# Effect of Random Road Profile on Multi-objective Optimization of a Five-degree of Freedom Vehicle Vibration Model

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***Abstract*—Ride quality and road holding capacity of a vehicle is significantly influenced by its suspension system. In the design process, a number of criteria related to comfort and road holding capacity is taken into consideration in order for achieving the optimum vibration performance. Therefore, multiple design objectives have to be optimized. In this paper, a five-degree-of-freedom system of vehicle vibration model with passive suspension is investigated. This paper formulates the model into multi-objective optimization problem consists two design objectives. The improved compressed objective genetic algorithm (COGA-II), a Pareto-based multi-objective optimizer, is used as the search algorithm. The vehicle model is excited by the bump that the model passes on. Since there might be some differences on optimized solutions on regular and random road profiles, the study on the differences should be consequently investigated. There are 4 cases – 0%, 10%, 20%, and 30% randomization on the bump profile to be studied. Simulation results reveal that there is some significant difference on optimized solutions.**

***Index Terms*— vehicle vibration, multi-objective optimization, genetic algorithm, random road profile**

## I. INTRODUCTION

Suspension system, road surface roughness, and speed of the vehicle considerably influence to quality of ride of a vehicle [1]. The road surface roughness and speed of the vehicle are beyond vehicle design process. Therefore, the suspension system must be designed with optimum vibration performance. The primary performance measure of a suspension system is traditionally measured in terms of ride quality. The two principal variables for design and evaluation of the suspension system are sprung mass which determines ride comfort, and suspension deflection which indicates the limit of the vehicle body motion [2].

Gündoğdu [3] used GAs for optimization of a four-degrees-of-freedom quarter car seat and suspension system to achieve the best performance of a driver. There are four design objectives to be optimized, namely, head acceleration, crest factor, suspension deflection, and tire deflection. The design objectives were transformed to only one mixed objective function. Therefore, single-objective GAs were used in the optimization process. Nariman-Zadeh et al. [4] and Boonlong [5] formulated five-degree-of-freedom vehicle vibration model as multi-objective optimization problems. The design objectives were optimized simultaneously without the combination of design objectives as [3], [6].

In optimization process, there are two main optimization approaches, derivative-based and derivative-free methods. Compared to the derivative-based schemes, the derivative-free methods do not need functional derivative of a given objective function. They, instead, rely on repeated evaluation of the objective function and obtain the search direction under nature-inspired heuristic guidelines. Although the derivative-free schemes are generally slower than the derivative-based methods, they are much more effective for complicated objective functions and combinatorial problems as the methods do not require differentiable objective functions. GA is a derivative-free population-based optimization method of which search mechanisms are based on the Darwinian concept of survival of the fittest. Originally, the GA is established to solve single-objective optimization problems (SOOPs) [7]; subsequently it is adapted to solve multi-objective optimization problems (MOOPs) which have a number of objective functions to be minimized or maximized.

In general, it is almost improbable that only one solution can optimize all objectives for a given MOOP. Based on the Pareto approach, the multiple optimum solutions of the MOOP – the Pareto optimal solutions – are used in decision making process. Solutions of MOOPs are compared by the Pareto domination [8], which is originally defined by Vilfredo Pareto. If a given solution dominates other solutions, it is better than the rest. Thus, for a given solution set, the non-dominated solutions are the best solutions of the set. A Pareto-based MOGA embeds the Pareto domination concept into a genetic algorithm (GA). In a single-objective GA, an objective of a solution i is directly used to evaluate the fitness of the solution. On the other hand, the Pareto-based MOGA employs Pareto domination concept to assign fitness or rank of a solution from objectives of the solution. Previous researches such as [4], [5], [9] employ road profile represented by certain explicit function, harmonic function. This paper studies the effects of

Manuscript received July 6, 2019; revised February 1, 2020.



doi: 10.18178/ijmerr.9.4.582-586

random road profile on the multi-objective optimization of vehicle vibration model, in which a Pareto-based MOGA, the improved compressed objective genetic algorithm (COGA-II) [5], [10] as the search algorithm for multi-objective optimization of a five-degree of freedom vehicle vibration model.

## II. Test Problem

A five-degree of freedom system of vehicle model with passive suspension is used for performance investigations as shown in Fig. 1. There are 5 independent coordinates of the system – vertical displacement of seat mass ($z_c$), vertical displacement of sprung mass ($z_s$), rotation angle of sprung mass ($\theta$), vertical displacement of front tire ($z_{tf}$) and vertical displacement of rear tire ($z_{tr}$). Nine fixed parameters – seat mass ($m_c$ = 75 kg), sprung mass ($m_s$ = 730 kg), moment of inertia of sprung mass ($I_s$ = 130 kg-m$^2$), forward tire mass ($m_{tf}$ = 40 kg), rear tire mass ($m_{tr}$ = 35.5 kg), equivalent spring constant of forward tire ($k_{tf}$ = 175,500 N/m), equivalent spring constant of rear tire ($k_{tr}$ = 175,500 N/m), relative position of front tire to the center of sprung mass ($l_f$ = 1.011 m), and relative position of rear tire to the center of sprung mass ($l_r$ = 1.803 m), are used. Seven design variables which are equivalent spring constant of seat ($k_{ss}$), equivalent damping constant of seat ($c_{ss}$), equivalent spring constant of suspension at forward tire ($k_{sf}$) equivalent spring constant of suspension at rear tire ($k_{sr}$), equivalent damping constants of suspension at forward tire ($c_{sf}$) equivalent damping constants of suspension at rear tire ($c_{sr}$) and relative position of seat to the center of sprung mass ($r$), have to be optimized. The range values for the decision variables are shown in Table I.

The vehicle is moved directly with constant velocity ($v$) of 20 m/s and excited by a double road bump. It is assumed that the rear tire follows the same route of the front view with a delay time $\Delta t = (l_f + l_r)/v = 0.1407$ seconds. Due to the excitation of double road bump, the vertical displacements of a point at bottom of forward tire ($z_{bf}$) are displayed in Fig. 2. There are 4 amounts of randomized factor – 0%, 10%, 20%, and 30% as shown. In case of the 0% randomization, the vertical displacements of a point at bottom of forward tire ($z_{bf}$) are given by (1). In the figure, the length of road bump is actually equal to 20×2.5 = 50 m. In randomization process, the length is divided into a number of elements so that each of them has length of 0.2 m. The bump profile without randomized factor is used as the basis in order to create the bump profile in the randomization.

$$z_{bf} = \begin{cases} 0, & 0 \le t < 0.5 \\ 0.05\sin\left(2\pi(t-0.5)\right), & 0.5 \le t \le 2.5 \\ 0 & t > 2.5 \end{cases} \quad (1)$$

There are two objective functions – seat acceleration ($x_1$), and forward tire acceleration ($x_2$) to be optimized. The numerical indicators, $f_1$ and $f_2$, of these objective functions, $x_1$ and $x_2$, are given by the equation (2).

$$f_i = \sqrt{\int_0^\infty x_i^2 dt}, i = 1,2 \quad (2)$$

where $x_1 = \ddot{z}_c$ and $x_2 = \ddot{z}_{tf}$ .

## III. Simulation Results and Discussions

The parameter settings for COGA-II are illustrated in Table II. There are two objective functions – seat acceleration ($x_1$), and forward tire acceleration ($x_2$) to be optimized. The numerical indicators, $f_1$ and $f_2$, of these objective functions, $x_1$ and $x_2$, are given by the following equation. After the search, in each case solutions of all runs are merged; Pareto optimal solutions of each case can be obtained.

TABLE I. Decision Variables

| Parameters | Values |
|---|---|
| $k_{ss}$ | 50,000 – 100,000 N/m |
| $c_{ss}$ | 1,000 – 4,000 Nm/s |
| $k_{sf}$ and $k_{sr}$ | 10,000 – 20,000 N/m |
| $c_{sf}$ and $c_{sr}$ | 500 – 2,000 Nm/s |
| $r$ | 0 – 0.5 m |

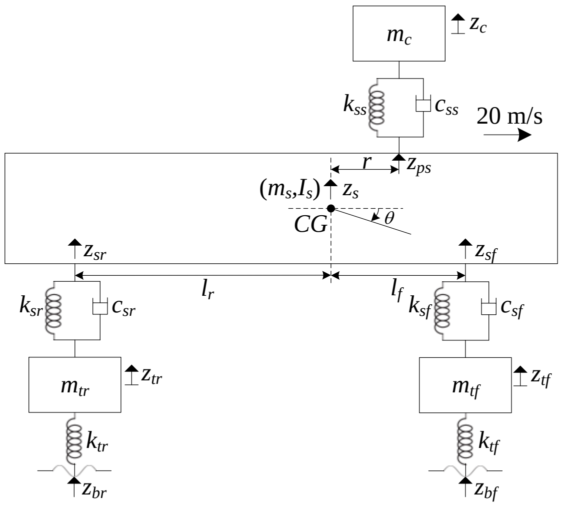


Figure 1. Five-degree of freedom vehicle vibration model.

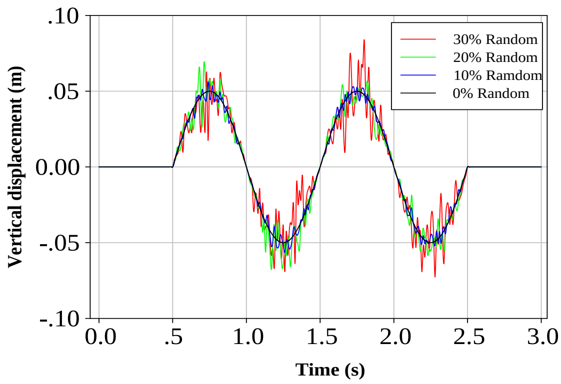


Figure 2. Five-degree of freedom vehicle vibration model.

The values of decision variables of the Pareto optimal solutions are plotted in Fig. 3. There is some significant difference on the optimized solutions. For instance, $k_{sf}$ and $c_{sf}$, value of these variables is high for the bump profile without randomization, but value of these variables is lower with the increase of randomized factor.

Table III shows the values of the decision variables of solutions with the best values of each design objective. In the table, B100 is a solution with the best value of the first design objective of the case with 0% randomized, B110, B120, and B130, have the best value of the first design objective of the cases with 10%, 20%, 30%, respectively. Solutions B200, B210, B220, B230, have the best value of the second design objective of the cases with 0%, 10%, 20%, 30%, respectively.

TABLE II. COGA-II PARAMETER SETTINGS

| Parameters | Settings and values |
|---|---|
| Chromosome coding | Real-value chromosome |
| Crossover method | SBX crossover [8] with probability = 0.9 |
| Mutation method | Variable-wise polynomial mutation [8] with probability = 0.1 |
| Population size | 80 |
| Archive size | 80 |
| Number of generations | 240 |
| Number of repeated runs | 10 |

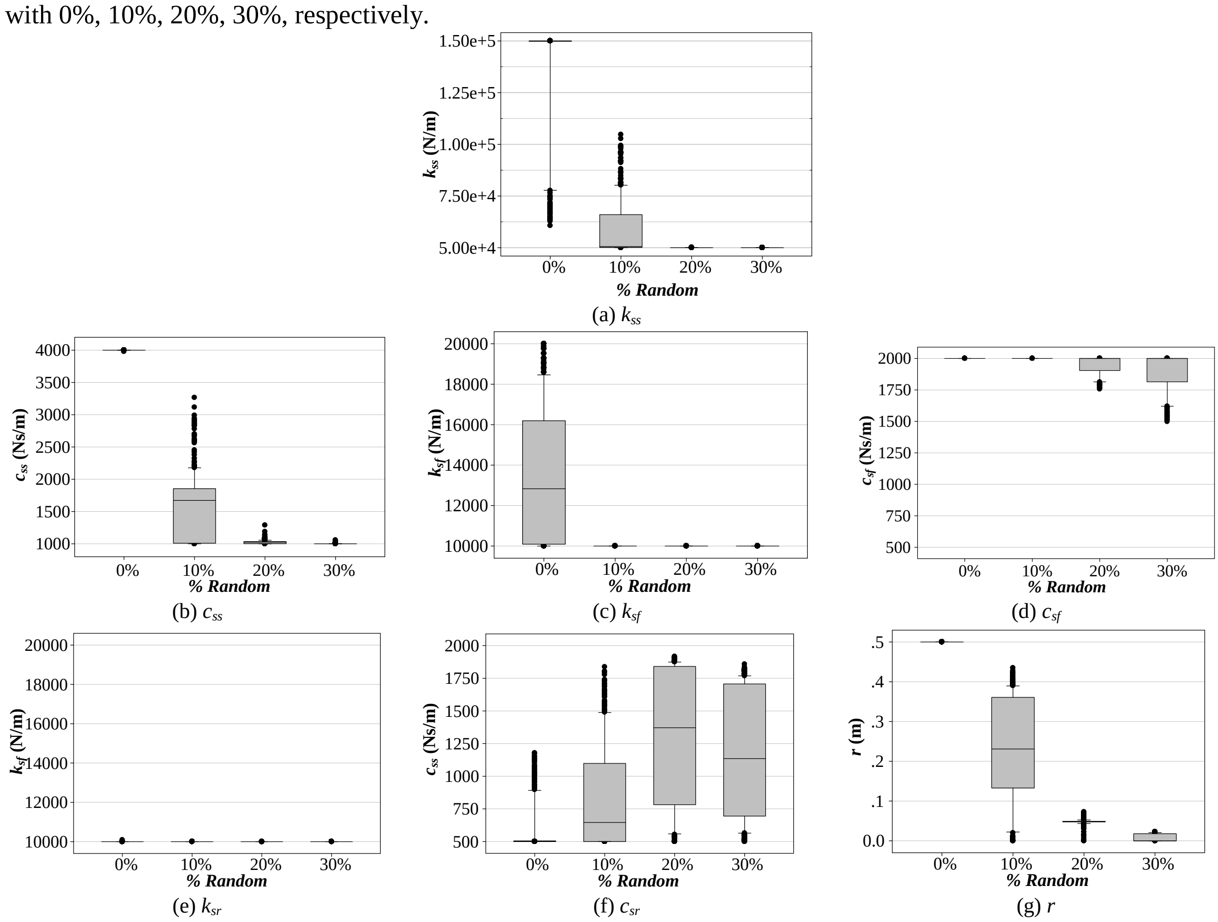


Figure 3. Decision variables of the Pareto optimal solutions.

TABLE III. SOLUTIONS WITH THE BEST VALUES OF EACH DESIGN OBJECTIVE

| Solutions | $k_{ss}$ | $c_{ss}$ | $k_{sf}$ | $k_{sr}$ | $c_{sf}$ | $c_{sr}$ | $r$ |
|---|---|---|---|---|---|---|---|
| **B100** | 64,806 | 4,000 | 10,000 | 2,000 | 10,000 | 1,077 | 0.500 |
| **B110** | 96,011 | 2,827 | 10,000 | 2,000 | 10,000 | 1,733 | 0.131 |
| **B120** | 50,000 | 1,019 | 10,000 | 1,760 | 10,000 | 1,826 | 0.048 |
| **B130** | 50,000 | 1,000 | 10,000 | 1,521 | 10,000 | 1,671 | 0.021 |
| **B200** | 149,999 | 4,000 | 19,759 | 2,000 | 10,000 | 500 | 0.500 |
| **B210** | 50,027 | 1,000 | 10,000 | 2,000 | 10,000 | 500 | 0.000 |
| **B220** | 50,003 | 1,000 | 10,000 | 2,000 | 10,000 | 500 | 0.000 |
| **B230** | 50,000 | 1,000 | 10,000 | 2,000 | 10,000 | 500 | 0.000 |

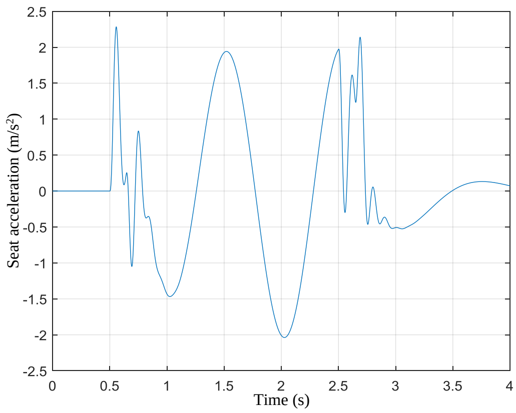


Figure 4. Seat accelerations of B100 on 0% randomized bump profile.

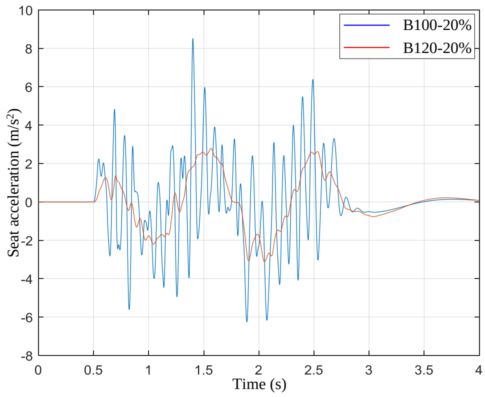


Figure 6. Comparison of seat accelerations of B100 and B120 on 20% randomized bump profile.

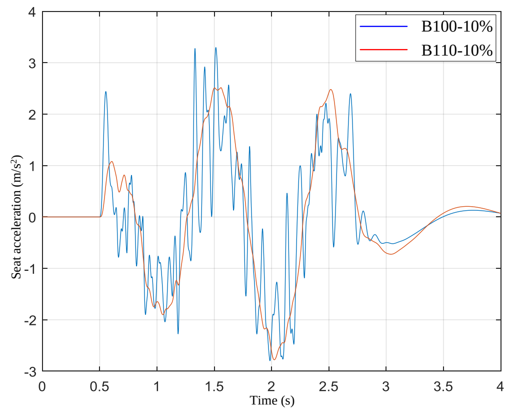


Figure 5. Comparison of seat accelerations of B100 and B110 on 10% randomized bump profile.

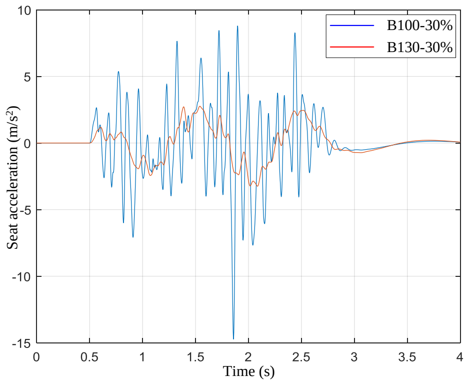


Figure 7. Comparison of seat accelerations of B100 and B130 on 30% randomized bump profile.

Figs. 4-7 show seat accelerations, first objective functions, of the optimized solutions with the best values of the objective. It is found that the performance of B100, the solution with the best value of the first design objective, is worse with the increase of randomized factors.

## IV. Conclusion

This paper proposes the study of effect of random road profile on multi-objective optimization of the five-degree-of-freedom vehicle model. The bump profile of road, that is activated the vehicle to vibrated, is considered in this study. Without randomization, the bump profile is represented by harmonic function. There are 3 nonzero randomized factors, 10%, 20%, and 30%, are included in the harmonic bump profile. Simulation results reveal that the values of decision variables of optimized solutions in the cases of non-zero randomized factors are quite different those in the case of the zero randomized factor, as also presented in the previous study [5].

The optimized solution in the case without randomization is poor in the cases of randomization. In general road profile is in random condition, so that the homogeneous response displayed in the entire of time. It is probable that some natural frequencies probably are higher than frequencies due to the road. The high vibration frequencies probably make more ride uncomfortable than the lower ones. Random road profile, that supplies high vibration frequencies due to homogeneous response, should be therefore taken into account in multi-objective optimization of vehicle vibration.

## Conflict of Interest

The authors declare no conflict of interest.

## Author Contributions

Kittipong Boonlong and Puttha Jeenkour conducted the research, analyzed the data and wrote the paper. All authors had approved the final version.

## Acknowledgment

The authors wish to thank Faculty of Engineering, Burapha University for their financial support.

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