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Road Profile Identification by Genetic Algorithm with Multistage Search using Vibration Response of a Quarter Vehicle Model

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Abstract: Vehicle performance is affected by road profile since the road profile supplies vibration to the vehicle. The road profile can be identified by vibration response of the vehicle. By using the vibration response, road profile identification can be, in fact, formulated as a single-objective optimization in which an objective, a minimization criterion, is the numerical difference between vehicle vibration response of actual road profile and that of predicted road profile. This paper present multistage search in genetic algorithm (GA), an optimization algorithm, in the road profile identification. In the multistage search, a solution is divided into a number of parts and each part is consequently evolved as GA process separately from other parts. A quarter vehicle models with two test cases of double bump on road profiles are used. Simulation runs reveal that the multistage search can enhance performance of GA. In addition, the multistage search using the least number of decision variables in each solution part gives the best results of the optimized solutions.

Keywords: Genetic algorithm (GA), road profile, vibration

1. Introduction

Here Road profile affects vehicle performance by contributing vibration to the vehicle. The road profile can be actually detected by the vibration signal measured on the vehicle [1], [2], [3], [4]. By using vibration response, the road profile identification can be formulated as a single objective optimization problem. 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 a functional derivative of a given objective. They, instead, rely on the repeated evaluations of the objective functions and perform the search direction under the nature-inspired heuristic guidelines. Although the derivative-free schemes are generally slower than the derivative-based methods, they are much more effective for the complicated objective functions and combinatorial problems as the methods do not require differentiable objective functions. Genetic algorithm (GA) [5], [6], [7], [8] is a derivative-free population-based optimization method of which search mechanisms are based on the Darwinian concept of survival of the fittest.

This paper proposes a multistage search for GA in road profile identification using vibration response of a quarter vehicle model. In multistage search, a full solution is divided into a number of solution parts. A part of a full solution is evolved by GA generation in each solution search stage. The multistage search is quite different from co-operative co-evolution employed in genetic algorithm (CCGA) [9], [10], [11] in which a solution is also divided into a number of parts, the so-called species. In CCGA, each species is evolved simultaneously with other species. In contrast, each solution part in multistage search is evolved separately to other parts. In multistage search, the first part is optimized until termination condition is satisfied, the second part is started to be optimized, and so on.

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2. Quarter vehicle model in road profile identification

A quarter vehicle model, two-degree of freedom system, as shown in Fig. **1**(a) is used in the road profile identification. There are 2 cases of the road profiles which are shown in Figure 1(b) and Figure 1(c). The road profile for cases (a) and (b), displayed in Fig. **1**(b) and Fig. **1**(c), is expressed as equations (1) and, respectively. In the vehicle model, there are 2 independent coordinates of the system – vertical displacement of seat mass (z_c), and vertical displacement of sprung mass (z_s). The vehicle is moved directly with constant speed of 10 m/s and excited by the road profile. In the model, sprung mass (m_s), tire mass (m_t), equivalent spring constant of suspension (k_s), equivalent damping constant of suspension (c_s), equivalent spring constant of tire (k_t) are 250 kg, 53 kg,10 kN/m, 200 kN/m, 1,000 Ns/m, respectively.

$$z_r = \begin{cases} 0 & 0 \le x \le 5 \\ 0.05\sin\left(\dfrac{\pi(x-5)}{5}\right) & 5 < x \le 10 \\ 0 & 10 < x \le 15 \\ -0.04\sin\left(\dfrac{\pi(x-15)}{5}\right) & 15 < x \le 20 \\ 0 & 20 < x \le 25 \end{cases} \tag{1}$$

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Equations and formulae should be typed in Mathtype, and numbered consecutively with Arabic numerals in parentheses on the right-hand side of the page (if referred to explicitly in the text). They should also be separated from the surrounding text by one space.

$$f = \sum_{i=1}^{N} \left| (a_{sp})_i - (a_{sa})_i \right| \tag{2}$$

where $(a_{sp})_i$ and $(a_{sa})_i$ is acceleration obtained from the predicted road profile and that obtained from the actual road profile. In optimization, a solution is encoded into a real chromosome consisting of N decision variables in which each variable $x_i \in [0,1]$. The increment of road profile in a time interval j ($\Delta z_{r,j}$) is defined as equation (3).

$$\Delta z_{r,j} = (x_j - 0.5) \times \Delta z_{r,\max} \tag{3}$$

In this paper maximum value of the increment of road profile in a time interval $\Delta z_{r,\max}$ is predefined to equal to 0.005 m. The height of road at a time interval i is then equal to the cumulative summation of $\Delta z_{r,j}$ as equation (4).

$$z_{r,i} = \sum_{j=1}^{i} \Delta z_{r,j} \tag{4}$$

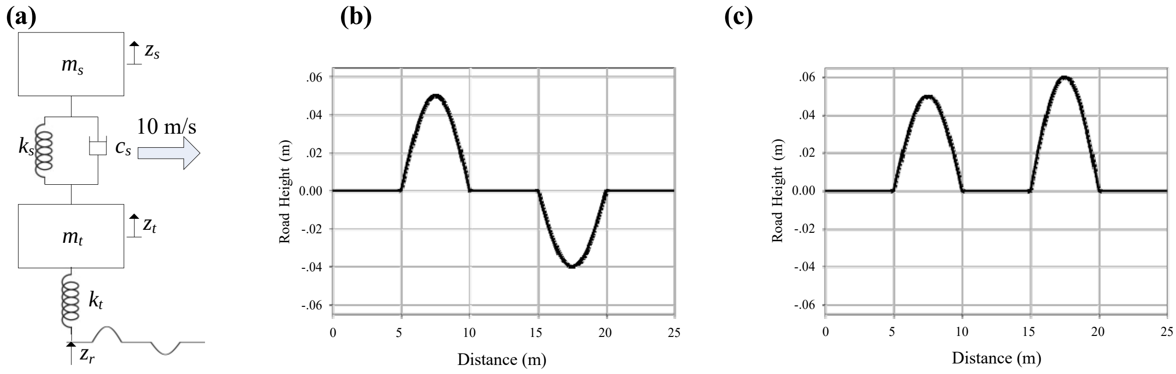


Fig. 1 - A quarter vehicle model and road profile (a) Vehicle model (b) Road profile of case 1 (c) Road profile of case 2

3. Genetic algorithm with multistage search

The genetic algorithm (GA) has been extensively explained in [5] and is discussed here to illustrate the basic components and mechanisms of the GA. The GA procedure of the GA starts with the generation of random individual of an initial population which are a set of solutions to an optimization problem. A solution is encoded into a string of number which generally called "chromosome". The chromosome of every individual is decoded in order to obtain corresponding solutions to the optimization problem. The objective value of each individual in the population can be then calculated. The fitness value is then evaluated based on the objective value obtained. The fitness scaling technique [8] is introduced in order to improve the performance of search mechanism. The aim of this technique is to encourage the difference between the maximum and average fitness values to be used in the following selection process by the introduction of a scaling factor which is actually more than one. Based on the fitness values, a parent population is then selected from the current population. The parent population are performed a transformation using genetic operators, crossover and mutation, to obtain the resulting offspring population. The offspring population is then merged with the elite individuals to form the new population. Finally, termination condition is verified. If the condition is satisfied, the best solution to the current population is reported as the output solution. If the condition is not satisfied, chromosome of every individual is decoded again in order to obtained a represented solution. It is noted that one loop after the current population is created until the population is updated is called one GA generation. The main procedure of GA is shown in

Fig. **2**.

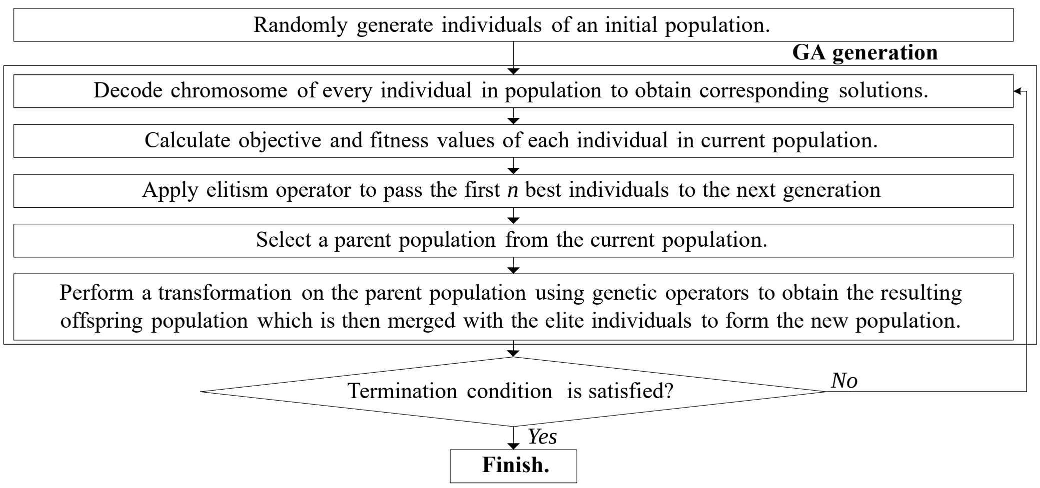


Fig. 2 - the Main procedure of GA

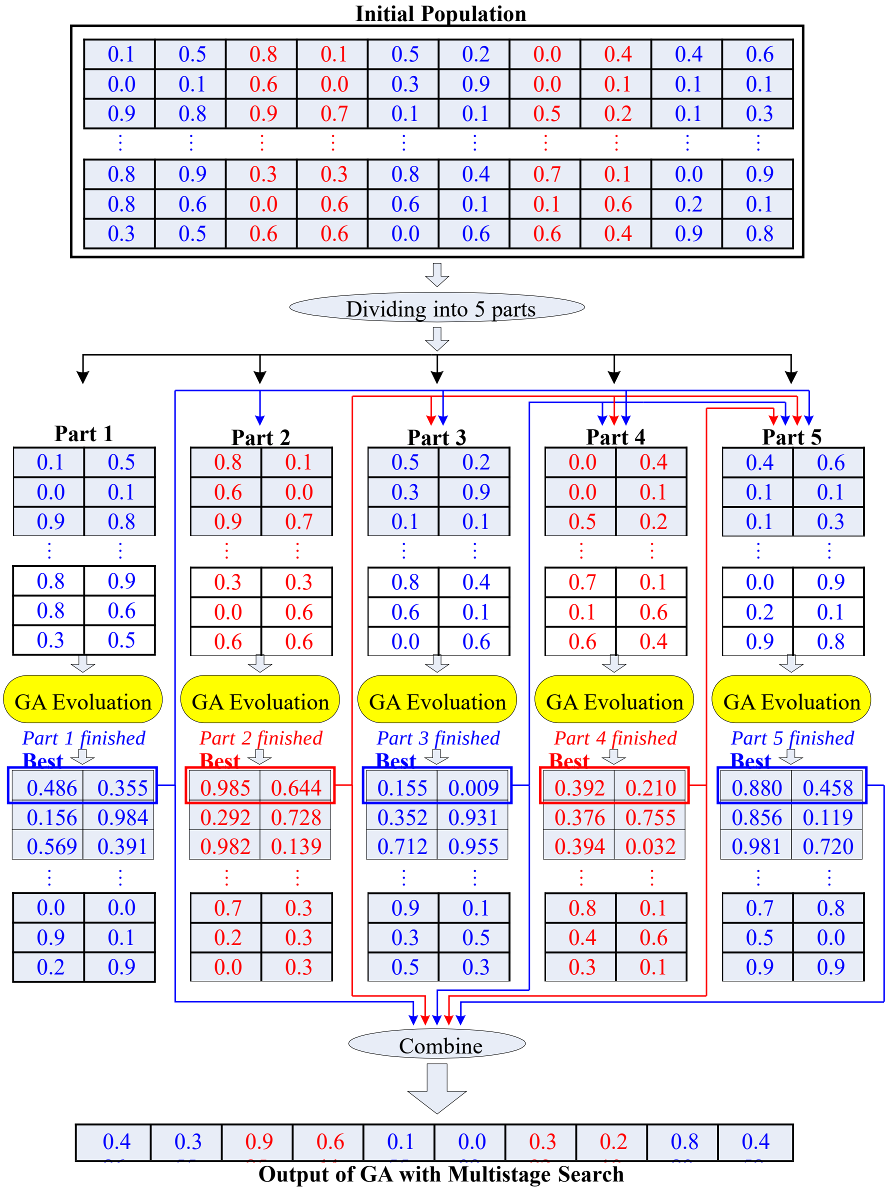


Fig. 3 - Genetic algorithm with multistage search for 10 decision variables real coded chromosome divided into 5 parts

This paper multistage search (MS) in the genetic algorithm (GA) for the optimization in the road profile identification. In the multistage search, a solution is divided into a number of parts. A part of a full solution is evolved in ascending order by GA generation in each solution search stage. For instance, if a full solution is represented by 10 decision variables real coded chromosome and divided into 5 equal parts of which each contains 2 variables as shown in

Fig. **3**. At first solution search stage, the first part which has 2 first design variable is evolved by GA process. In objective calculation, only the first 2 design variables are used in order to achieve the corresponding objective of an individual. After the termination condition, the first 2 optimized variables are consequently obtained. Thereafter, the second part is then evolved in which the optimized design variables in the first parts is used. In objective calculation of an individual in the second part, corresponding objective of the individual is calculated from 2 design variables from the individual by using the required coordinates numerically obtained from the optimized variables from the first part. The process is repeated until the GA evolution of the last solution parts is finished. The output solution of GA with multistage search is obtained from combination of the best solutions of all solution parts as displayed in

Fig. **3**. The multistage search (MS) is particularly proposed to reduce search space of this problem. For the case as shown in

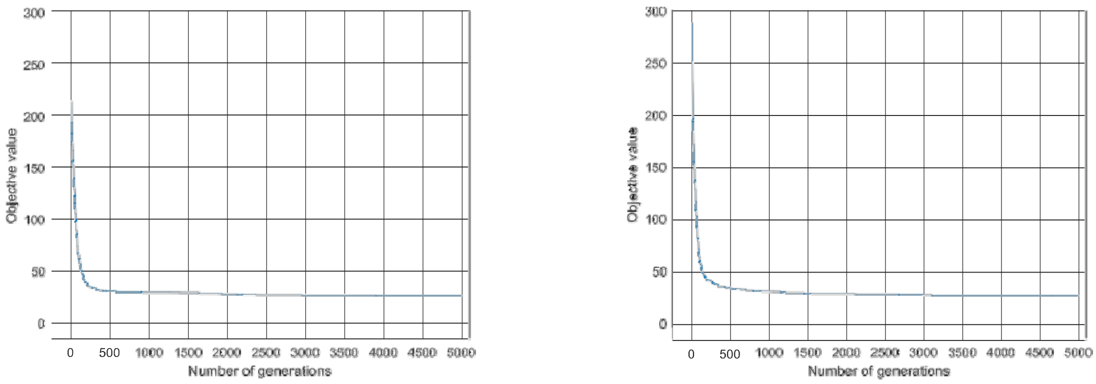
Fig. **3**, if normal GA is used in optimization with a full solution represented by 10 three decimal digits variables chromosome and each variable is from 0.000 to 1.000, the number of possible solutions is about $1000^{10} = 10^{30}$. By dividing a full solution into 5 equal parts in MS, the number of possible solutions is exponentially reduced to be only about $5 \times 1000^2 = 5 \times 10^6$. However MS is not suitable to enhance performance of GA in all optimization problems. The multistage search (MS) is particularly proposed for the road profile identification test problem. In the objective function, f, as shown in equation (2), sub-objective function, f_i, in time interval i is defined as equation (5).

$$f_i = \left| \left(a_{sp}\right)_i - \left(a_{sa}\right)_i \right| \tag{5}$$

where $(a_{sp})_i$ and $(a_{sa})_i$ is the acceleration obtained from the predicted road profile and that obtained from the actual road profile. From equations (3), (4), and (5), it is found that the sub-objective function f_m is numerically evaluated from x_1, x_2, ..., x_{m-1}, and x_m so that sub-objective functions f_1 to f_m are affected by only x_1, x_2, ..., x_{m-1}, and x_m. Therefore, by GA with multistage search using the sum of sub-objective functions f_1 to f_m as the optimized objective function, the optimum x_1, x_2, ..., x_{m-1}, and x_m can be obtained. After the first m decision variables are optimized, the next m decision variables x_{m+1}, x_{m+2}, ..., x_{2m-1}, and x_{2m} can be similarly obtained by the use of the sum of sub-objective functions f_1 to f_m as optimized objective function. The optimization of the decision variables are repeated until all N decision variable, x_1, x_2, ..., x_{N-1}, and x_N are optimized. With the use of the multistage search, the solution search space is significantly reduced so that the optimized solution obtained from the multistage search is better than an optimized solution searched from a full solution represented by N decision variables by normal GA.

Table 1 - GA parameters settings

Parameters	Settings and values
Chromosome coding	The real-value chromosome with 250 decision variables.
Number of decision variables in each solution search (NVE)	GA with no MS: 250 GA with MS : 125, 25, 5
Fitness scaling	Linear fitness scaling with a factor of 2.0
Crossover method	SBX crossover [12], [13] with probability = 1.0
Mutation method	Variable-wise polynomial mutation [14] with probability = 0.025
Population size	100
Number of generations in each solution search stage	20×number of decision variables
Number of repeated runs	10

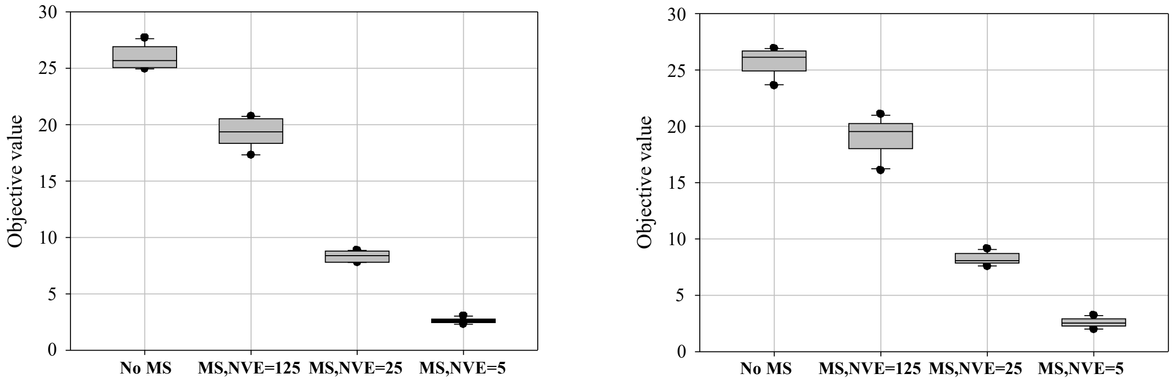


(a) **(b)**

Fig. 4 - Convergence of objective value of GA with no MS for both 2 cases (a) Case 1 a) Case 2

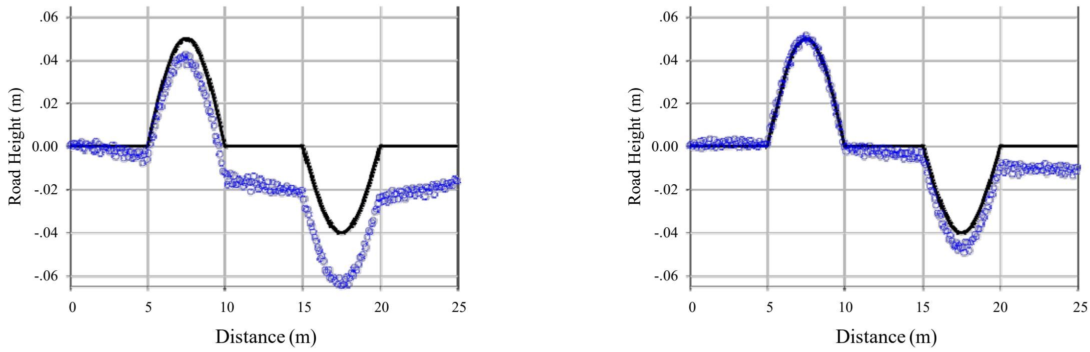
4. Results and Discussions

The parameter settings for GA are illustrated in Table 1. Fig. 4 show convergence of objective value against the number of generations of GA with no MS from one simulation run. This figure shows that number of generations in Table 1 is enough for the study in this paper. The box plots of objective values of the optimized solutions obtained from GA without MS, GA with MS, number of decision variables in each solution search (NVE)= 125, GA with MS, NVE = 25, and GA with MS, NVE = 5, are shown in Fig. 5. The figure shows that GAs with MS outperforms GA without MS. For GA with MS, the objective values are better with the decrease of the NVE. Fig. 6 and Fig. 7 display road profiles from optimized solutions, which is the best solution of all repeated runs, of case 1 and case 2 respectively. The coefficient of determination (R^2), a maximum criterion, is also shown in the figures. R^2 is equal to its maximum number which is 1, means the predicted road profile is same as the exact one. From the figures, the road profiles from the optimized solutions of GA with MS are obviously better than GA without MS. In addition, GA with MS and NVE = 5 provides the best road profiles.

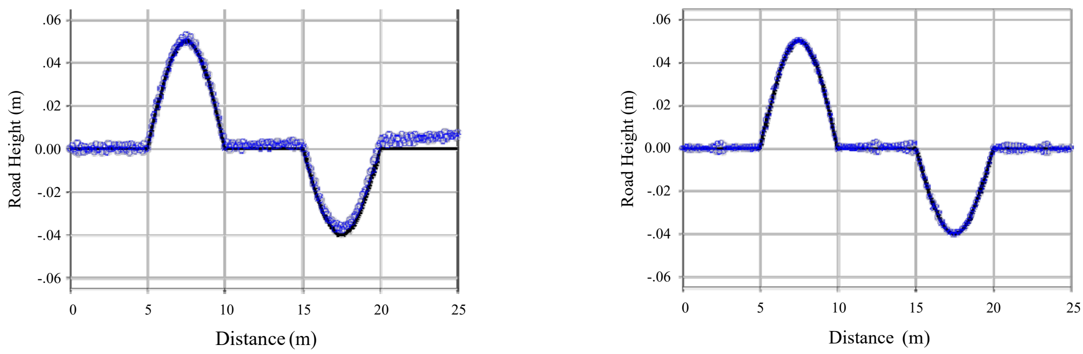


(a) (b)

Fig. 5 - Objective values of optimized solutions (a) Case 1 b) Case 2

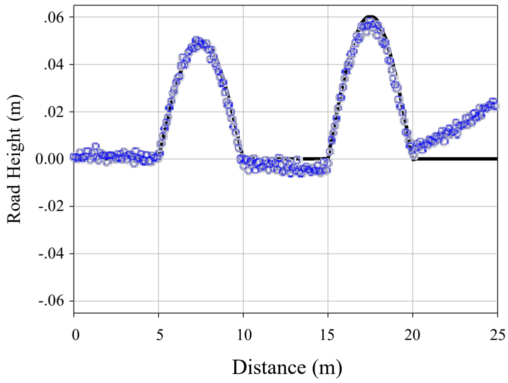


(a) No MS (R^2 = 0.543801) (b) MS with *NVE* = 125 (R^2 = 0.927261)

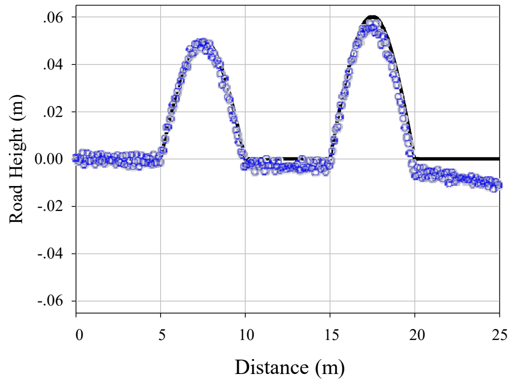


(c) MS with *NVE* = 25 (R^2 = 0.979223) (d) MS with *NVE* = 5 (R^2 = 0.998281)

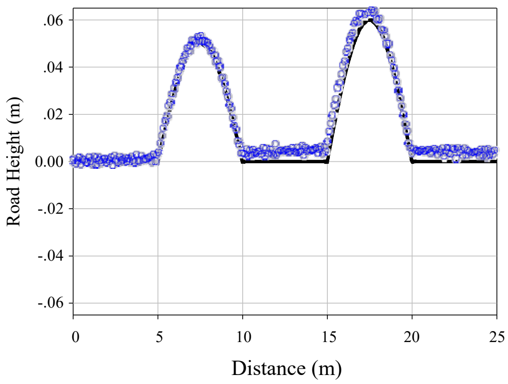
Fig. 6 - Road profile from optimized solutions of case 1 (black line is actual, blue circle = predicted)



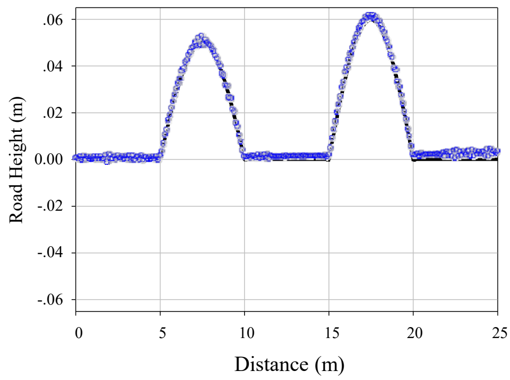
(a) No MS (R^2 = 0.877653)



(b) MS with *NVE* = 125 (R^2 = 0.947894)



(c) MS with *NVE* = 25 (R^2 = 0.971267)



(d) MS with *NVE* = 5 (R^2 = 0.995888)

Fig. 7 - Road profile from optimized solutions of case 2 (black line is actual, blue circle = predicted)

5. Summary

This paper proposes the multistage search in a genetic algorithm (GA) in the road profile identification using vibration response of a quarter vehicle model. In the multistage search, a part of solution is optimized separately in each of solution search stage. There are 2 test cases of double bump on-road profiles to be studied. In both cases, the road distance is equally divided into 250 elements each of which has length of 10 cm. In GA, a full solution is encoded into real-coded chromosome which contains 250 decision variable. In the multistage search, the full solution is partitioned in a number of parts of which each has equal decision variables in which are 3 numbers of decision variables in each solution search (NVE) which are 125, 25, and 5. From the simulation runs, optimized solutions by GA with the multistage search are better than GA without the multistage search regardless of numbers of decision variables in each solution search. In addition, the multistage search using the least number of decision variables contributes the best-optimized solutions to the road profile identification. Due to the reduction of the number of possible solutions by the multistage technique as previously described. the number of possible solutions of GA with small NVE is less than that of GA with large NVE. Therefore solutions obtained from GA with the small NVE is better than those obtained from GA with the large NVE.

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