COMPARISON OF COMPUTATIONAL EFFICIENCY OF MOEA\D AND NSGA-II FOR PASSIVE VEHICLE SUSPENSION OPTIMIZATION

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KEYWORDS

Passive suspension optimization, multi-objective evolutionary algorithms, genetic algorithms, quarter vehicle model, ride comfort.

ABSTRACT

This paper evaluates new optimization algorithms for optimizing automotive suspension systems employing stochastic methods. This method is introduced as an alternative over the conventional approach, namely trial and error, or design of experiment (DOE), to efficiently optimize the suspension system. Optimizations algorithms employed are the multi-objective evolutionary algorithms based on decomposition (MOEA\D), and non-sorting genetic algorithm II (NSGA-II). A two-degree-of-freedom (2- DOF) linear quarter vehicle model (QVM) traversing a random road profile is utilized to describe the ride dynamics. The road irregularity is assumed as a Gaussian random process and represented as a simple exponential power spectral density (PSD). The evaluated performance indices are the discomfort parameter (ACC), suspension working space (SWS) and dynamic tyre load (DTL). The optimised design variables are the suspension stiffness, K_s and damping coefficient, C_s. In this paper, both algorithms are analyzed with different sets of experiments to compare their computational efficiency. The results indicated that MOEA\D is computationally efficient in searching for Pareto solutions compared to NSGA-II, and showed reasonable improvement in ride comfort.

INTRODUCTION

In vehicle dynamics, the suspension system isolates the vehicle body from the roughness of the road surfaces. Optimizing the suspension system in terms of ride is crucial to maintain the passenger comfort when traversing these road profiles. Traditionally, experienced engineers employ trial and error approach or DOE to tune the suspension. The major drawback of these methods is that, it is time consuming and does not provide reliable global optimal solution. These drawback can be overcome by employing the stochastic method as proposed in this paper. In this paper, the main aim is to evaluate the computational efficiency and to provide the best Pareto optimal solution to optimize a passive suspension system using stochastic methods.

Many researchers (Reimpell et al. 2001; Crolla and Whitehead 2003; Mastinu et al. 2006; Schiehlen 2007; Guglielmino et al. 2008; Jazar 2008; Genta and Morello 2009a; Genta and Morello 2009b) have attempted to derive suspension model with basic engineering rules. In this paper, stochastic optimization is employed in a QVM to obtain the optimized design variable i.e. the spring stiffness (K_s) and damping coefficient (C_s). To achieve the best ride comfort, the QVM with passive suspension is optimized against the suspension working space (SWS), the discomfort parameter (ACC) and the dynamic tire load (DTL). However, there is a design constraint of the SWS since the suspension travel is limited. Therefore, stochastic optimization is required to find the best compromise solutions for K_s and C_s within the design constraint.

Alternative approach in solving similar problem can be done using gradient-based optimization (Lina and Zhang 1989; Tamboli and Joshi 1999; Sun et al. 2000; Els and Uys 2003; Thoresson et al. 2009a; Thoresson et al. 2009b). The drawback of this technique is that it may trap in local minimal point (depending on the starting point). Additionally, it requires complex auxiliary equations to execute and to derive the system dynamic as the degree of freedom increases. It is proven that optimization using genetic algorithms performs better than gradient-based method as reported by (Baumal et al. 1998).

In stochastic method, Alkhatib et. al. (Alkhatib et al. 2004) employs simple genetic algorithm (GA) method for a 2 DOF QVM, aims at minimizing absolute acceleration (RMS) sensitivity to changes in relative displacement (RMS). However, the use of simple GA is not robust thus, does not provide a reliable solution near to the global minimum as compared to the presently improved algorithms (Konaka et al. 2006). In this paper, two recently develop optimization methods to produce reliable and robust of the solution for a linear two DOF QVM are examined. They are the non-sorting genetic algorithm-2 (NSGA-II) and multi-objective evolutionary algorithms based on decomposition (MOEA\D). NSGA-II is the current state-of-art optimization technique known for its fast convergence and robust (Deb et al. 2002). MOEA\D is the new algorithm developed by Zhang et. al. (Zhang et al. 2009). It employs decomposition method to decompose a multi-objective optimization problem into a number of scalar optimization sub-problems and optimizes them

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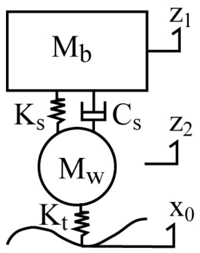
simultaneously. This method produced less computational complexity at each generation as compared to NSGA-II and it is capable of generating evenly distributed solutions, as reported by Zhang et. al. (Zhang et al. 2009).

QUARTER VEHICLE MODEL (QVM)

The simplest form of analytical derivation for the estimation of dynamic response of vehicle traversing a randomly road profiled is QVM. Sharp (Sharp 1987), reported that QVM has proven to produce reasonably accurate prediction of the dynamic behavior in terms of ACC, SWS and DTL. The random road profile can be represented as a simple exponential power spectral density (PSD). This one slope PSD is accurate in estimating the amplitudes of the road irregularity, especially at low frequency excitation. There are other complex power spectral densities but is generally complex and impractical to solve using analytical approach as reported by (Gobbi and Mastinu 2001; Karamihas 2005). A generic QVM propose by (Crolla and Whitehead 2003) is used as illustrated in Figure 1.



Where,
$M_b = body\ mass$
$M_w = wheel\ mass$
$K_s = spring\ stiffness$
$C_s = damping\ coefficient$
$K_t = tire\ stiffnes\ coefficient$
$x_0 = road\ profile\ input$

Figures 1: Quarter Vehicle Model Representation

The equation of motion for the QVM can be formulated using Newtonian methods as shown,

$$M_w \ddot{z}_1 = K_t(x_0 - z_1) - K_s(z_1 - z_2) - C_s(\dot{z}_1 - \dot{z}_2) \quad (1)$$

$$M_b \ddot{z}_2 = K_s(z_1 - z_2) + C_s(\dot{z}_1 - \dot{z}_2) \quad (2)$$

The frequency response functions of z_1/x_0 and z_2/x_0 can be found by solving the equation (1) and (2) using state-space approach. Since the road profile input is in PSD, the output of PSD can be calculated using the following formula:

$$PSD_{output} = |H(\omega)|^2 . PSD_{input} \quad (3)$$

where, *H(ω)* is the frequency response function and ω is the frequency. The objective function of optimization is defined as the following:

Discomfort parameter (ACC) evaluates ride quality by combining the frequency components according to the ISO recommended weighting scheme shown in Figure 2. These weighting functions are applied to the multi frequency acceleration spectra prior to integration, to give a root mean squared (RMS) value of frequency-weighted acceleration or discomfort parameter.

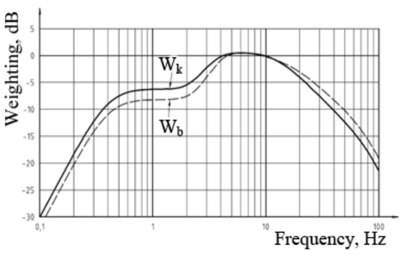
The discomfort parameter (ACC) is calculated as follows:

$$H(\omega)_{M_b} = \left|-\omega^2 . \frac{z_2}{x_0}\right| \quad (4)$$

$$PSD_{M_b} = \left|-\omega^2 . \frac{z_2}{x_0}\right|^2 . Sf \quad (5)$$

where, *Sf = road input power spectral density*. Then PSD_{M_b} is transformed into the discomfort parameter measured on human ($PSD_{weighted}$) using ISO 2631 in Figures 2.

$$ACC = RMS\ PSD_{weighted} = \sqrt{\int PSD_{weighted}} \quad (6)$$



Figures 2: ISO2631 Weighting Function of Acceleration Spectra (ISO 2001)

Suspension working space (SWS) is a parameter defined as the RMS value of wheel to body displacement (Z_2 - Z_1). It measures the variation of the displacement about its static position.

Suspension working space (SWS) is calculated as follows:

$$H(\omega)_{SWS} = \left|\frac{z_2}{x_0} - \frac{z_1}{x_0}\right| \quad (7)$$

$$PSD_{SWS} = \left|\frac{z_2}{x_0} - \frac{z_1}{x_0}\right|^2 . Sf \quad (9)$$

$$SWS = RMS\ PSD_{SWS} = \sqrt{\int PSD_{SWS}} \quad (10)$$

Dynamic tyre load (DTL) is defined as the RMS value of tire load variation about the static value. This parameter can be considered a measure of the vehicle's road holding ability, since a variation in the tire load results in a varying contact length and a net reduction in side or braking force.

Dynamic tyre loading (DTL) is calculated as follows:

$$H(\omega)_{DTL} = K_t \left|\frac{z_1}{x_0} - 1\right| \quad (11)$$

$$PSD_{DTL} = \left(K_t \left|\frac{z_1}{x_0} - 1\right|\right)^2 . Sf \quad (12)$$

$$DTL = RMS\ PSD_{DTL} = \sqrt{\int PSD_{DTL}} \quad (13)$$

OPTIMIZATION ALGORITHMS

Non-sorting genetic algorithms II (NSGA-II)

NSGA-II developed by Deb et. al. (Deb 2002) was an improved version of NSGA (Srinivas N 1994). The development of the improved version of NSGA-II employs different strategy to solve the previous three main issues in NSGA approach.

```
Initialize Population
  * Generate random population
  * Evaluate objective values (SWS, ACC, and
    DTL)
  * Assign rank (level) based on Pareto dominance
  * Generate child population
          - Tournament selection
          - Recombination and mutation

For i = 1 to number of generations
  * Parent and child population are assign rank based on
    Pareto
  * Generate sets of non-dominated fronts
  * Determine the crowding distance between points on
    each front
  * Select points based on crowding distance calculation
    and fill into the parent population until full.
  * Create next generation
  * Tournament Selection
  * Recombination and Mutation
  * Evaluate Objective Values (SWS, ACC, and DTL)
  *Increment generation index
End.
```

Figures 3: NSGA-II Pseudo Code

The main issues in NSGA approach are:

- The non-dominated sorting approach is time consuming and involves high computational complexity.
- It lacks of elitism, which is important in preventing the loss of good solutions once they are found.
- It requires the user to specify the sharing parameters, which is difficult for the user to know the ideal value for the parameters.

Therefore, in NSGA-II, two new approaches have been proposed to solve these issues. First, it employs a fast non-dominated sorting aims at reducing the complexity of sorting as compare to old non-dominating sorting. Secondly, it introduces a crowd-comparison approach to replace the sharing parameter needed in NSGA. The pseudo code of the NSGA-II is shown in Figure 3.

Multi-objective evolutionary algorithms based on decomposition (MOEA\D)

In recent years, the progresses on evolutionary algorithms (EAs) that deal with multi-objective problems have increased significantly. MOEA\D is one of the multi-objective evolutionary algorithms (MOEAs) aims at finding a set of representative Pareto optimal solutions in a single run. MOEA\D is also one of the Pareto dominance-based MOEA like NSGA-II (Deb 2002; Zhang et al. 2009) . The algorithm is developed by Zhang (Zhang et al. 2009) that include the use of Tchebycheff approach as the decomposition method, with dynamical resource allocation, to improve the efficiency of the MOEA\D. The following are the details of the algorithms:

```
Define [termination condition, N (number of sub-
problems), a uniform spread weight vectors, T (number of
the weight vectors in the neighborhood of each weight
vector)]

Initialization
  * Generate initial population by uniformly spreading and
    randomly sampling from search space
  * Calculate the reference point for the Tchebycheff
    approach.
  * Evaluate Objective Values (SWS, ACC, and DTL)
  * Selection using tournament selection method based on
    utility π^i
  * Selection of mating and updating range
  * Reproduction
  * Repair
  * Update of solutions

While (not equal to termination condition)
  * Evaluate Objective Values (SWS, ACC, and DTL)
  * Selection using tournament selection method base on
    utility π^i
  * Selection of mating and update range
  * Reproduction
  * Repair - if the searching element is out of boundary
 * Update the solutions

If (generation is a multiplication of a pre-set value of x),
   * Update utility function;
End

End
```

Figures 4: Pseudo Code of MOEA\D

The Tchebycheff decomposition approach (Zhang et al. 2009) can be described as the scalar optimization problems of the form:

$$Minimize\ g^{te}(x|\lambda, z^*) = max\ 1 \leq i \leq m\ \{\lambda_i|f_i(x) - z^*|\}$$
$$\text{subject to } x \in \Omega \qquad (14)$$

where $z^* = (z_1^*, \dots, z_m^*)^T$ is the reference point, i.e. $z_i^* = min\{f_i(x)|x \epsilon \Omega\}$ for each $i = 1, \dots, m$. Under certain mild conditions, in each Pareto optimal point x^*, there exists a weight vector, λ such that x^* is the optimal solution of (14) where each one is a Pareto optimal solution of the objective function ($minimize\ F(x) = (f_1(x), \dots, f_m(x))^T$). Eventually, this allows the user to obtain different Pareto optimal solutions by solving a set of single objective optimization problem defined by the Tchebycheff approach with different weight vectors.

MOEA\D with Dynamical Resource Allocation:

MOEA\D (Zhang et al. 2009) minimizes the entire N objective simultaneously in a single run. Neighbourhood relations among these single objective sub-problems are defined from the distances among their weight vectors. In the previous version of MOEA\D proposed by (Zhang and Li 2007), all the sub-problems are treated equally and received about the same amount of computational effort. However, in the real situation, each sub-problems may encounter different level of difficulty in obtaining the solution. Therefore, the new version of MOEA\D with a dynamical resource allocation (MOEA\D-DRA) is introduced (Zhang et al. 2009) by computing a utility parameter π^i for each of the sub-problems i, allowing computational efforts to be distributed based on their utilities.

RESULTS AND DISCUSSIONS

The computational efficiency of both algorithms i.e. NSGA-II and MOEA\D is evaluated based on the number of iteration and population size. Clearly, this is crucial as the complexity of the vehicle degree-of-freedom increases. The experiment is conducted with two different termination conditions i.e. at 10 iterations and at 20 iterations. For each termination conditions, two different number of population of 500 and 1000 are chosen, where the average solution time is evaluated. Additionally, the diversity of the Pareto solutions is also evaluated. In MOEA\D, the parameter is set as the default value (Zhang et. al. 2009). In NSGA-II, the parameter is also set as the default value from MATLAB GA toolbox. All experiments are executed on a standard desktop PC powered by Intel Processor E7300 with 4GB RAM.

For each of the experiment, the solution time is averaged for five repeats. The optimization aims at minimizing all three objectives i.e. SWS, ACC, and DTL for the QVM with the following variables shown in Table 1. Here, the optimization routine will search for the best sets of solutions for the spring stiffness, K_s and the damping coefficient, C_s. Therefore, a range of K_s and C_s must be specified (Table 1). The reference value of K_s and C_s are used as the design target since these values represent the experimentally optimized solution for the suspension setting.

The results shown in Figures 5 indicate that MOEA\D algorithm is significantly faster than NSGA-II for same number of iteration and population size. This is because NSGA-II has higher computational complexity for each generation which can be expressed as mN^2, where m is the number of the objectives and N is its population size (Deb et al. 2002). As the number of population size increases, the time needed by NSGA-II increases exponentially affected by the term N^2. However, in MOEA\D the computational complexity is only mNT, where T is the number of the weight vectors in the neighborhood, usually has smaller value than N. Therefore, MOEA\D can solve much faster than NSGA-II at each generation (Table 4).

Table 1: Quarter vehicle model parameter (Crolla and Whitehead 2003)

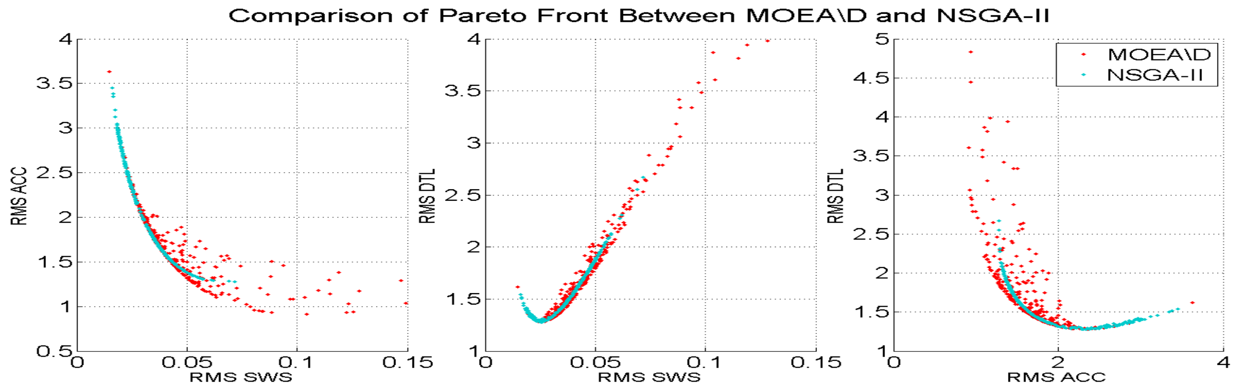
Body mass, M_b	317,5 kg
Wheel mass, M_w	45,4 kg
Spring stiffness, K_s	1 - 30 kN/m (**Ref: 22 kN/m**)
Damping coefficient, C_s	1 - 5 kNs/m (**Ref: 1,5 kNs/m**)
Tire stiffness coefficient, K_t	192 kN/m
Vehicle traveling speed, V	20 m/s
PSD road input	$\frac{5 \times 10^{-6}. V^{1.5}}{f^{2.5}}$
Working frequency range, f	0 - 20 Hz

Table 2: Computational Efficiency of NSGA-II

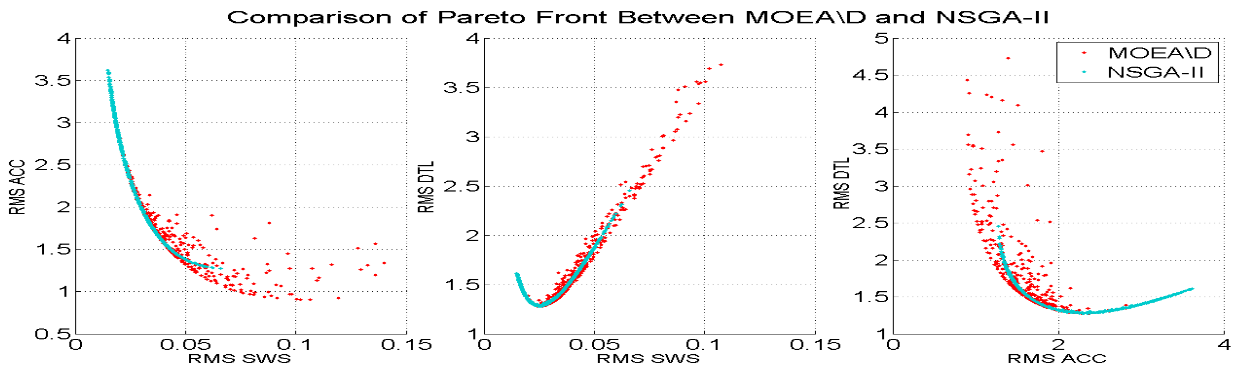
Iteration		10	20	10	20
Population size		500	500	1000	1000
Instance	1	117,4	218,8	276,4	533,7
	2	117,8	223,4	284,0	549,3
	3	116,8	225,2	293,7	550,3
	4	119,0	226,7	293,8	546,5
	5	117,8	227,4	288,4	549,4
Average time, sec		117,8	224,3	287,3	545,8

Table 3: Computational Efficiency of MOEA\D

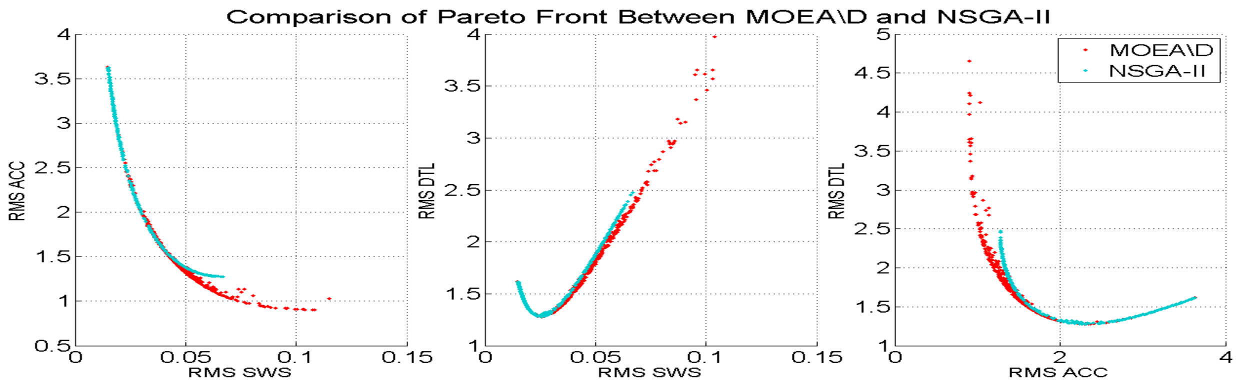
Iteration		10	20	10	20
Population size		500	500	1000	1000
Instance	1	49,8	84,7	96,6	176,9
	2	49,5	85,9	97,2	168,0
	3	48,5	85,0	98,7	190,9
	4	49,4	86,0	98,1	192,4
	5	48,7	87,3	99,0	173,3
Average time, sec		49,2	85,8	97,9	180,3



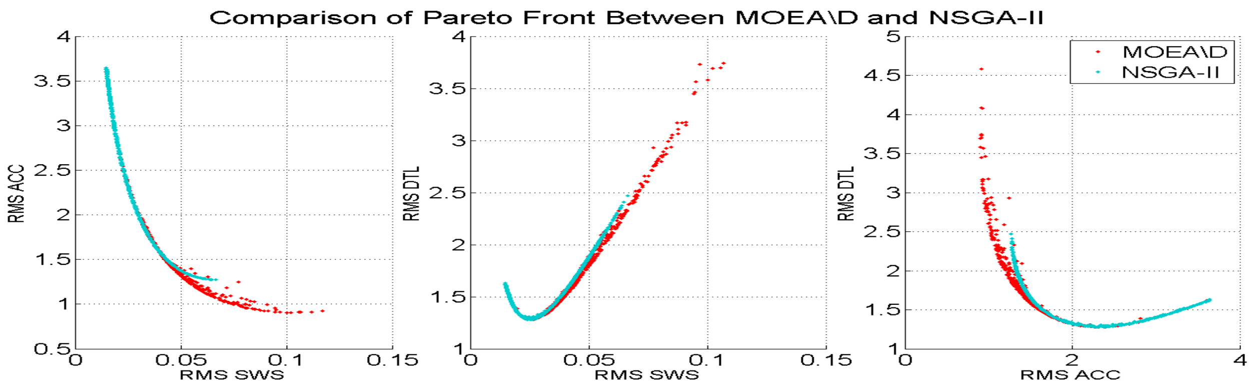
Case 1 (10 Iteration, Population size 500)



Case 2 (10 Iteration, Population size 1000)



Case 3 (20 Iteration, Population size 500)



Case 4 (20 Iteration, Population size 1000)

Figures 5: Plots of Final Populations with MOEA\D and NSGA-II in the Objective Space of SWS, ACC, and DTL

Another aspect of the performance indicator can be observed from the diversity between MOEA\D and NSGA-II. In Figures 5, the termination iteration at 10 suggested that MOEA\D provides a better diversity and more explorative in reaching the Pareto Front than those of the NSGA-II. This gives MOEA\D the advantage in the preliminary run to indicate the Pareto shape and the range of interest to achieve the objective. When the iteration termination is increased to 20 iterations, the MOEA\D showed larger spread suggesting a better searching capability throughout the Pareto Fronts as compared to those from NSGA-II. The computational efficiency of the algorithm is critical since the ultimate algorithm is critical since the ultimate aim of this research will focus on optimizing high fidelity vehicle model. For example, full vehicle model with increased degree-of-freedom.

Table 4: Comparison of the Computational Efficiency for the Two Competing Optimization Algorithms

Iteration	10	20	10	20
Population size	500	500	1000	1000
NSGA-II	117,8	224,3	287,3	545,8
MOEA\D	49,2	85,8	97,9	180,3
Percentage of MOEA\D faster than NSGA-II, %	239	261	293	302

Optimal Solution for quarter vehicle model

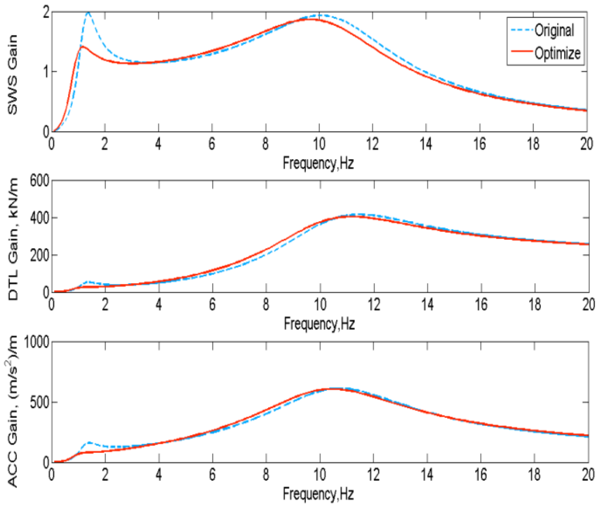
Generally, in designing vehicle suspension, the SWS is chosen as a design constraint. This is because there is a limited clearance between the vehicle body mass and the wheel mass. In this experiment, the design limit of 0.0287m is employed which is similar to the SWS value used in the reference car design (Crolla and Whitehead 2003).

To determine the best range for K_s & C_s, MOEA\D is chosen since earlier results suggest that this algorithm is more computationally efficient. It produces different combinations of K_s and C_s that is capable to achieve the same SWS criteria of 0.0287 m. The optimal combination of K_s and C_s showed reasonable improvement on the ACC and DTL as illustrated in Table 5.

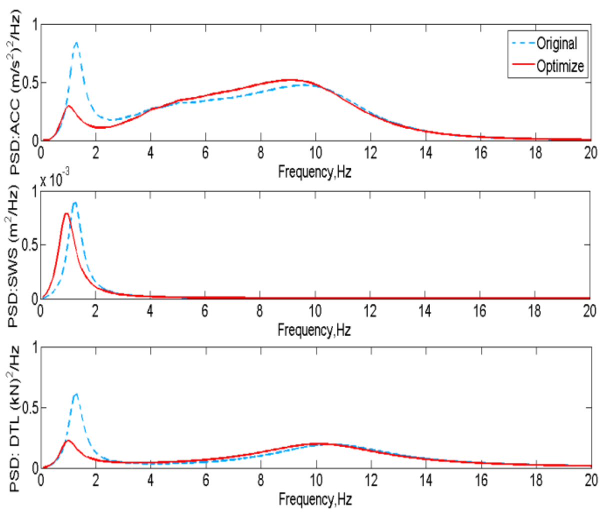
Table 5: Comparison Result between the Original Parameter with Optimize Parameter

Original Reference Vehicle Parameters		Optimized parameters	Improvement, %
K_s , kN/m	22	12,3892	N/A
C_s , kNs/m	1,5	1,6163	N/A
RMS SWS	0,0287	0,0287	0
RMS ACC	2,1152	2,066	2,33
RMS DTL	1,3649	1,3051	4,38

The result of the optimization can be further analyzed by plotting them against its frequency responses as shown in Figures 6 and 7. Here, the optimization process not only improves the overall RMS response of ACC and DTL, but further reduces the natural frequency of vehicle as compare to the reference vehicle. This will further reduce the possibility of excitation to occur at such low frequency on normal road condition.



Figures 6: Bode Plots for SWS, ACC and DTL.



Figures 7: Bode plots for PSD SWS, PSD ACC and PSD DTL

CONCLUSIONS AND FUTURE WORK

In this paper, NSGA-II and MOEA\D are employed to optimize a two DOF QVM. Performance comparison between both algorithms showed that MOEA\D is more computationally efficient and robust than the NSGA-II in finding the Pareto Front. Improvement in ride comfort has been achieved using MOEA\D based on the optimum value of suspension stiffness and damping coefficient. This demonstrates that the proposed method is efficient to be employed in the automotive industry to reduce product development time. In addition, it also provides Pareto Front as a flexible design option for designer to optimize the suspension system in the early stage of design cycle. Future work will include the usage of this algorithm on multi-body vehicle model (high fidelity model) which involves with increase number of degree-of-freedom and more parameters to simultaneously optimize the ride and handling performances.

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