BGA and RGA. FLC tuned with BGA is denoted as BGAFLC and FLC tuned with RGA is denoted as RGAFLC in the remaining of this paper. The discussion of BGA and RGA based optimizations are detailed in the following sections.

1) *Binary coded Genetic Algorithm (BGA)*: In BGA, each chromosome represents a binary string and each bit corresponds to a gene.

The following are the steps involved in function optimization using BGA:

Step 1: Initialize the parameters like crossover probability, mutation probability and size of population (n).

Step 2: Initialize a set of random possible solutions called the initial population such that the values range uniformly throughout the search space. Each of the individual are called chromosomes and are in the form of binary string using 0's and 1's.

Step 3: Calculate the fitness value for each of the individuals in the population and sort in the descending order of the fitness.

Step 4: By using the Roulette wheel method of selection select few individuals to undergo crossover.

Step 5: Generate the point of crossover randomly for each set of parents to produce a child. The genes after the crossover point are exchanged between the two parent chromosomes to give the child chromosomes which contain the attributes of both the parents.

Step 6: Using the mutation probability mutate few individuals. In the process of mutation a bit is randomly chosen from the parent and the bit value is reversed to obtain the mutated chromosome. At the end of performing crossover and mutation child individuals along with the parent population forms the super set for the next generation population.

Step 7: Evaluate the fitness value and perform the sorting of the individuals. Then select "n" best fit values as the next generation population.

Step8: This process should be repeated till the termination condition is converged. The best & optimal solution can be found with obtained.

The Roulette wheel selection, Single point crossover and mutation operators are selected in this work for optimization.

Parameters for BGA optimization used are given below.

Number of generation : 100
Population size : 10
Number of chromosomes in each generation : 50
Crossover probability : 0.8
Mutation probability : 0.05

2) Real coded Genetic Algorithm (RGA): RGA deals with continues search space with large domain and high precision, it is difficult to achieve in BGA where increasing the domain sacrifices the precision. In RGA, each gene represents the problem variable and the size of chromosomes is equal to the length of the solution to the problem. It possesses capacity of local tuning and integrates the domain knowledge, so it improves the GA performance. The slight variation in the variable possesses slight change in the function. There is no difference between genotype and phenotype, so it reduces the computation time and the discretization error is zero.

The following are the steps involved in function optimization using RGA:

Step 1: Initialize the parameters like probability of crossover, probability of mutation, the cross over range α, mutation range β and size of population (n).

Step 2: Initialize the population such that the values range uniformly throughout the search space.

Step 3: Calculate the fitness value for each of the individuals and sort the population in the descending order of the fitness.

Step 4: Select few individuals using the "Roulette wheel" method of selection to undergo crossover.

Step 5: Perform the crossover between two individuals to produce two child chromosomes. A common form of real crossover involves an averaging of two parent genes.

Step 6: Perform the real mutation operation by selecting a gene and adding a random value from within a specified mutation range. At the end of performing crossover and mutation child individuals along with the parent population forms the super set for the next generation population.

Step 7: Evaluate the fitness value and perform the sorting of the individuals. Then select "n" best fit values as the next generation population.

Step8: Repeat this process till the termination condition is reached. The best population obtained at last is the optimal solution.

Step 8: The fitness value evaluation and sorting of the individuals is followed by the selection of "n" best fit values as the next generation population.

Step 9: This process is repeated over and over again till the termination condition was reached. The best population obtained at last is the optimal solution.

Number of generation : 100
Population size : 10
Number of chromosomes in each generation: 50
Mutation probability : 0.05
Cross over probability : 0.8

The cross over range α and mutation range β are selected randomly between 0 to 1.

IV. Simulation Results and Discussion

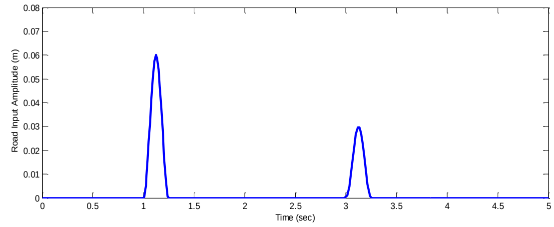


Fig. 3. Road Input for Quarter car and

The QC system discussed in section II are simulated with the controllers explained in section III to nullify the effect of the disturbance from the road inputs (Fig. 3). The vehicle system parameters for QC model considered for this study are listed below.

QC parameters :

Sprung mass	m_s	: 240 kg
Unsprung masses	m_u	: 36 kg
Suspension stiffness	k_s	: 16000Nm^{-1}
Damping coefficient	c_s	: 980Nsm^{-1}
Tire stiffness	k_t	: 160000Nm^{-1}

On performing the optimization of FLC with both the algorithms, the RGA yields rapid convergence compared to BGA (Fig. 4) with the optimized results listed in Table II and III. The slow convergence is one of the draw back with BGA because it needs the conversion of real value into binary and conversion of binary into real value.

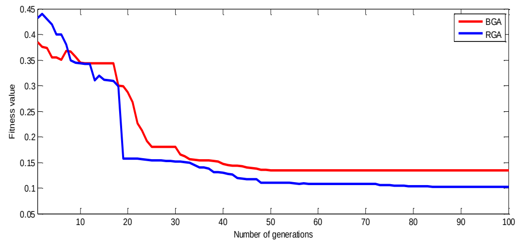
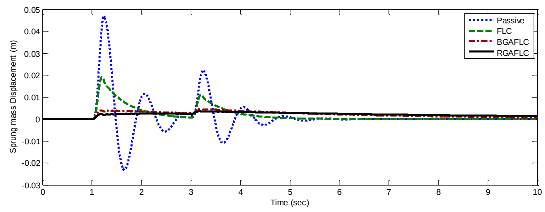


Fig. 4. Statistics of the search process for Quarter car

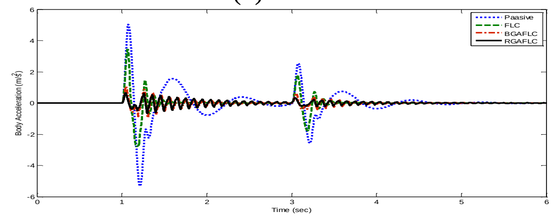
TABLE II Scaling Factors of FLC for Quarter Car

Controller	Fuzzy scaling factors		
	G_{sv}	G_{sd}	G_{out}
FLC	5.0000	2.0000	0.9900
BGAFLC	21.623	0.4696	0.9993
RGAFLC	35.001	0.0200	0.9870

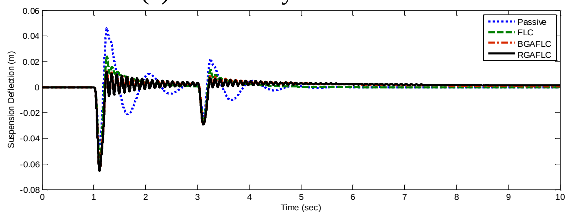


(a) Sprung mass displacement

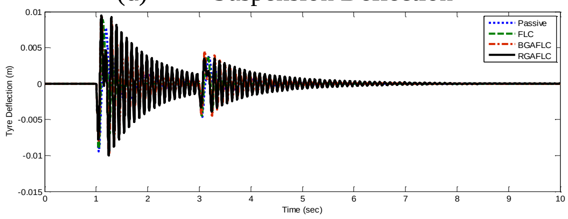
(b)



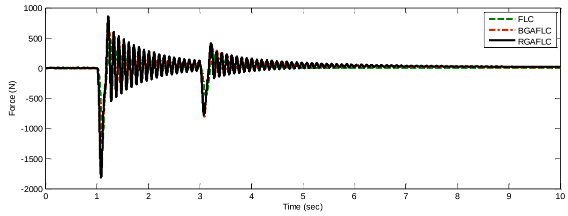
(c) Body acceleration



(d) Suspension Deflection



(e) Tyre Deflection



(f) Actuator force

Fig. 5. Time responses of QC with dual bump road input

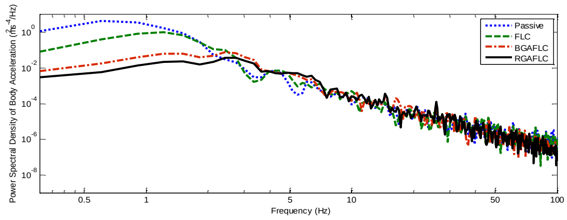


Fig. 6. Power Spectral Density of body acceleration for QC

TABLE IIII RMS VALUES OF QC

Controller	Sprung mass Displacement ($x10^{-6}$)	Body Acceleration ($x\ 10^{-4}$)
Passive	822.0	737.0
FLC	390.0	381.7
BGAFLC	248.4	134.7
RGAFLC	225.2	102.8

From the QC simulation results shown in (Fig. 5), it is inferred that the RGAFLC reduces the sprung mass displacement compared to passive, FLC and BGA-FLC. Among these controllers, RGAFLC reduces the BA to a great extend (Fig. 5b). Also (Fig. 5c) shows that the suspension deflection is maintained within the static deflection ±8cm by all the controllers. (Fig. 5d) illustrates the road holding ability maintained by all the controllers. Tyre deflection for the active systems is almost higher than that of the passive suspension system. (Fig. 5e) shows the actuator force required to produce the control action. The RMS values of the time responses of the sprung mass displacement and BA of active systems are listed in Table III which shows the effectiveness of RGAFLC for the enhancement of travelling comfort. (Fig. 6) for passive, FLC, BGAFLC and RGAFLC with specified road input for QC model. All the discussed controllers suppress the acceleration of sprung mass in the lower frequency band and apparently between 0.4 Hz to 8 Hz.

CONCLUSION

In this paper, for linear QC system the FLC is designed to reduce the body acceleration and then compared with the BGAFLC and RGAFLC. The performance comparison of RGA and BGA shows the rapidity of RGA in yielding the results. This work can be extended for the tuning of membership function of FLC using RGA.

VI. ACKNOWLEDGEMENT

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