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Traffic Noise Estimation using Genetic Algorithm (GA) Approach

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Abstract

In the present work, vehicular traffic noise prediction models have been developed for Patiala city (Punjab) using GA and regression approach. The various terminologies related to GA and acoustics analysis are discussed. The models predict equivalent continuous sound level (L_{eq}) as the function of vehicle volume (Log Q) and percentage of heavy vehicles (P %). A large number of data have recorded at different dates/timings to account variability. Three commonly used GA selection operators (uniform, roulette wheel, and tournament) are used to analyze the accuracy of GA models. The GA model performs better as compared to regression model. The average mean square error (MSE) using GA model is 0.59 as compared to 0.76 for regression model. Among all GA selection operators, tournament selection shows better result.

Keywords

Regression, Genetic Algorithm, Modelling, traffic noise, vehicle volume, percentage of heavy vehicles.

Introduction

In India, the growing number of vehicles creates a serious threat to the environment. The noise pollution level increases with increases in number of vehicles. Traffic noise problem is contributed by various kinds of vehicles including heavy, medium trucks/buses, automobiles and two wheelers. Researchers have developed various noise prediction model in India and abroad using traditional [1-9] and advanced [10, 11] techniques. Campbell [8] has critically reviewed the most commonly used traffic noise prediction models like CORTN, FHWA and ASJ etc. Kumar P. [9] developed two mathematical models to predict, equivalent continuous sound level (L_{eq}) and 10 percentile exceeded sound level (L_{10}), traffic noise descriptors Rahmani et al. [10] have modelled road traffic noise using genetic algorithm. Kumar et al. [11] developed a multilayer feed forward back propagation (BP) neural network (ANN) for predicting highway traffic noise.

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The ANN has been trained using Levenberg–Marquardt (L–M) algorithm. The developed ANN model predicts 10 Percentile exceeded sound level (L_{10}) and Equivalent continuous sound level (L_{eq}) in dB (A).

Different researchers have adopted different methodology and traffic noise parameters to predict different traffic noise descriptors. Very few researchers have advanced with newer techniques like artificial neural network [11] and GA [10]. In the present work, two different noise prediction models have been developed and compared using GA and regression analysis. Models predict equivalent continuous sound level (L_{eq}) as the function of vehicle volume (Log Q) and percentage of heavy vehicles (P %). Different GA crossover operators have also been explored to predict the accuracy of developed GA models. A large number of data sets have measured and recorded at different dates/timings to account variability.

Measuring Instrument and procedure

A smooth flowing straight road patch is selected at 4 km away from Patiala (Punjab, India) toward Sirhind road. Sound pressure level is obtained using a Sound level meter (SLM) (CESVA SC-310). SLM is placed at a height of 1.2 m and at distance of 8.5 m from centre of the inner and outer lanes to measure equivalent continuous sound level (L_{eq}) in dB (A) (Fig.1). The SLM is first calibrated before any measurement. Number of Vehicle of each category are also measured in inner and outer lanes and then the total vehicle volume (Q) and percentage of heavy vehicles (P %) are computed. The measurements are made at different date and timing to account variability in measured data.

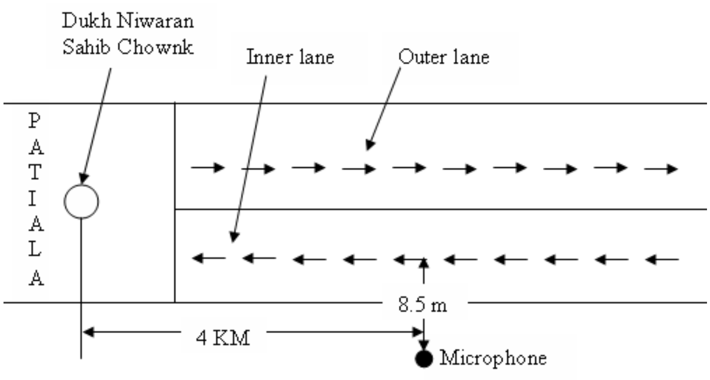

Figure 1: Data collection points (same location as right on left side) [9]

Genetic Algorithm (GA)

GA was invented by John Holland in the year 1975 and is based on the principle of survival of fittest. It is popularly used optimizing technique in frontier area of research. The important steps include population initialization, fitness function evaluation, crossover, mutation, elitism and next generation population etc. Various step involved in GA implementation are:

1. Generate random population of given size and calculate fitness function at each population.

2. Ranked according to the fitness value.
3. Produce next offspring from parent using crossover and mutation operator.
4. Repeat step 1-3 until the stopping criterion (maximum generation reached, elapse time, no change in fitness function, stall time limit) meets or the desired goal achieves.

Table-1 Measured input and output parameters

Sample No	Log(Q)	P (%)	L_{eq} dB (A)
1	3.14	10.2	75.3
2	3.06	9.4	74.1
3	3.03	7.4	73.7
4	3.01	12.9	74.5
5	3.09	10.7	74.4
6	3.2	9.1	75.9
7	3.24	7.1	75.0
8	3.23	8.1	75.0
9	3.11	10.3	72.9
10	3.23	10.4	76.1
11	3.18	9.2	75.7
12	3.17	9.4	75.4
13	3.16	8.1	75.5
14	3.1	9.9	74.5
15	3.14	9.6	75.4
16	3.21	8.9	77.4
17	3.14	11.0	75.4
18	3.11	9.3	75.0
19	3.07	12.1	74.2
20	3.19	10.2	76.8
21	3.20	8.8	75.8
22	3.24	6.3	75.2
23	3.22	7.2	75.9
24	3.08	9.7	74.4
25	3.23	6.1	74.1

The main objective of the present study is to minimizing the sum of squared error between experimental and predicted output and find the various multiplication factors of different input variables to fit into linear model. The objective function is defined as

$$E=\min \sum [(L_{eq})_{exp} - (L_{eq})_{prd}]^2 \quad (1)$$

The linear model to predict equivalent continuous sound level (L_{eq}) is expressed as

$$L_{eq}\,[dB\,(A)] = a(1)+a(2)*\text{Log}\,Q + a(3)*P \quad (2)$$

The model written by Eq.-2 inputs total vehicle volume (Q) and percentage of heavy vehicles (P %) and predicts equivalent continuous sound level in dB (A).

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Results and discussion

The measured input and output parameters are shown in Table-1. After measuring total vehicle volume (Q), percentage of heavy vehicles (P %) and equivalent continuous sound level (L_{eq}), a regression models is fitted as shown in Eq.-3.

$$L_{eq}\,[dB\,(A)] = 57.56+5.357*\,Log\,Q+0.0325*\,P \qquad (3)$$

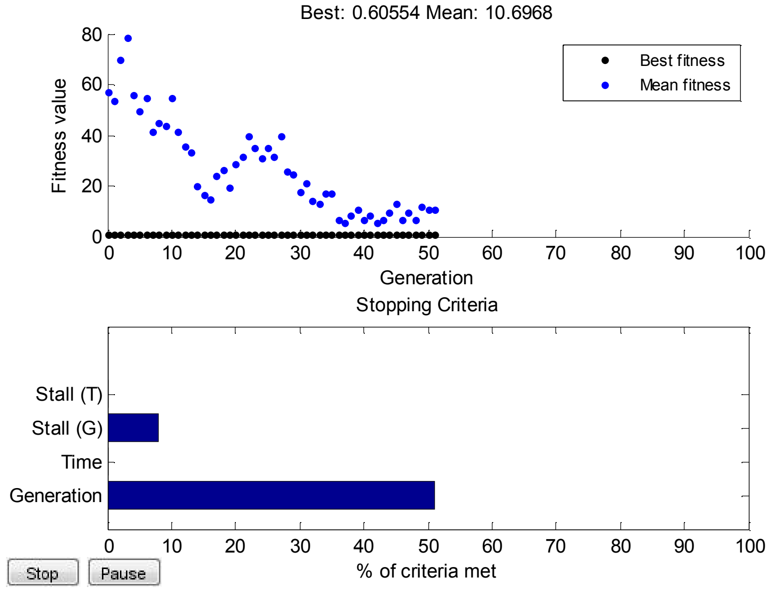

Figure 2(a): Convergence and stopping criterion (Uniform crossover operator)

As far as GA is concern, an initial population of size 30 is selected uniformly. The other parameters settings are default except crossover function (=two point). The minimum and maximum range for three constant a(1), a(2) and a(3) are LB=[50 5 0.2] and UB=[60 10 0.08] . Three different crossover operator namely uniform, roulette wheel, and tournament selection are also used to predict the accuracy of noise descriptors.

Figures-2(a) and 2(b) show the convergence and comparision of various results for unform crossover operator. At each chromosome , fitness function value are calculated and converges as shown in Fig.2(a). In each iteration two values are plotted, one is best fitness and other mean fitness value. At 50^{th} interation the algorithm terminates since it fulfil the stopping criterion of stall gneration and no further improvement in the fitness value has observed.

On the other hand, Fig.-2(b) compares the experimental, regression and GA results. The GA shows better results as compared with regression by showing less mean square error of 0.6055.

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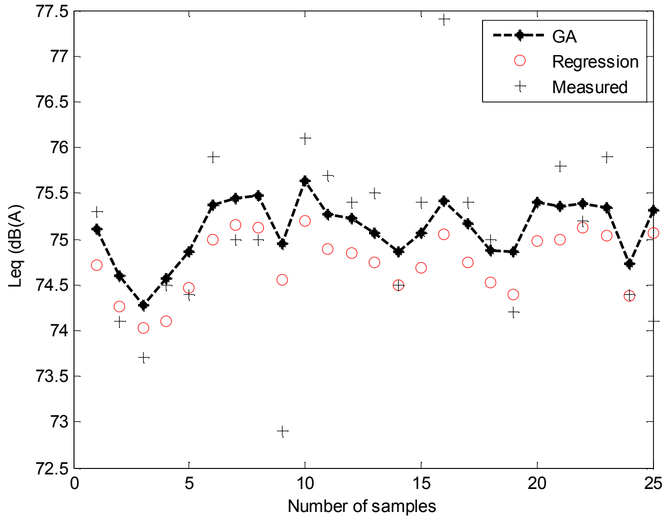

Figure 2(b): Comparison of experimental, regression and GA results (Uniform crossover operator)

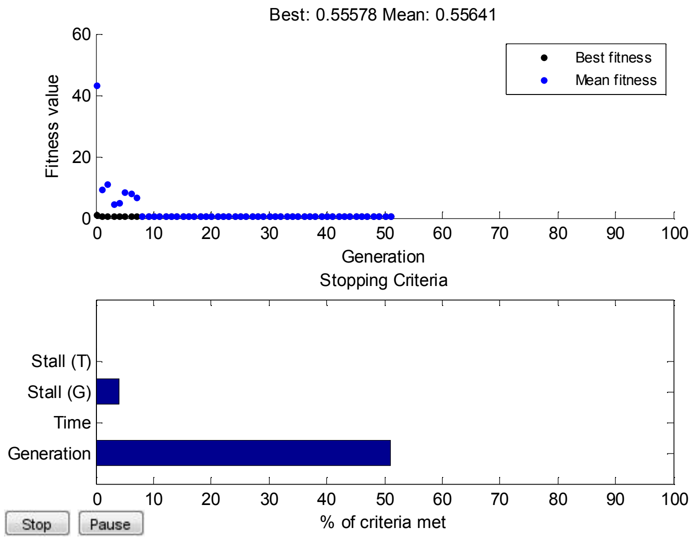

Figure 3(a): Convergence and stopping criterion (Tournament selection)

Figures 3(a) and 3(b) show the convergence and comparison results for Tournament selection. Fig.3 (a) shows faster convergence as compared with uniform crossover.

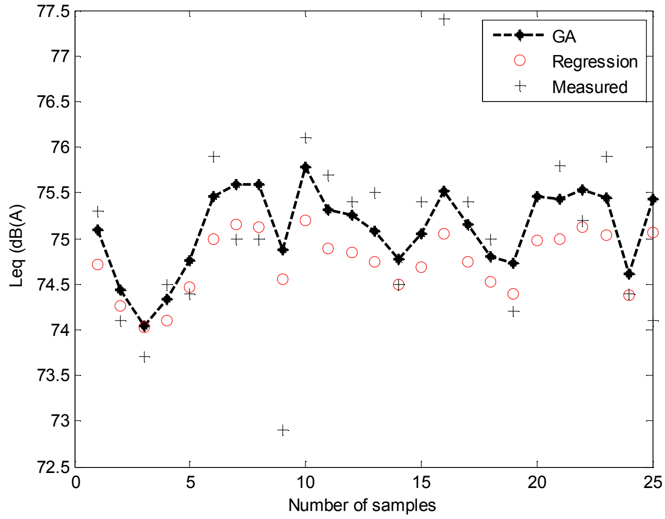

Figure 3(b): Comparison of experimental, regression and GA results (Tournament selection)

The compared results, as shown in Fig.3 (b), shows better performance as compared with uniform crossover. The mean square error (MSE) in GA is 0.5558 as compared with 0.7575 in regression.

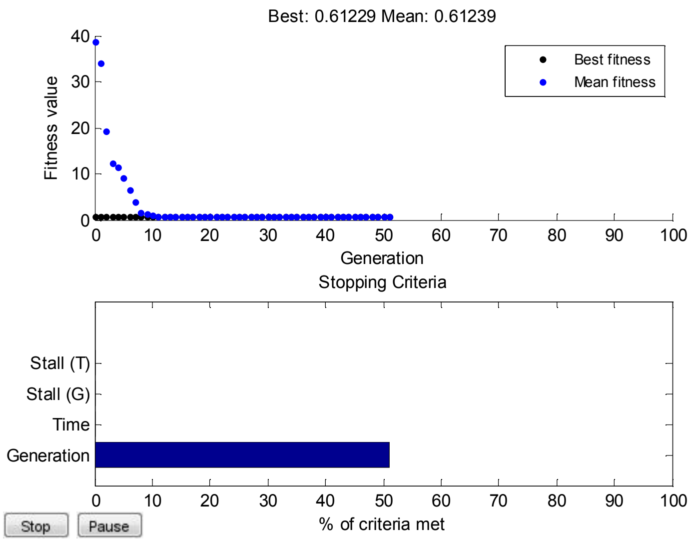

Figure 4(a): Convergence and stopping criterion (Roulette wheel selection)

Figures 4(a) and 4(b) compare results using Roulette wheel selection. The convergnce is better than unform but slower as compred to Tournament selection.

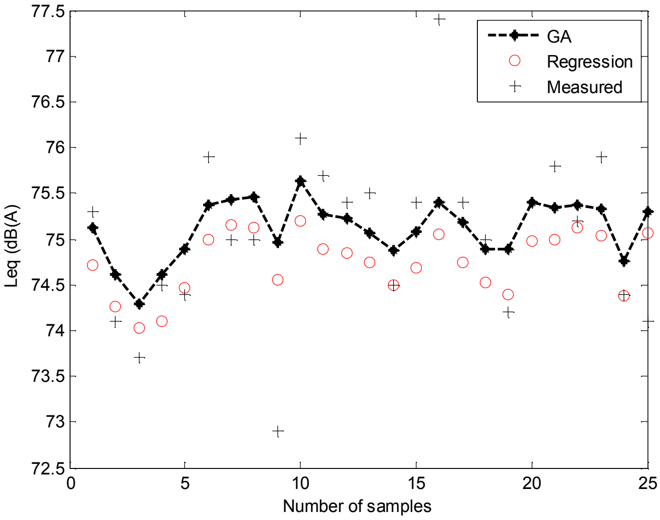

Figure 4(b): Comparison of experimental, regression and GA results (Roulette wheel selection)

Figure 4(b) shows better performance in GA by showing lesser mean square error as compared with regression. Some time the experimental data shows higher fluctuation due to honking or more traffic density during that time duration.

Table-2 optimum parameters setting for different crossover operator

GA Crossover operator	Optimum parameters setting			Fitness function	MSE between	
	a(1)	a(2)	a(3)		Experimental and GA	Experimental and regression
Uniform	56.4303	5.7064	0.0750	0.6055	0.6055	0.7595
Tournament selection	**50.8439**	**7.4631**	**0.0799**	**0.5558**	**0.5558**	**0.7575**
Roulette wheel	57.0111	5.5136	0.0782	0.6123	0.6123	0.7623

Table-2 compares the performance of GA with regression analysis. Out of the 30 population after 50^{th} iteration, the parameters values [a(1), a(2) a(3)] in the table show the best parameters setting to minimize the objective function. The mean square value for GA shows better performance as compared to regression in all the cases. Among GA performance, the Tournament selection shows best result by registering least value of MSE as 0.5558.

Conclusions

The present work compares the performance of GA with regression. The regression and GA models have developed from experimentally measured observation. The models input total vehicle volume (Q), percentage of heavy vehicles (P %) and predicts equivalent continuous sound level (L_{eq}) in dB (A). The following conclusions are drawn from the analysis:

1. The mean square error (MSE) for GA models is in range of 0.5558-0.6123, while the regression model shows error range from 0.7575-0.7623.
2. The GA models perform better as compared with regression model.
3. Among all the GA models, the model using Tournament selection shows best output.
4. The experimental data at some instances shows higher values due to honking noise more traffic in that time duration.

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