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Optimization of Vehicle-to-Vehicle Frontal Crash Model based on Measured Data using Genetic Algorithm

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***Abstract*—In this paper, a mathematical model for vehicle-to-vehicle frontal crash is developed. The experimental data are taken from the National Highway Traffic Safety Administration (NHTSA). To model the crash scenario, the two vehicles are represented by two masses moving in opposite directions. The front structures of the vehicles are modeled by Kelvin elements, consisting of springs and dampers in parallel, and estimated as piecewise linear functions of displacements and velocities respectively. To estimate and optimize the model parameters, a genetic algorithm (GA) approach is proposed. Finally, it is observed that the developed model can accurately reproduce the real kinematic results from the crash test.**

Key–Words: Modeling, vehicle-to-vehicle crash, parameters estimation, genetic algorithm.

I. Introduction

Car accidents are one of the major causes of mortality in modern society. While it is desirable to maintain the crash-worthiness, car manufacturers perform crash tests on a sample of vehicles for monitoring the effect of the occupant in different crash scenarios. Car crash tests are usually performed to ensure safe design standards in crash-worthiness (the ability of a vehicle to be plastically deformed and yet maintains a sufficient survival space for its occupants during the crash scenario). However, this process is very time consuming and requires sophisticated infrastructure and trained personnel to conduct such a test and data analysis. Therefore, to reduce the cost associated with the real crash test, it is worthy to adopt the simulation of a vehicle crash and validate the model results with the actual crash test. Nowadays, due to advanced research in simulation tools, simulated crash tests can be performed beforehand the full-scale crash test. Therefore, the cost associated with the real crash test can be reduced. Finite element method (FEM) models and lumped parameter models (LPM) are typically used to model the vehicle crash phenomena and hence can help the designer to better design the vehicle with less number of crash tests. Vehicle crash-worthiness can be evaluated in four distinct modes: frontal, side, rear and rollover crashes.

In the past few decades, much research has been carried out in the field of vehicle crash-worthiness, which resulted in several novel computational models of vehicle collisions in the literature, and a brief review is given in this paper. An application of physical models composed of springs, dampers and masses joined in various arrangements for simulating a real car collision with a rigid pole, was presented in [1]. The same authors in [2], proposed a method of modeling for vehicle crash systems based on viscous and elastic properties of the materials and explained the differences in simulating vehicle-to-rigid barrier collision and vehicleto-pole collision. A method to reproduce car kinematics during a collision using a nonlinear autoregressive (NAR) model, where parameters are estimated by the use of feed-forward neural network model, was proposed in [3]. In [4], a Five-Degrees of Freedom (5-DOFs) lumped parameter model for the frontal crash was investigated to analyze the response of occupant during the impact. Ofochebe et al. in [5], studied the performance of vehicle front structure using a 4-DOFs lumped mass-spring model composed of body, engine, the cross-member, the suspension and the bumper masses.

In [6] and [7], an optimization procedure to assist multi-body vehicle model development and validation was proposed. In the work of [8], the authors proposed an approach to control the seat belt restraint system force during a frontal crash to reduce thoracic injury. Klausen et al. [9] used firefly optimization method to estimate parameters of vehicle crash test based on a single-mass. Munyazikwiye et al. in [10] and [11], used different approaches to model the vehicle frontal crash using a double-spring-mass-damper model. In [12], a mathematical model for vehicle-occupant frontal crash was studied using genetic algorithm. Tso-Liang et al. in [13], examined the dynamic response of the human body in a crash event and assessed the injuries sustained to the occupant's head, chest and pelvic regions.

Apart from the commonly used approaches, recently intelligent approaches have been used in the area of vehicle crash modeling. The most commonly used, are Fuzzy logic in [14], Neuro-fuzzy in [15], genetic algorithm and firefly algorithm in [9]. Vangi in [16] developed an approach to determine the impact severity indexes of oblique impact with a non-

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zero restitution. While in [17], the author developed a fuzzy logic model for vehicle frontal crash to predict vehicle crash severity from acceleration data. The kinetic energy and jerk inputs data were used to find the crash severity index. Vangi and Begani [18], demonstrated the usefulness of the triangle method for evaluating the kinetic energy loss of a vehicle during road traffic accident, while in [19], the authors used a fuzzy approach to reconstruct the accident history at time of crash and calculated the velocity of an impacting vehicle. A genetic algorithm has been used in [20] for calculating the optimized parameters of a 12-DOFs model for two vehicle types in two different frontal crashes.

The main challenge in accident reconstruction is the system identification, described as the process of constructing mathematical models of dynamical systems using measured input-output data, where the input data is the acceleration measurement and output data is the deformation of the vehicle. In [21], a novel wavelet-based approach was introduced to reproduce acceleration pulse of a vehicle involved in a crash event. In the case of a vehicle crash, system identification algorithm is used to retrieve the unknown parameters such as the spring stiffness and damping coefficient. A possible approach is to identify these parameters directly from experimental data. From the literature, System Identification Algorithms (SIA) have been developed based on various methodologies, for instance, subspace identification, genetic algorithm, eigensystem realization algorithm and data-based regressive model approaches.

After scanning through the literature, it is noted that the authors could reconstruct the kinematics of the car crash, but less attention was taken on the nonlinearity behavior of the deformed vehicles involved in crash scenarios. To the best of our knowledge, the problem of reconstruction of a piecewise linear model for a vehicle-to-vehicle frontal crash scenario based on the genetic algorithm has not yet been completely considered in the literature and this forms our motivation for the present study.

The main contribution of this paper is threefold: 1) A mathematical model is developed to reconstruct a vehicle-to-vehicle frontal crash scenario and to estimate the nonlinear behaviors of the front parts of the vehicle undergoing crash deformation; 2) A genetic algorithm is proposed to estimate the parameters of the vehicle's front structures in terms of piecewise linear functions, which can assist car designers or manufacturers to reduce the cost associated with the real physical crashes which are generally costly and time consuming; 3) The accuracy of the predicted results are verified using the available experimental data. It should be mentioned that according to the methodology proposed in this paper, the dynamic crash can be predicted and allows the designer to redesign the vehicle for vehicle crashworthiness.

II. Experimental set up

Two physical crash tests data sets for the Caravan crashing into the Neon and the Chevrolet crashing into the Dodge are obtained from the NHTSA Database [22]. These tests were carried out on typical mid-speed vehicles colliding each other in the frontal direction. The test set up consisting of vehicle-to-vehicle crash (Caravan into Neon) is shown in Figure 1. The data were obtained relative to the Federal Motor Vehicle Safety Standards (FMVSS) No. 208 - Occupant Crash Protection. In the first test, the target vehicle (a 1996 Plymouth Neon) and the bullet vehicle (a 1997 Dodge Caravan) were instrumented with seven longitudinal axis accelerometers, three lateral axis accelerometers, four vertical axis accelerometers, and their specified impact velocity range was 55.5 km/h to 57.1 km/h.

The bullet vehicle's centerline was aligned with the target vehicle's centerline. This test was a full frontal car-to-car moving test. The test weights and impact speeds of the target and bullet vehicles were: 1378.0 kg and 55.9 km/h, and 2059.5 kg and 56.5 km/h respectively.

The same test set up was used on a Chevrolet car crashing into a Dodge car. The test weights and impact speeds of the Chevrolet and Dodge cars were: 2109 kg and 50.3km/h, and 1997 kg and 50 km/h respectively.

In general during vehicle frontal crash, the vehicles are subjected to impulsive forces. When a vehicle crashes into another vehicle, the heavier one is less deformed than the lighter one and at time of crash, both vehicles loose their kinetic energy in a fraction of a second through front-end structural deformations. The amount of deformation is equal to the stopping distance of the vehicle. Since the stopping distance of a vehicle in the crash is normally short, a much higher force is generated at the front interface. The vehicle stopping distance (or dynamic crash) in vehicle-to-vehicle crash tests largely depends on crash pulses. The dynamic crash can be determined by double integration of the vehicle crash pulse with known initial impact velocity. The decelerations for both, bullet and target vehicles are shown in Figure 2.

Figure 1: Vehicles deformations after crash (Caravan left front-view, Neon right front-view)

III. Model development

The main objective of this section is to develop a dynamic model which can represent a vehicle-to-vehicle frontal crash scenario. The real crash test results are shown in Figure 2, and the model which can reproduce these results consists of two masses moving in opposite directions, as shown in Figure 3. In line of the model development to capture the values as mentioned earlier during the crash scenario, the dynamical model proposed in [23] for the free vibration analysis are

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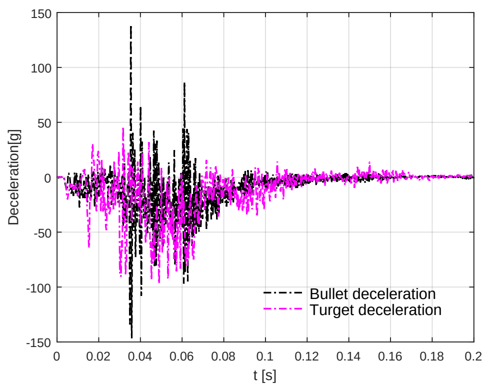

Figure 2: Test decelerations for bullet and target vehicles

adopted for solving the impact responses. Then, the genetic algorithm is used to estimate the model parameters.

A. *Vehicle-to-Vehicle crash model*

An impact between two masses can be represented schematically as in Figure 3, where each of the two masses has a contact with the Kelvin element, a set of spring and damper in parallel. If the connection between the mass and the element is a rigid contact, the element may undergo tension and compression. If not, due to separation between the mass and element, the element can only be subjected to compression. To simplify the analysis, the two sets of Kelvin elements can be combined into one resultant Kelvin element as shown in Figure 4. The parametric relationship between the two individual Kelvin elements and the resultant Kelvin element can be obtained in the sequel. From the spring deformation relationship, the total deformation of the combined spring k is equal to the sum of the deformations of the two individual springs (an additive deflection relationship). The spring force relationship can then be established as follows:

$$\alpha = x_1 + x_2 \tag{1}$$

$$\frac{F_k}{k} = \frac{F_k}{k_1} + \frac{F_k}{k_2} \tag{2}$$

where α and F_k are total deflection and force due to mass m_1 and m_2 respectively. Similarly, by taking the time derivative of the deformation relationship, the deformation rates are also found to be additive for the dampers. The damping relationship is shown as follows.

$$\dot{\alpha} = \dot{x_1} + \dot{x_2} \tag{3}$$

$$\frac{F_c}{c} = \frac{F_c}{c_1} + \frac{F_c}{c_2} \tag{4}$$

The equivalent relationships for spring stiffness and damping coefficients are then established as follows:

$$k = \frac{k_1 k_2}{k_1 + k_2}$$

$$c = \frac{c_1 c_2}{c_1 + c_2}$$

In a two-mass system, shown in Figure 4, the mass M_2 is

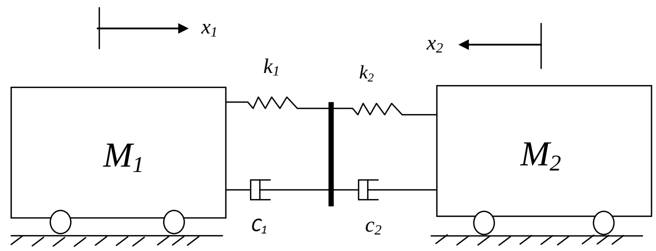

Figure 3: A vehicle-to-vehicle impact model - Two Kelvin elements in series [23]

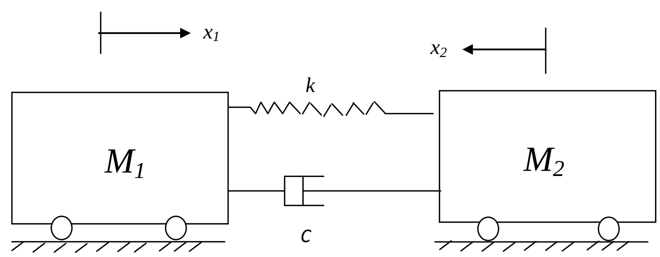

Figure 4: A vehicle-to-vehicle impact model - A Kelvin model

impacted by M_1 at an initial relative speed (or closing speed) of v_{12} where $v_{12} = v_1 + v_2 = v_0$. If one of the masses in the two-mass system is infinite, the system becomes a vehicle-to-barrier (VTB) model.

The only mass moving in this system is referred to as the effective mass, M_e. The relative motion of the mass with respect to the fixed barrier is the same as the absolute motion of the mass with respect to a fixed reference frame. In a system where there are multiple masses involved in an impact, the analysis can be simplified by using the relative motion and effective mass approaches. The relative displacement of the effective mass, M_e, is α. The dynamic responses of the two-mass system and one effective mass system are summarized as referred to [23]

$$\ddot{x}_1 = \gamma_1 \ddot{\alpha} \qquad \ddot{x}_2 = \gamma_2 \ddot{\alpha} \tag{5}$$

where

$$\ddot{\alpha} = -v_{12}\omega_e sin(\omega_e t) \tag{6}$$

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$$\omega_e = \sqrt{\frac{k}{M_e}} \tag{7}$$

$$\gamma_1 = \frac{M_2}{M_1 + M_2} \tag{8}$$

$$\gamma_2 = \frac{M_1}{M_1 + M_2} \tag{9}$$

$$M_e = \frac{M_1 M_2}{M_1 + M_2} \tag{10}$$

where ω_e is the natural frequency, γ_1 and γ_2 denote mass reduction factors and M_e is the effective mass. The dynamic equation of the effective mass system is represented as follows:

$$M_e \ddot{\alpha} = -c\dot{\alpha} - k\alpha \tag{11}$$

or

$$\ddot{\alpha} = (-c\dot{\alpha} - k\alpha)/M_e \tag{12}$$

Substituting (1) and (3) into (12), we get:

$$\ddot{\alpha} = (-c(\dot{x}_1 + \dot{x}_2) - k(x_1 + x_2))/M_e \tag{13}$$

From the response obtained from the test, the displacement and velocity are nonlinear. Therefore the Kelvin element of the model should be estimated as nonlinear parameters. In the first estimation the spring and the damping forces in the model are nonlinear cubic function of x and $\dot{x}$, respectively. Therefore, the dynamic responses of the two-mass system in Equation (5) are:

$$\begin{aligned}\ddot{x}_1 = \gamma_1(&-c(\dot{x}_1 + \dot{x}_2) - c_{nl}(\dot{x}_1 + \dot{x}_2)^3 \\ &- k(x_1 + x_2) - k_{nl}(x_1 + x_2)^3)/M_e\end{aligned} \tag{14}$$

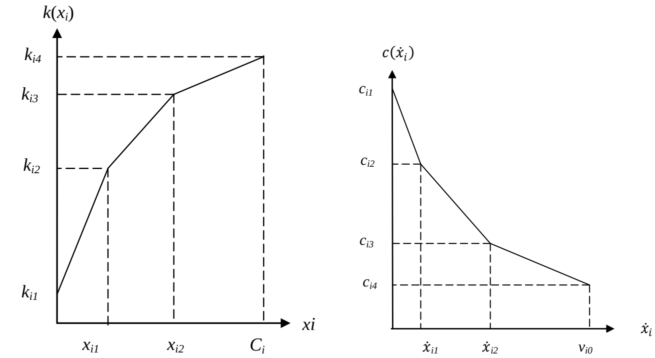
$$\begin{aligned}\ddot{x}_2 = -\gamma_2(&-c(\dot{x}_1 + \dot{x}_2) - c_{nl}(\dot{x}_1 + \dot{x}_2)^3 \\ &- k(x_1 + x_2) - k_{nl}(x_1 + x_2)^3)/M_e\end{aligned} \tag{15}$$

where c_{nl} and k_{nl} are nonlinear components of the damping coefficient and the spring stiffness in the model respectively.

B. *Piecewise linear approximations for springs and dampers*

The springs and damping coefficients in the model described in the previous sections, are defined by the piecewise functions in (16) - (17) and shown graphically in Figure 5.

The predefined shape of the spring and damper characteristics in Figure 5, are chosen based on the shapes of the displacement and velocity responses from the crash test. The maximum displacement occurs when the velocity of the target vehicle reduces to zero, during the breaking phase, where the vehicle is overdamped and undamped during low and high velocities respectively. This justifies a high damping coefficient at the time of crash and a low value of damping coefficient at the initial velocity. The stiffness is low during elastic deformation, but after crash, the vehicle is plastically deformed, therefore the stiffness increases drastically to maintain the deformation.



(a) Stiffness coeficients (b) Damping coefficients

Figure 5: Predefined stiffness and damping coefficient characteristics of the vehicle's front structure

$$k(x_i) = \begin{cases} k_{i1} + \frac{k_{i2}-k_{i1}}{x_{i1}} x_i & x_i \leq x_{i1} \\ k_{i2} + \frac{k_{i3}-k_{i2}}{x_{i2}-x_{i1}}(x_i - x_{i1}) & x_{i1} \leq x_i \leq x_{i2} \\ k_{i3} + \frac{k_{i4}-k_{i3}}{C_i-x_{i2}}(x_i - x_{i2}) & x_{i2} \leq x_i \leq C_i \end{cases} \tag{16}$$

$$c(\dot{x}_i) = \begin{cases} c_{i1} - \frac{c_{i1}-c_{i2}}{\dot{x}_{i1}} \dot{x}_i & \dot{x}_i \leq \dot{x}_{i1} \\ c_{i2} - \frac{c_{i2}-c_{i3}}{\dot{x}_{i2}-\dot{x}_{i1}}(\dot{x}_i - \dot{x}_{i1}) & \dot{x}_{i1} \leq \dot{x}_i \leq \dot{x}_{i2} \\ c_{i3} - \frac{c_{i3}-c_{i4}}{v_0-\dot{x}_{i2}}(\dot{x}_i - \dot{x}_{i2}) & \dot{x}_{i2} \leq \dot{x}_i \leq v_0 \end{cases} \tag{17}$$

Therefore, using the piecewise linear functions defined in Equations (16) and (17), the dynamic responses in Equation (5) can be represented as follows:

$$\ddot{x}_1 = \gamma_1(c(\dot{x}_1 + \dot{x}_2) - k(x_1 + x_2))/M_e \tag{18}$$

$$\ddot{x}_2 = -\gamma_2(-c(\dot{x}_1 + \dot{x}_2) - k(x_1 + x_2))/M_e \tag{19}$$

C. *Optimization Scheme of the Genetic Algorithm*

Genetic Algorithm (GA) is an adaptive heuristic search based on the evolutionary ideas of nature selection and genetics. It represents an intelligent exploitation of a random search used to solve optimization problems. This Evolutionary Algorithm holds a population of individuals (chromosomes), which evolve by means of selection and other operators like crossover and mutation. Every individual in the population gets an evaluation of its adaptation (fitness) to the environment. In the terms of optimization this means that the function which is maximized or minimized is evaluated for every individual. The selection chooses the best gene combinations (individuals), which through crossover and mutation should drive to better solutions in the next population. The Genetic Algorithm consists of seven steps [24].

1) Generate initial population: in most of the algorithms the first generation is randomly generated, by selecting the genes of the chromosomes among the allowed alphabet

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for the gene. Because of the easier computational procedure, it is accepted that all populations have the same number (N) of individuals. In our problem N is 24, the number of parameters to be estimated.

2) Calculation of the values of the function that we want to minimize or maximize. In our work the cost function minimizes the error between the experimental results and the model results.
3) Check for termination of the algorithm: as in the most optimization algorithms, it is possible to stop the genetic optimization by:
   - Value of the function: the value of the function of the best individual is within defined range around a set value. It is not recommended to use this criterion alone, because of the stochastic element in the search the procedure, the optimization might not finish within sensible time;
   - Maximal number of iterations: this is the most widely used stopping criteria. We have set 10^9 iterations to get the optimum solution. It guarantees that the algorithm will give some results within some time, whenever it has reached the extremum or not;
   - Stall generation: if within the initially set number of iterations (generations) there is no improvement of the value of the fitness function of the best individual, the algorithms stops.
4) Selection: this is used to select the fittest from the population among all individuals. This step is followed by crossover and mutation, which produce the population offspring. At this stage the best n individuals are directly transferred to the next generation.
5) Crossover: this is used to explore the search space. Here, the aim is to get offspring individuals that inherit the best possible combination of the characteristics (genes) of their parents.
6) Mutation: is used to remove the problem like genetic drift (some individuals may leave behind a few more off-springs than other individuals), and replacement is used to progress to the next new generation.
7) New generation: the elite individuals chosen from the selection are combined with those who passed the crossover and mutation, and form the next generation.

The proposed algorithm seeks to find the minimum function between several variables as can be stated in a general form $minf(p)$,

The cost function $f(p)$ is the objective function which should be optimized. The cost function to be minimized is the norm of the absolute error between the displacement, velocity and acceleration of the simulated cash and the experimental crash data and is defined as:

$$[Error] = sum(|Est - Exp|^T \times |Est - Exp|) \tag{20}$$

where Est and Exp are the model and experimental variables (displacement, velocity and acceleration) respectively.

The algorithm for solving the problem defined by Equations (14) and (15) is shown in Figure 6. An initial guess of parameters is chosen and substituted in equations (16) and (17). Then the obtained stiffness and damping coefficients are substituted into equations (14) and (15) which in turn are numerically solved using time integration to get the simulated kinematic results i.e., accelerations, velocities and displacements. These kinematic results are finally compared with the time history from the crash test. Then the cost function is evaluated. When the cost function is minimum the solver terminates. Otherwise the GA is used to tune the parameters to match the experimental results.

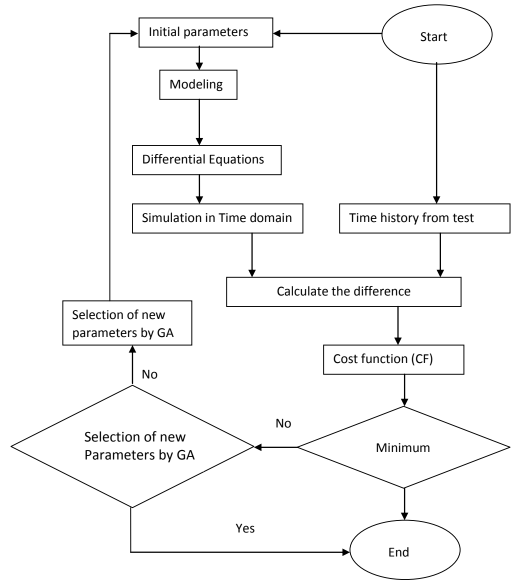

Figure 6: A flowchart for problem solving

The GA method is used here for optimization of the cost function. The GA-type of search schemes is function-value comparison-based, with no derivative computation. It attempts to move points through a series of generations, each being composed of a population which has a set number (population size, 24 in this work) of individuals or parameters. Each individual is a point in the parameter space (in our case, the displacement and velocity of experimental data). The schemes that are applied to the evolution of generations have some analogy to the natural genetic evolution of species, hence the term genetic.

IV. Results and discussion

This section presents the simulation results for two crash tests. The fist crash scenario is a Caravan car crashing into a Neon car, and the second is the Dodge car crashing into a Chevrolet car. Finally, some concluding remarks in regards to implementation of GA to the vehicle-to-vehicle model development are drawn.

The results of the model presented in (14) and (15) are shown in Figure 7 which reconstructs the dynamic crash of a Caravan crashing into a Neon. The results show a trend similar

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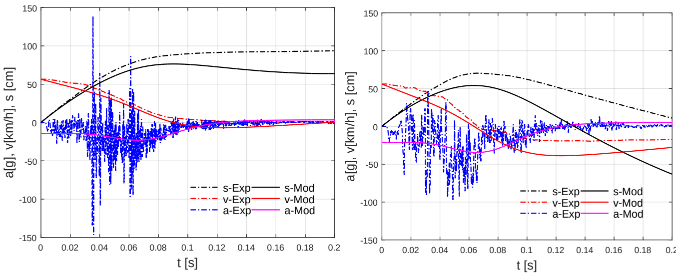
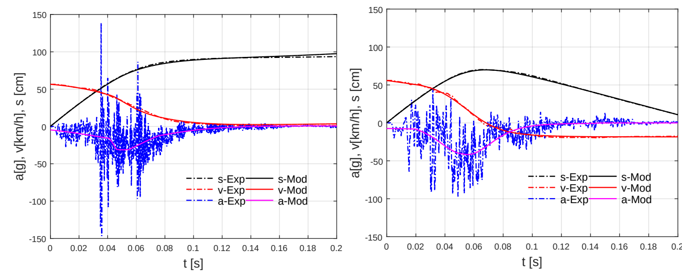


(a) Caravan (b) Neon

Figure 7: Model vs Experimental results for vehicle-to-vehicle (Caravan-Neon) crash using IPA



(a) Caravane (b) Neon

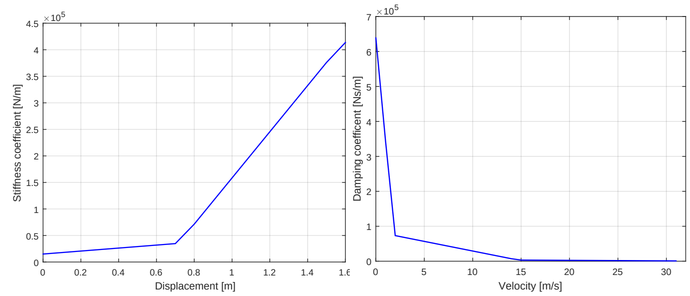
Figure 8: Model vs Experimental results for vehicle-to-vehicle (Caravan-Neon) crash using GA

to that obtained from the test. But the maximum dynamic crash is less than that from the test. The result presented in Figure 7 were obtained using $fmincon$, an optimization function available in MATLAB, with interior point algorithm (IPA). A big difference between the bullet (Caravan) model response and the test results is noted. The bullet model presents a rebounces velocity which is not observed on the test results.

To solve this problem, the genetic algorithm was used to optimize the parameters defined by the piecewise functions presented in Figure 5 and Equations (16) and (17), where the stiffness and damping coefficients are a function of x and $\dot{x}$ respectively. The improved results are presented in Figure 8. It is noted that the model results are much closer to the experimental results from the crash test. The maximum dynamic crash of 70.24 cm is observed on the target (Neon) from the test, while the dynamic crash from the model is 69.92 cm. At the maximum dynamic crash, the bullet vehicle keeps on moving in the same direction as before crash, but the target vehicle rebounces. The rebound velocities are -19.6 m/s and -18.3 m/s from the test and the model respectively. This is observed by the velocity curves of the two vehicles, where a negative velocity is noted for the target vehicle and a positive velocity is noted for the bullet vehicle after the maximum dynamic crash. The front structure of the target vehicle is plastically deformed, while the front structure of the bullet vehicle experiences an elastic deformation. The accuracy of the model is also observed on the time at the maximum dynamic crash, t_m. The time at the maximum dynamic crash, t_m is 0.06568 s from the test and 0.06824 s from the model respectively, as observed on the Neon's kinematic results.

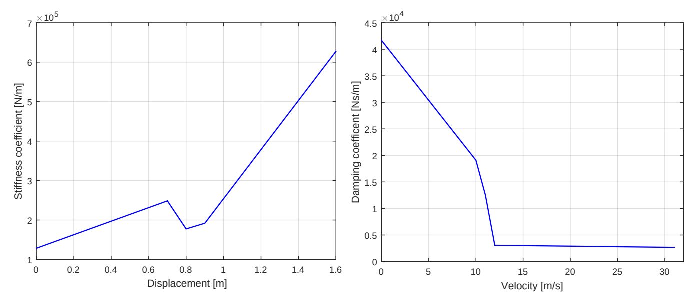
The labels s-Exp, v-Exp, a-Exp, s-Mod, v-Mod, a-Mod, in Figures 7 and 8 stand for: experimental and model displacements, velocities and accelerations, respectively.

The stiffness coefficient (k) and damping coefficient (c) characteristics of the target and bullet vehicle's front structure are shown in Figure 9 and Figure 10, respectively. From these Figures it is noted that the stiffness and damping coefficients are piecewise functions with high magnitude at the maximum dynamic crash, when the velocity of the target vehicle is reduced to zero. This justifies the forced breaking of the target



(a) Stiffness coeficients (b) Damping coefficients

Figure 9: Piecewise spring and damper coefficients of the Neon's front structure



(a) Stiffness coefficients (b) Damping coefficients

Figure 10: Piecewise spring and damper coefficients of the Caravan's front structure

vehicle at the time of collision. A high damping coefficient at the time of crash and a low value of damping coefficient at the initial velocity are observed. It is also noted that the stiffness is low during elastic deformation, but after crash, the vehicle is plastically deformed, therefore stiffness increases drastically to maintain deformation. A summary of estimated parameters for the Caravan - Neon crash is shown in Table I.

To verify the model, the Chevrolet-Dodge crash test was used to demonstrate the accuracy of the GA. The comparison between the model and the crash test results are shown in Figure 11. It is observed from Figure 11 that the maximum dynamic crashes and their occurrence time , for both vehicles,

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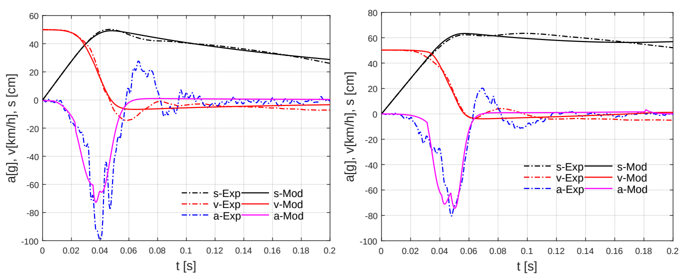
Table I: Estimated Parameters for Caravan-to-Neon model

Parameter for Bulet vehicle	*Value*	*Unit*	*Parameter for Target vehicle*	*Value*	*Unit*
k_{11}	1.2843e+05	N/m	k_{21}	1.5030e+04	N/m
k_{12}	2.5142e+05	N/m	k_{22}	3.5161e+04	N/m
k_{13}	1.4932e+05	N/m	k_{23}	4.1930e+05	N/m
k_{14}	6.5159e+05	N/m	k_{24}	5.1878e+04	N/m
x_{11}	0.7168	m	x_{21}	0.7168	m
x_{12}	0.8316	m	x_{22}	1.5994	m
c_{11}	4.1688e+04	Ns/m	c_{21}	6.3884e+05	Ns/m
c_{12}	1.7727e+04	Ns/m	c_{22}	7.3768e+04	Ns/m
c_{13}	3.0696e+03	Ns/m	c_{23}	3.3250e+03	Ns/m
c_{14}	2.6614e+03	Ns/m	c_{24}	860.3030	Ns/m
$\dot{x}_{11}$	10.6044	m/s	$\dot{x}_{21}$	1.9138	m/s
$\dot{x}_{12}$	11.7252	m/s	$\dot{x}_{22}$	14.6957	m/s



(a) Dodge (b) Chevrolet

Figure 11: Model vs Experimental results for Dodge-to-Chevrolet crash using GA

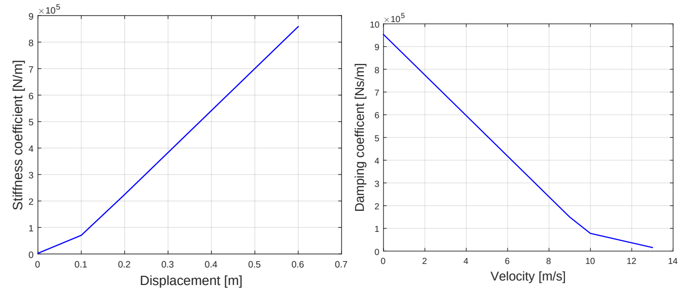
are almost equal to those observed from the physical crash tests. The maximum dynamic crashes and the times of crash, for the Chevrolet and Dodge cars are: 62.20 cm and 0.055 s, and 49.63 cm and 0.048 s respectively.

A summary of estimated parameters for Dodge- Chevrolet crash is shown in Table II. The stiffness and damping coefficients characteristics of the Dodge's and Chevrolet's front structures are shown in Figures 12 and 13 respectively.

V. Conclusion and Future Work

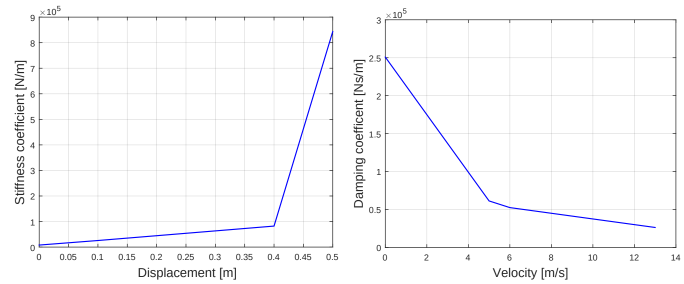
In this paper, a mathematical-based method is presented to estimate the parameters of a vehicle-to-vehicle frontal crash. It is observed that the model results in responses in vehicle crash model match with the experimental crash tests. Therefore, the overall behavior of the models matches the real vehicle's crash well. Hence the implication of the proposed model is that it can help vehicle designer to better design the vehicle with fewer physical crash tests. Two of the main parameters characterizing the collision are the maximum dynamic crash (C_m), which describes the highest car's deformation, and the time (t_m) at which it occurs. They are pertinent to the occupant crashworthiness since they help to assess the maximum intrusion into the passenger's compartment. The results show that we can obtain an optimum solution with GA Toolbox Matlab than the $fmincon$ optimization algorithm. It has been demonstrated that the model and the GA parameter optimization procedure used in this work can be successfully extended for different range of crash speeds.

The authors will extend the work by including other parts of the vehicle such as an engine in the model. The authors also intend to investigate the application of genetic algorithm for different crash scenarios such as oblique crash and side impact. Further investigations will be carried out using Finite



(a) Stiffness coeficients (b) Damping coefficients

Figure 12: Piecewise spring and damper coefficients of the Dodge's front structure



(a) Stiffness coeficients (b) Damping coefficients

Figure 13: Piecewise spring and damper coefficients of the Chevrolet's front structure

Table II: Estimated Parameters for Dodge-to-Chevrolet model

Parameters for Dodge	***Value***	***Unit***	***Parameters for Chevrolet***	***Value***	***Unit***
k_{11}	2.5726e+03	N/m	k_{21}	7.9266e+03	N/m
k_{12}	4.9029e+03	N/m	k_{22}	6.8819e+03	N/m
k_{13}	7.3699e+04	N/m	k_{23}	8.9521e+04	N/m
k_{14}	9.1342e+05	N/m	k_{24}	8.6448e+05	N/m
x_{11}	2.8633e-06	m	x_{21}	1.5314e-06	m
x_{12}	0.1048	m	x_{22}	0.4387	m
c_{11}	9.5321e+05	Ns/m	c_{21}	2.5087e+05	Ns/m
c_{12}	8.3382e+04	Ns/m	c_{22}	5.5703e+04	Ns/m
c_{13}	7.4707e+03	Ns/m	c_{23}	5.2663e+03	Ns/m
c_{14}	5.0879e-07	Ns/m	c_{24}	363.1498	Ns/m
$\dot{x}_{11}$	9.7443	m/s	$\dot{x}_{21}$	5.1470	m/s
$\dot{x}_{12}$	13.4024	m/s	$\dot{x}_{22}$	13.6221	m/s

Element Model (FEM) approach for validation of the results form Lumped Parameter model of vehicle-to-vehicle crash scenario.

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