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Research Paper

Enhanced Modeling of Crumple zone in Vehicle Crash Simulation Using Modified Kamal model Optimized with Gravitational Search Algorithm

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Abstract

The effectiveness of a vehicle crash system depends on how well it can simulate the behavior of a real vehicle in a crash scenario and accurately identifies the correct working limits of the model parameters, including mass, spring, and damper. Therefore, this study explores the modelling vehicle front crumple zone to represent the behaviors of real crash scenario. The modelling process using Kamal approach is used to develop a precise vehicle crash model for analyzing the impact of a collision on both the vehicle and its passengers. In this study, a complex mass-spring-damper system representing the front crumple zone of an actual car is re-designed to modify the existing vehicle crash model. The gravitational search algorithm (GSA) is implemented in the simulation model's code to obtain optimized values of damping coefficient (c) and spring constant (k). The simulation results show that the deformation response of crumple zone and the deceleration response of vehicle body match the experimental results, indicating the model's accuracy. Additionally, this study investigates the effects of varying the GSA parameters number of agents (N), the beta parameter (β), and the gravitational constant (G) to improve the model's accuracy by minimizing the root mean square error (RMSE) between model response and crash test data. The optimal GSA parameter chosen in this study were $N = 50$, $\beta = 0.3$ and $G = 20$ with the lowest RMSE of 22.3874, 22.26664 and 23.86638 respectively.

Keywords: Crumple zone; Vehicle crash simulation; Modified Kamal model; Gravitational search algorithm

1. Introduction

The media frequently reports on the serious injuries or fatalities that occur as a result of head-on collisions. These types of collisions often cause significant damage to the car body that cannot be repaired [1]. To better understand the impact of frontal collisions on both the vehicle and its occupants, researchers have developed a mathematical model of the vehicle system. This crash model involves replicating both the deformable and non-deformable components of the car into a spring-mass-damper system, which is commonly referred to as a lumped parameter model [2]. By using this model, researchers can analyze how the vehicle and its occupants behave during a collision, and how the vehicle's components deform and transfer energy during impact [3].

Fekry et al. [4] proposed a novel approach to minimize the impact of collisions on vehicles by using a smart front-end structure. This approach considers both full and offset frontal collisions between smart and standard vehicles. To model the plastic deformation of the vehicle's components, the authors used longitudinal members such as spring elements to produce linear and cubic non-linear stiffness coefficients. The hydraulic cylinders were represented by linear and cubic non-linear damping coefficients, while the passenger and occupant compartment were represented by lumped masses. To determine the dynamic response, deformation, and deceleration of the vehicle and its occupants, an incremental harmonic balance method was employed to solve the multi-degree-of-freedom systems in the model [5]. The simulation results demonstrated that the proposed model could reduce intrusion while keeping occupant deceleration within the desired limit.

Ofochebe et al. [6] proposed the use of data-driven regression in mathematical modeling and analysis of car crashes. Their model simulated car-to-pole collisions using the Kelvin model with a viscoelastic element, where the combined mass, spring, and damper that represent the vehicle behavior were connected in parallel. The researchers divided the front part of the car into six components, each determined based on the car's actual specifications. The car mass was set to 1000 kg, and the spring stiffness and damping coefficient values were assigned using a trial-and-error method based on vehicle crash mechanics tests. This model was able to verify full-scale crash tests for various scenarios, including low-speed, high-speed, and side impacts [7].

The mathematical model used a double-spring-mass-damper system that divides the car structure into two parts, with the vehicle chassis representing the front mass and the passenger compartment the rear mass. Due to the complexity of the system equation, it was not possible to derive the physical spring damper parameters of the model. As a result, Munyazikwiye et al. [8] utilized finite element model and the piecewise lumped parameter (LMP) to simplify and estimate the model parameters. This model can represent a real vehicle crash scenario as long as the conditions for each mass are met.

Elkady et al. [9] developed a six-degree-of-freedom mathematical model for simulating full high-speed collisions and offset front crashes. The model was based on Kamal's study of a simple mass-spring model, which represents the vehicle body as a lumped mass and the suspension system as four units of springs and dampers that absorb crash energy. The authors improved the model by co-simulating the vehicle dynamics control systems (VDCS), including the anti-lock braking system (ABS) and active suspension control system (AS), to control vehicle deformations.

The contribution of this study is to further improve the existing Kamal vehicle crash model for analyzing the car body during front collisions. The model is a complex mass-spring-damper system that represents the front crumple zone of the vehicle. The c and k parameters for the compartments were obtained from the actual vehicle system. The model was validated through simulation in MATLAB-Simulink, where the optimized c and k parameters were obtained using the Gravitational Search Algorithm (GSA) and compared with the experimental results from Real Crash Test Data (RCTD) [10]. To enhance the deformation response, the study varied the parameters in the GSA coding, including the number of agents (N), the beta parameter (β), and the gravitational constant (G). The paper contributes to determining the vehicle kinematics using a mass-spring-damper system that estimates the effect of primary and secondary impacts in crash collisions. It also suggests potential countermeasures to resolve the problem, such as developing a control system or using materials such as magnetorheological elastomer (MRE) to absorb the impact on the front bumper. Other related studies that have explored these solutions include Archakam and Muthuswamy [11] and Rahmat et al. [12].

The structure of this paper is as follows. The first section provides an overview of the project's objectives, which aimed to develop a vehicle crash model and validate the simulation model using the GSA optimization method. The second section provides a detailed explanation of the method used in the Kamal model and the approach adopted in this study. Section three introduces the role played by GSA in optimizing the c and k parameters of the model. Section four discusses the simulation results, and the final section presents the findings of the study and concludes the paper.

2. Six-Degree-of-Freedom Vehicle Crash Model

The Kamal model is a vehicle crash model that combines analytical and experimental techniques through three approaches: a computer simulation program for barrier impact, a vehicle component crusher, and a mathematical model that represents the vehicle body [13]. The experimental data used to develop the Kamal model were collected in a designated test, where a stationary car collided with a barrier at speeds ranging from 0 to 30 mph, with a predetermined amount of force. The collision resulted in identifying the parts of the vehicle that sustained light or heavy damage. The output from the frontal impact was analyzed in terms of vehicle motion, body deformation, and the dynamic forces transmitted to the passenger compartment through simulations carried out on the model. **Figure 1** illustrates the complete barrier impact simulation model, which includes three lumped masses representing crucial parts of the vehicle, namely the body, engine, and cross-members, along with eight nonlinear resistances as shown in **Figure 2**.

2.1. Modified Kamal Model

This study develops a modified Kamal model (MKM) with six degrees of freedom which adopts the previously proposed model, namely Kamal model due to it detail representation for crumple zone using mass-spring-damper system which makes it function exactly as an actual car used in our daily life. A minor adjustment was made to the mathematical modeling for the front collision, considering the positioning of the spring and damper elements in the model, which can impact the performance of the vehicle crash model. Previous studies by Pawlus et al. [14] and Radu et al. [15] have demonstrated that the Maxwell model, where the spring-damper elements are connected in series, produces a response similar to actual car crash data. Therefore, the modified Kamal model in this study considers six lumped masses representing different vehicle parts, connected by ten springs and four dampers arranged in parallel, as shown in **Figure 3**. This modeling process is based on observations of the front crumple zone of an actual vehicle system, considering the parts of the car that are affected in a front collision. This approach is expected to yield improved results as it captures the precise behavior of the vehicle collision [16].

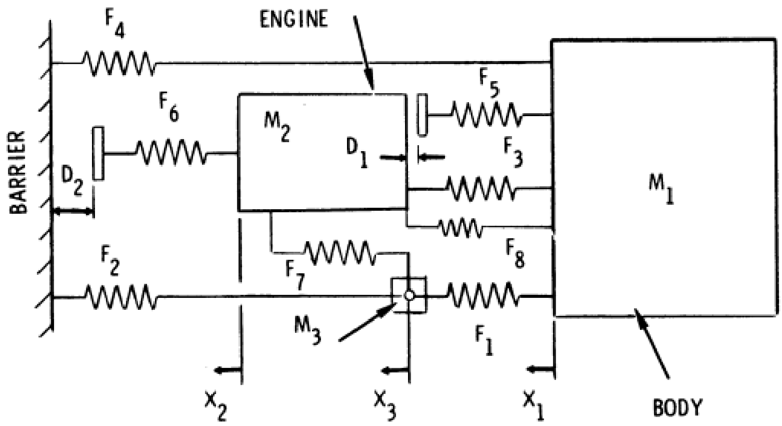

Figure 1. Mathematical model of a barrier impact [13]

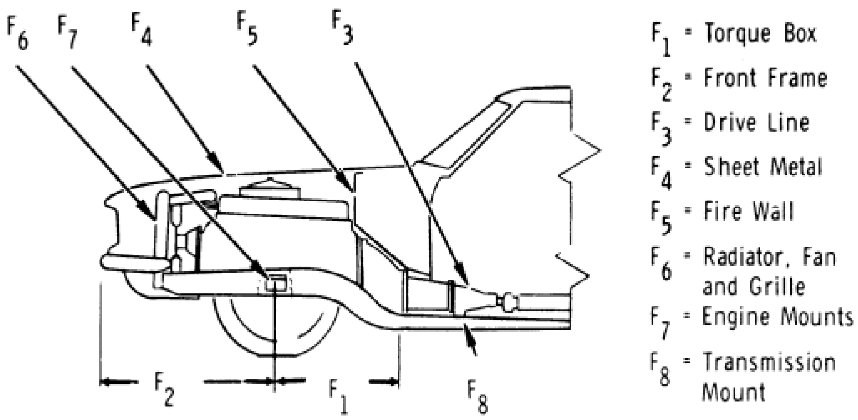

Figure 2. The dynamic forces acting on the front crumple zone [13]

2.2. Equations of Motion of the Modified Kamal Model

The mathematical model of the modified Kamal model is shown in **Figure 3**. The derivation for Mass 1 using Lagrange formulation based on the kinetic (T), dissipative (Q), and potential (V) energies of the mass, spring, and damper as in Eq. (1), Eq. (2), and Eq. (3). The product of differentiation for kinetic with respect to $\dot{x}_1$ and x_1, dissipative, and potential energies for Mass 1 given by Eq. (4), to Eq. (7) respectively.

Eq. (8) is the general equation for the Lagrange formulation consisting of kinetic, dissipative and potential energies. The derivation of each energy are written in Eq. (9) the final acceleration for Mass 1 was derived as follows.

Final acceleration formulation of the vehicle body is written as Eq. (10). The derivation of the final acceleration equations for Mass 2, 3, 4, 5, and 6 are similar to Mass 1 and used the respective forces for the masses as presented in Eq. (11) to Eq. (15).

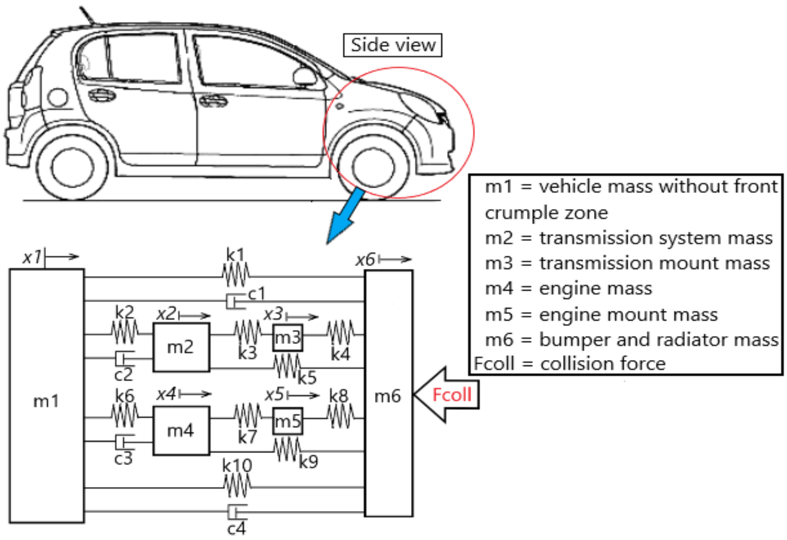

Figure 3. Free-body diagram of the crumple zone modeling

$$T_1 = \frac{1}{2} m_1 \dot{x}_1{}^2 \tag{1}$$

$$Q_1 = \frac{1}{2} c_1 (\dot{x}_6 - \dot{x}_1)^2 + \frac{1}{2} c_2 (\dot{x}_2 - \dot{x}_1)^2 + \frac{1}{2} c_3 (\dot{x}_4 - \dot{x}_1)^2 + \frac{1}{2} c_4 (\dot{x}_6 - \dot{x}_1)^2 \tag{2}$$

$$V_1 = \frac{1}{2} k_1 (x_6 - x_1)^2 + \frac{1}{2} k_2 (x_2 - x_1)^2 + \frac{1}{2} k_6 (x_4 - x_1)^2 + \frac{1}{2} k_{10} (x_6 - x_1)^2 \tag{3}$$

$$\frac{\partial T_1}{\partial \dot{x}_1} = m_1 \dot{x}_1 \tag{4}$$

$$\frac{\partial T_1}{\partial x_1} = 0 \tag{5}$$

$$\frac{\partial Q_1}{\partial \dot{x}_1} = - c_1(\dot{x}_6 - \dot{x}_1) - c_2 (\dot{x}_2 - \dot{x}_1) - c_3 (\dot{x}_4 - \dot{x}_1) - c_4 (\dot{x}_6 - \dot{x}_1) \tag{6}$$

$$\frac{\partial V_1}{\partial x_1} = - k_1 (x_6 - x_1) - k_2 (x_2 - x_1) - k_6 (x_4 - x_1) - k_{10} (x_6 - x_1) \tag{7}$$

$$\frac{d}{dt}\left(\frac{\partial T}{\partial \dot{x}_i}\right) - \left(\frac{\partial T}{\partial x_i}\right) + \left(\frac{\partial Q}{\partial \dot{x}_i}\right) + \left(\frac{\partial V}{\partial x_i}\right) = F_i \tag{8}$$

$$\begin{aligned} m_1 \ddot{x}_1 - c_1(\dot{x}_6 - \dot{x}_1) - c_2 (\dot{x}_2 - \dot{x}_1) - c_3 (\dot{x}_4 - \dot{x}_1) - c_4 (\dot{x}_6 - \dot{x}_1) - k_1 (x_6 - x_1) - k_2 (x_2 - x_1) \\ - k_6 (x_4 - x_1) - k_{10} (x_6 - x_1) = 0 \end{aligned} \tag{9}$$

$$\ddot{x}_1 = \frac{1}{m_1}\begin{bmatrix} c_1(\dot{x}_6 - \dot{x}_1) + c_2 (\dot{x}_2 - \dot{x}_1) + c_3 (\dot{x}_4 - \dot{x}_1) + c_4 (\dot{x}_6 - \dot{x}_1) \\ + k_1 (x_6 - x_1) + k_2 (x_2 - x_1) + k_6 (x_4 - x_1) + k_{10} (x_6 - x_1) \end{bmatrix} \tag{10}$$

$$\ddot{x}_2 = \frac{1}{m_2}[-c_2(\dot{x}_2 - \dot{x}_1) - k_2(x_2 - x_1) + k_3(x_3 - x_2) + k_5(x_6 - x_2)] \tag{11}$$

$$\ddot{x}_3 = \frac{1}{m_3}[k_4(x_6 - x_3) - k_3(x_3 - x_2)] \tag{12}$$

$$\ddot{x}_4 = \frac{1}{m_4}[k_7(x_5 - x_4) + k_9(x_6 - x_4) - k_6(x_4 - x_1) - c_3(\dot{x}_4 - \dot{x}_1)] \tag{13}$$

$$\ddot{x}_5 = \frac{1}{m_5}[k_8(x_6 - x_5) - k_7(x_5 - x_4)] \tag{14}$$

$$\ddot{x}_6 = \frac{1}{m_6}\begin{bmatrix} F - k_1(x_6 - x_1) - c_1(\dot{x}_6 - \dot{x}_1) - k_4(x_6 - x_3) - k_5(x_6 - x_2) \\ -k_8(x_6 - x_5) - k_9(x_6 - x_4) - k_{10}(x_6 - x_1) - c_4(\dot{x}_6 - \dot{x}_1) \end{bmatrix} \tag{15}$$

3. Development of Modified Kamal Model in MATLAB Simulink

This section describes the methodology for selecting the optimal values of c and k using a combination of the modified Kamal model simulation results and optimization using GSA. The vehicle crash model was implemented in MATLAB 2014, utilizing the Lagrange equation for six lumped masses, which were represented as a block diagram. The inputs to each lumped mass were the displacement (x), velocity ($\dot{x}$), and acceleration ($\ddot{x}$) of the spring (F_s) and damper (F_d) forces. **Figure 4** illustrates the simplified arrangement of this model, with the collision force (F_{coll}) as the output.

3.1. *Simulation Parameters*

The model configuration parameters for the solver in MATLAB-Simulink were adjusted based on a fixed-step size of 0.001 using the ODE8 (Dormand-Prince) method. The GSA coding simulation was then executed for 0.5 seconds in the editor.

3.2. *Vehicle Parameters*

The c and k parameters for the six lumped masses were obtained from the estimated standard vehicle specification and the Kelvin model data [17]. These parameters were then inputted into the workspace and are presented in **Table 1** for reference.

4. Optimization of the Six-Degree-of-Freedom Modified Kamal model using Gravitational Search Algorithm (GSA)

After developing the model, the next step is to optimize the parameters for the Modified Kamal model (MKM). There are several methods available for optimizing the parameters of developed models, such as genetic algorithm (GA), particle swarm optimization (PSO) and ant colony optimization (ACO) [18]. The gravitational search algorithm (GSA) developed by Rashedi et al. [19] is a more recent heuristic algorithm used for data optimization. It involves a set of agents, also known as masses, and incorporates gravitational law and Newton's law of motion in

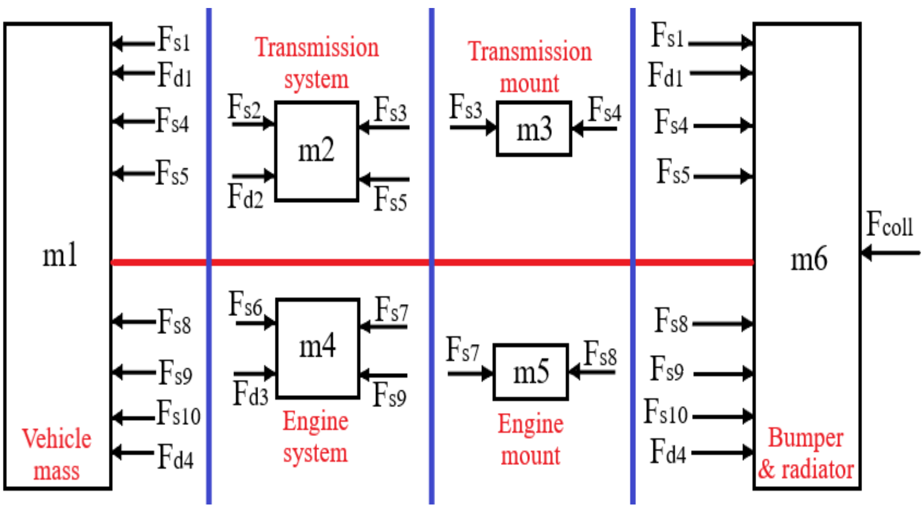

Figure 4. Schematic diagram of the modified Kamal model

the coding to obtain an optimal result with a flexible implementation concept. GSA follows a similar approach to PSO, where data optimization is achieved through the agents' abilities to explore and exploit the search space. However, their movement strategies differ [20], [21].

In this study, GSA was chosen over other methods due to its effectiveness of optimization algorithms that can vary the parameters of spring constant and damping coefficient in Modified Kamal model based on specific cases. The optimized Modified Kamal model parameters can closely represent the vehicle collision scenario. Here, the lower boundary (LB) and upper boundary (UB) for the coding were determined based on estimated parameters for an actual vehicle. The simulation output was then refined in terms of deformation response by adjusting the parameters in GSA iteratively until the simulation output matched the desired response, which was obtained from experimental results of Real Crash Test Data (RCTD), thus validating the effectiveness of this method using the Root Mean Square Error (RMSE). GSA was used to explore the impact of varying the number of agents (N), beta parameter (β), and gravitational constant (G) on the overall optimization results, with the aim of improving the final outcomes.

4.1. *Effects of Varying the Number of Agents (N)*

The parameter N, representing the number of agents, stands as a pivotal configuration within the GSA framework. Its determination is typically achieved through empirical exploration across diverse applications and remains fixed throughout the algorithm's execution. In this study, N was systematically adjusted in four distinct scenarios: 20, 30, 40, and 50. These values were subsequently compared against the deformation response.

Illustrated in Figure 5 is the RMSE graph, unveiling a discernible pattern wherein augmenting the count of agents correlates with diminished simulation errors. This observation contrasts with the approach advocated by Rashedi et al., wherein diminishing agent numbers over time was projected to yield reduced errors due to heightened efficacy in surveying and exploiting the search landscape.

Table 1. Initial spring-mass-damper parameters

Mass [kg]	m_1	900
	m_2	120
	m_3	50
	m_4	180
	m_5	40
	m_6	45
Damper [kNs/m]	c_1	2.3
	c_2	230
	c_3	25
	c_4	2.1
Spring [kN/m]	k_1	20
	k_2	120
	k_3	25
	k_4	25
	k_5	25
	k_6	100
	k_7	25
	k_8	25
	k_9	25
	k_{10}	100

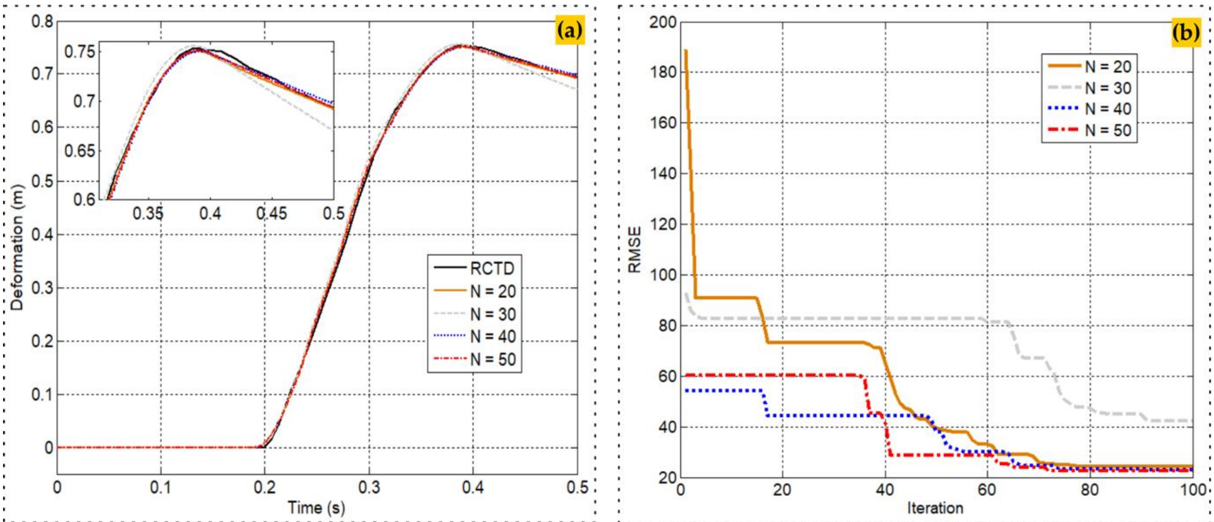

Figure 5. The outcome of varying the number of agents, N: (a) Deformation; and (b) Root means square error

In the context of this study, the preferred agent count was identified as 20, given its notable convergence velocity in contrast to the others. However, upon consulting **Table 2** showcasing outcomes delineating the optimal agent count, a counterintuitive decision was made. Specifically, $N = 50$ emerged as the favored choice for optimal agent count, substantiated by its remarkably low error rate of 22.38764. Furthermore, the deformation trend closely aligns with Real Crash Test Data, bolstering the selection of $N = 50$ as the most favorable configuration.

4.2. *Effects of Varying Beta Parameters (β)*

Figure 6 illustrates a notable observation: when the parameter β is set to 0.3, the Root Mean Square Error (RMSE), as described by Eq (16) pertaining to the gravitational constant, reaches its minimum value. This figure provides insight into the relationship between β and G, demonstrating a direct proportionality between the two while ensuring that β remains below the threshold of 1.

The gravitational constant, denoted as G, assumes a crucial role in the initial stages of the coding process, influencing search accuracy and computation time. This dependence stems from its reliance on both the initial value (G_0) and time (t), as represented by Eq (17).

$$G(t) = G(t_0) \times \left(\frac{t_0}{t}\right)^{\beta}, \beta < 1 \quad (16)$$

$$G(t) = G(G_0, t) \quad (17)$$

Table 2. The optimized parameters for all number of agents

Optimized parameter				
c_1	35.353	34.3826	33.2769	37.9628
c_2	6.2926	9.6909	5.5357	8.6283
c_3	40.7702	35.6913	34.9706	32.1876
c_4	7.5913	6.87	9.9752	5.3416
k_1	15.9686	13.2289	10.3059	13.4737
k_2	46.8022	50.6895	55.118	48.3042
k_3	60.2166	76.082	77.1763	79.0514
k_4	3.3638	5.8527	4.3144	1.253
k_5	1	5.6294	4.0542	4.3127
k_6	5.9605	4.6083	6.2977	7.1643
k_7	22.2546	32.4851	33.256	30.5722
k_8	5.3428	5.3541	8.1197	5.5551
k_9	3.3315	6.3604	1.016	5.1282
k_{10}	4.8553	6.7871	1.597	1.2252
Optimized result				
N	20	30	40	50
$RMSE$	24.0972	42.0905	23.0275	22.3874

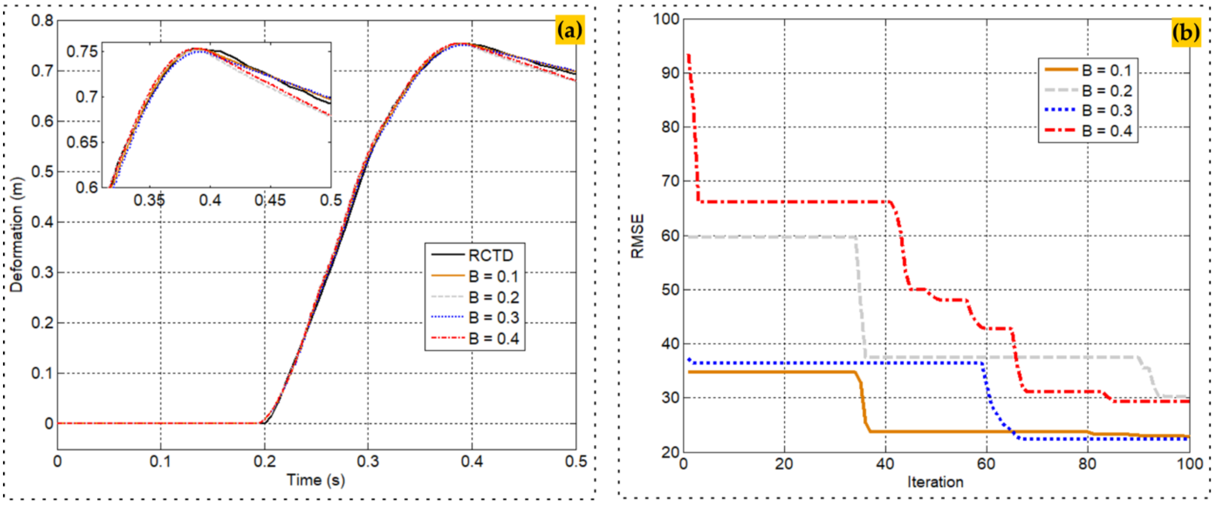

Figure 6. The outcome of varying the beta parameter, β: (a) Deformation; and (b) Root means square error

An intriguing finding emerges: the optimal value for the beta parameter is β = 0.3. This choice is supported by the data presented in **Table 3**, showcasing the lowest root mean square error. Moreover, the convergence rate of this optimal beta parameter is noteworthy, rivaling that of the beta parameter set at 0.4.

4.3. Effects of Varying Gravitational Constants (G)

Newton's law of gravity establishes that the gravitational force acting between two particles is directly proportional to the product of their masses, represented as $M1$ and $M2$, and inversely proportional to the square of the distance separating them, denoted as R. This fundamental relationship is formally expressed in Equation 18.

$$F = G\frac{M_1 M_2}{R^2} \quad (18)$$

Consequently, the efficacy of the Gravitational Search Algorithm (GSA) hinges upon the gravitational constant $G(t)$, which serves as a pivotal factor governing the step size for an agent's movement. The dynamic behavior of $G(t)$ follows an exponential decay pattern across iterations, holding G_0 as a constant during the entirety of the search process.

The selection of the optimal gravitational constant G is influenced by empirical analysis, as outlined in **Table 4**. Through careful evaluation, G = 10 emerged as the optimal choice for the gravitational constant. This selection is justified by its ability to yield the lowest Root Mean Square Error (RMSE) value of 23.86638. Notably, this optimal constant concurrently preserves a close alignment with the acceleration response of the Real Crash Test Data (RCTD) curve, as vividly depicted in **Figure 7**.

4.4. Simulation Results of the Optimized Parameters

The developed 6-DOF Modified Kamal model (MKM) was input with the optimized spring stiffness and damping coefficient values. The simulation utilized the optimized parameters from **Table 5** and compared the acceleration and deformation responses with the published experimental results from Real Crash Test Data (RCTD) obtained from [10] followed by Elkady and Elmarakbi model (E&E) and ADAMS multibody model (ADAMS) according to **Figure 10**. A performance indicator, RMSE, was used to assess the validity of the developed model, with the selected GSA parameters N = 50, β = 0.3, and G = 20. The simulation results demonstrated that the simulated values closely matched the experimental data, with an RMSE of 23.86638 (**Figure 8**).

In order to verify the effectiveness of the developed Modified Kamal Model (MKM), its acceleration is compared with the response obtained from original Kamal Model (KM). Here,

Table 3. The optimized data for all bheta parameters

Optimized parameter				
c_1	35.0573	36.6276	37.0354	34.4179
c_2	7.0951	5.9284	6.7428	5.9158
c_3	31.9851	31.479	31.6201	32.029
c_4	8.1994	5.2863	6.9712	7.9373
k_1	10	10	11.0005	22.5809
k_2	48.786	45.8902	39.1803	41.5241
k_3	82.8509	79.1433	78.5861	80.5374
k_4	4.3846	6.4879	2.6912	1
k_5	1.0124	6.7884	3.9491	1
k_6	5.7237	6.2898	9.6813	6.2481
k_7	28.4113	29.3615	32.5832	31.6644
k_8	4.9425	4.1405	3.1402	5.9
k_9	5.7758	5.4877	1.0566	4.8
k_{10}	3.5671	3.8815	4.8459	4.644
Optimized result				
β	0.1	0.2	0.3	0.4
$RMSE$	22.86615	30.25327	22.26664	29.23913

Table 4. The optimized data for all gravitational constants

Optimized parameter				
c_1	36.2674	37.3939	37.2959	34.2642
c_2	7.11	5.9434	5.4186	7.108
c_3	33.1669	34.2822	30.0933	33.7686
c_4	5.9277	5.5921	5.6399	7.849
k_1	25.7277	10	10.0002	19.0149
k_2	40.8918	38.5364	43.2798	43.5607
k_3	86.8623	82.1257	78.0412	78.4224
k_4	4.8958	5.3765	4.856	5.6677
k_5	1.0907	1.2006	5.5963	1
k_6	6.2669	6.6671	5.8774	5.9052
k_7	28.6827	34.4504	36.7404	31.1119
k_8	6.1519	5.8199	5.0808	3.5213
k_9	1.5821	4.1076	1.0057	4.7754
k_{10}	1	5.2167	4.5166	5.6777
Optimized result				
G	10	20	30	40
$RMSE$	33.97027	23.86638	24.87571	31.20340

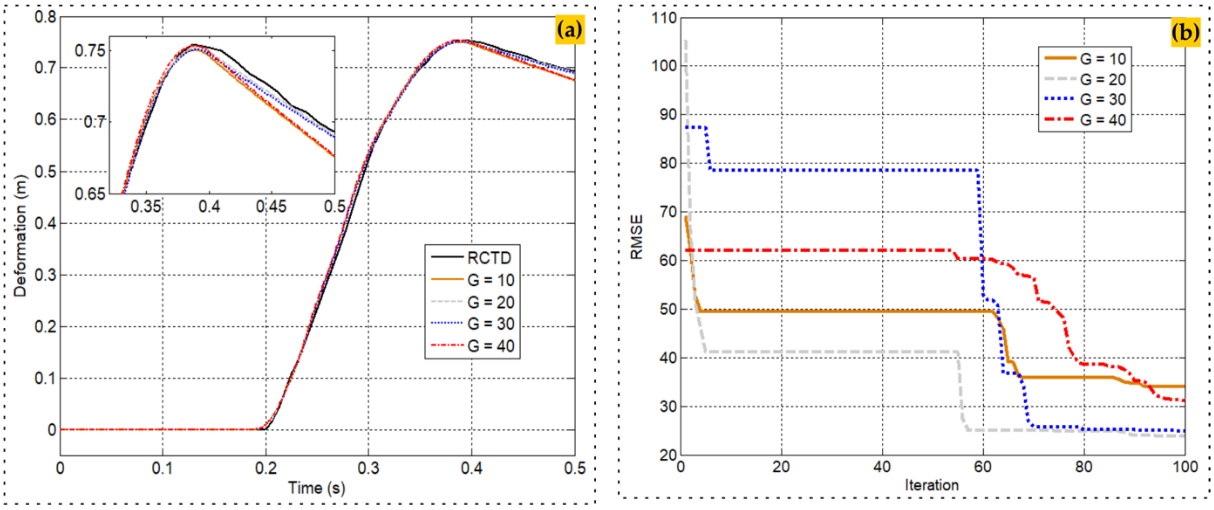

Figure 7. The outcome of varying the gravitational constant, G: (a) Deformation; and (b) Root means square error

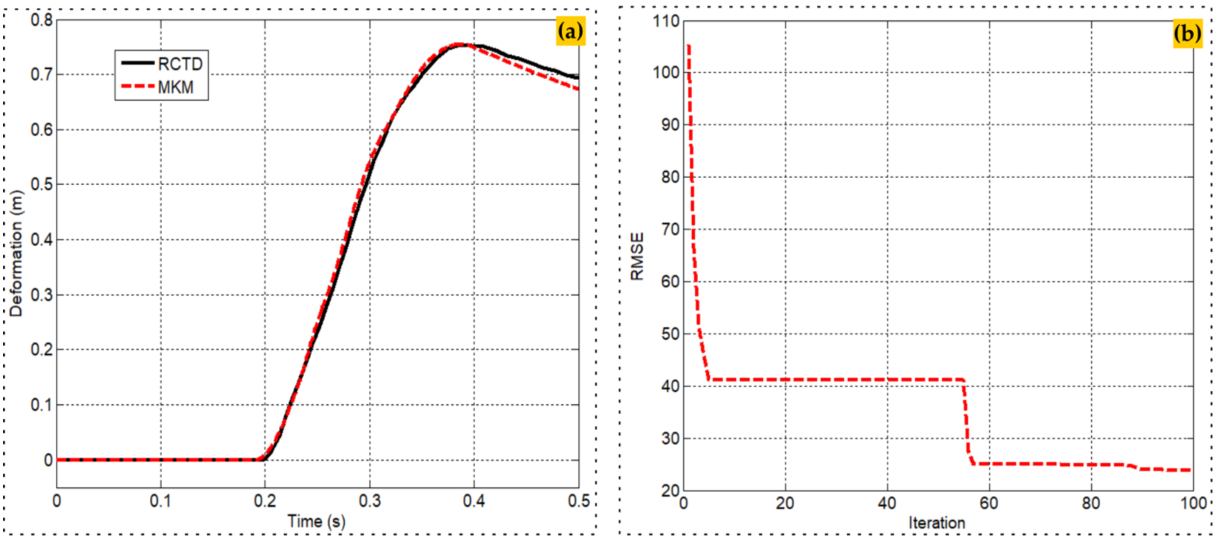

Figure 8. The optimum model parameters: (a) Deformation; and (b) Root means square error

the modelling approaches of both KM and MKM that have been explained in Sections 2 and 2.1 are then evaluated to see the advantage of the MKM in tracking the response obtained from the actual experimental data as presented in **Figure 9**. It can be seen from the result that the acceleration response of MKM is able to closely follow the experimental data in terms of trend and magnitude. However, the response obtain from KM shows the magnitude is less than the experimental data and produces inconsistent trend. This clearly shows that the developed MKM, with considering all aspects related to an actual vehicle component is able to represent an actual crash response.

Table 5. The optimal c and k values

Damper [kNs/m]	c_1	37.3939
	c_2	5.9434
	c_3	34.2822
	c_4	5.5921
Spring [kN/m]	k_1	10
	k_2	38.5364
	k_3	82.1257
	k_4	5.3765
	k_5	1.2006
	k_6	6.6671
	k_7	34.4504
	k_8	5.8199
	k_9	4.1076
	k_{10}	5.2167

Furthermore, MKM was compared with the simulation works from E&E and ADAMS model while maintaining RCTD as the benchmark for the overall results. **Figure 10** shows that there was a good agreement between the experimental results and MKM in terms of acceleration and deformation response compared to other simulation models. This clearly demonstrates that the suggested model has the capacity to deliver accurate results that are as close as possible to the benchmark while preserving minimal error as presented in **Table 6**.

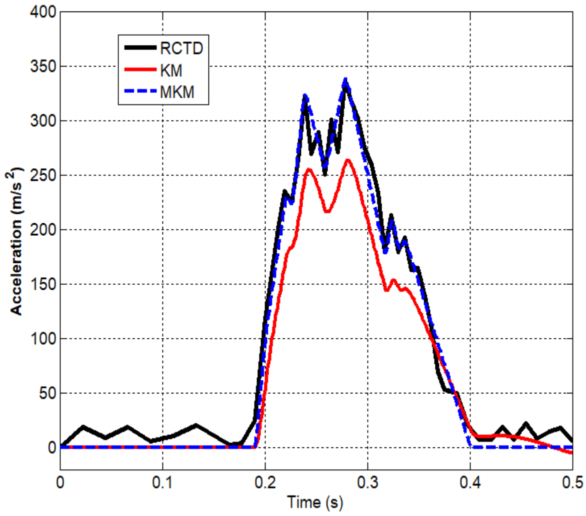

Figure 9. Acceleration responses of original Kamal and modified Kamal models

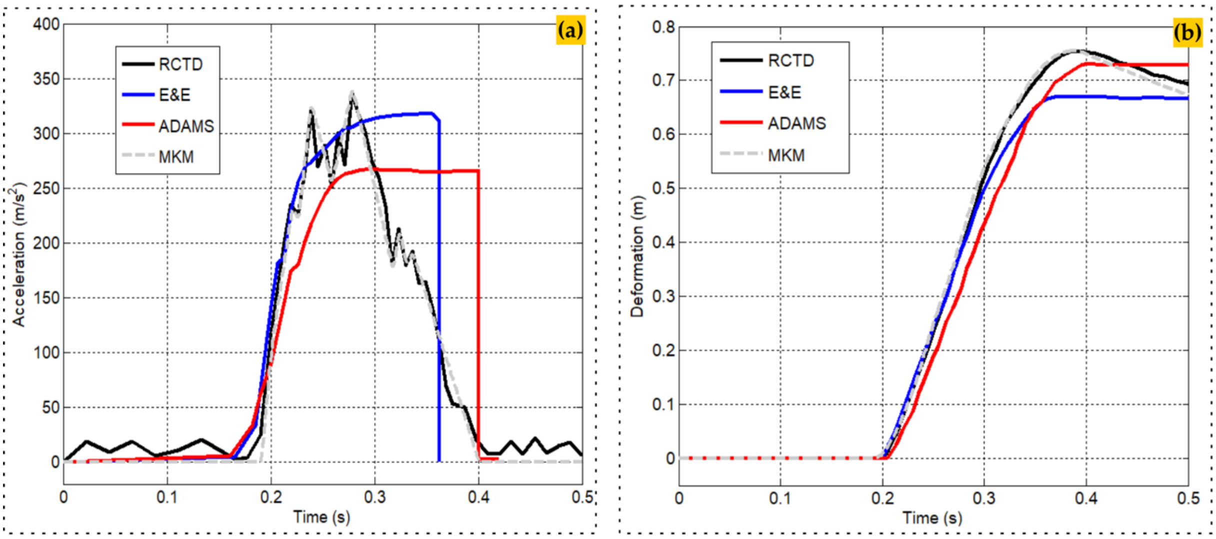

Figure 10. Comparison with others model: (a) Acceleration; and (b) Deformation

Table 6. The maximum percentage error for each model

Simulation model	Acceleration (m/s²)	Percentage error (%)	Deformation (m)	Percentage error (%)
E & E	317.73	5.8749	0.67136	12.3585
ADAMS	267.704	25.6598	0.73025	3.2975
MKM	338.4246	0.5993	0.7536	0.09687

5. Conclusion

This study presents a novel vehicle crash model that utilizes a mass-spring-damper system to accurately represent the various components of a vehicle body in order to analyze the impact of collisions on the front bumper. The proposed model's c and k parameters are optimized using the gravitational search algorithm (GSA). The model is based on the Kamal study, which utilized a six-degree-of-freedom (6-DOF) mathematical model, and its performance is compared with experimental data on vehicle body deformation. To enhance the simulation results, three important parameters in the GSA, namely the number of agents (N), the beta parameter (β), and the gravitational constant (G), are varied. The optimal damping coefficient and spring constant, are determined by selecting the positive value of vehicle parameters with minimum error. The optimized parameters are then used in the developed crumple zone model. In order to verify the crumple zone modelling, the proposed model was compared with other simulation models namely, Elkady & Elmarakbi model and ADAMS model. The modified Kamal model showed good agreement with the real crash test data obtained from the previous work, with a maximum percentage error of 0.5993% for acceleration response and 0.09687% for deformation response. The findings of this study demonstrate that varying these three parameters significantly improves the simulation output by minimizing errors and closely fitting the experimental data, thus validating the effectiveness of the proposed model.

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Author's Declaration

Authors' contributions and responsibilities

The authors made substantial contributions to the conception and design of the study. The authors took responsibility for data analysis, interpretation and discussion of results. The authors read and approved the final manuscript.

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Availability of data and materials

All data are available from the authors.

Competing interests

The authors declare no competing interest.

Additional information

No additional information from the authors.

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