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CRUMPLE ZONE MODELLING OF PASSENGER VEHICLE USING MULTIPLE KELVIN MODEL AND OPTIMIZED WITH PARTICLE SWARM OPTIMIZATION

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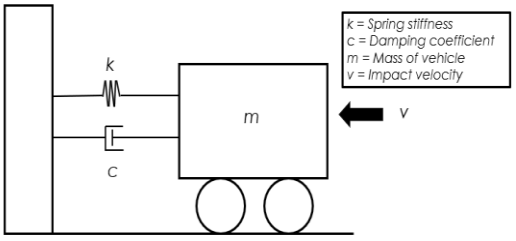
Graphical abstract



Abstract

This paper presents the mathematical modelling of a vehicle crash system using a mass-spring-damper approach to simulate the behavior of a real vehicle during a frontal impact. A Multiple Kelvin model is developed to represent a real vehicle crash situation where the impact is introduced on the frontal vehicle body. The modelling process of Multiple Kelvin model is based on a single Kelvin model that developed into a set of seven mass-spring-damper systems representing the front crumple zone of a real vehicle. The model is then optimized for the parameters *k* and *c* using an optimization method namely Particle Swarm Optimization (PSO) algorithm in MATLAB-Simulink. The simulation results demonstrate deformation and acceleration responses closely follow the previous experimental results where the parameters namely N_i, N_p, and i_w are varied to enhance the model's precision through the calculation of error of 12.15 using parameters N_i = 80, N_p = 40 and i_w = 0.9.

Keywords: Kelvin model, Multiple Kelvin model, Crumple Zone, Particle Swarm Optimization

Abstrak

Kajian ini membentangkan pemodelan matematik sistem kemalangan kenderaan menggunakan pendekatan jisim-pegas-peredam untuk mensimulasikan kelakuan kenderaan sebenar semasa hentaman hadapan. Model pelbagai Kelvin dibangunkan untuk mewakili tingkah laku zon renyuk semasa hentaman. Proses pemodelan model pelbagai Kelvin adalah berdasarkan model Kelvin-Voigt tunggal yang berkembang menjadi tujuh darjah kebebasan sistem jisim-spring-peredam yang mewakili komponen didalam zon renyuk kenderaan sebenar. Parameter model yang terdiri daripada *k* dan *c* dioptimumkan menggunakan kaedah Particle Swarm Optimization (PSO) dalam MATLAB-Simulink. Keputusan simulasi dibandingkan dengan data kemalangan sebenar dari segi tindak balas pecutan dan ubah bentuk. Parameter PSO iaitu N_i, N_p, dan i_w divariasikan untuk meningkatkan ketepatan model melalui pengiraan perbezaan yang mana penetapan parameter pada N_i = 80, N_p = 40 dan i_w = 0.9 telah menghasilkan perbezaan yang terendah iaitu 12.15.

Kata kunci: Model Kelvin, Model Lapis Kelvin, Zon Renyuk, Particle Swarm Optimization

1.0 INTRODUCTION

Car crash tests are typically conducted to verify that vehicles meet safe design standards for crashworthiness, which refers to a vehicle's ability to undergo plastic deformation while still providing sufficient survival space for occupants during a crash [1]. In recent times, advancements in computer crash simulation software have made it possible to conduct simulated crash tests prior to conducting full-scale tests. This development has led to a reduction in costs associated with real crash tests. By utilizing computer simulations, manufacturers can assess the crashworthiness of their vehicles and make necessary design improvements as well as optimize safety measures before physical testing, thereby saving resources and expenses.

Pawlus *et al.* [2] proposed a computational model to simulate how a crash looks like without performing any real test. The authors created a Kelvin model that has an element in which a mass connects to a spring and damper in a parallel arrangement. This model can be applied to component impact modelling such as vehicle-to-vehicle (VTV) collision and vehicle-to-barrier collision (VTB). The model is trained to identify a vehicle's maximum crush response such as the time it happens, the changes in acceleration and velocity performance during a collision. The outcomes of the simulation showed that the suggested model can simulate the actual vehicle crash with specific vehicle parameters. Marzbanrad and Pahlavani [3] studied a 5-DOF lumped model for the head-on crash to examine the behaviors of occupant during impact. The vehicle's body, suspension structure, and dampers that absorb collision energy are all represented by the model as lumped masses that modified from a basic mass-spring model. This lumped mass model managed to reduce the impact collision and can represent the car dynamic behavior during frontal crash. Ofochebe *et al.* [4] constructed a 4-DOF lumped mass-spring system to analyze the performance of the vehicle's front design. The engine, cross member, suspension, bumper system and body comprise the developed model. Next, the performance of the developed model was evaluated using trial-and-error techniques based on vehicle crash structural testing to determine the optimal spring and damping coefficients. The outcome of the analysis demonstrated that inner structures receive a huge amount of the total impact energy.

Optimization approaches in crumple zone modeling of vehicle systems are critical for ensuring vehicle safety and structural integrity during collisions. These approaches aim to design crumple zones that absorb kinetic energy efficiently, minimize occupant injury and maintain overall vehicle performance. These approaches leverage advanced computational methods, simulation tools and optimization algorithms to iteratively refine designs and parameters to achieve optimal solutions that meet stringent safety standards and regulatory requirements. Topology optimization focuses on determining the best material distribution within a given design space to achieve specified objectives. In crumple zone modeling, this approach helps in identifying the optimal shape and layout of the crumple zone structure to maximize energy absorption while minimizing weight and material usage [5]. Another optimization method usually used is Shape Optimization where it involves modifying the geometry of the crumple zone structure to enhance its crashworthiness performance [6]. This can include adjusting curvature, thickness, or adding features such as reinforcements or indentations to improve energy absorption and deformation characteristics. Finite Element Analysis (FEA) optimization is also commonly used for simulating the crash behavior of crumple zones [7]. Optimization techniques integrated with FEA enable engineers to iteratively refine the design based on simulation results. This may involve adjusting parameters such as mesh density, boundary conditions, or material models to improve accuracy and convergence of simulations. Crash Simulation-Based (CSB) optimization based on crash simulation models enables engineers to rapidly evaluate numerous design iterations under various impact scenarios [8]. These simulations can be coupled with optimization algorithms to automatically generate and evaluate designs, speeding up the design iteration process and allowing for more thorough exploration of design space. Marta and Jorge [9] introduced a mathematical dynamic modelling (MADYMO) optimization approach for analyzing crashes in a multibody vehicle model. This method aims to fine-tune vehicle parameters in alignment with the experimental results' trendline. By employing particle explorations within the optimization process, the model successfully achieved a close correspondence with the reference results. Carvalho *et al.* [10] have developed a crash analysis method to validate multibody vehicle models using a hybrid optimization method. The algorithms explore every design by reducing the error between the vehicle model's response and a reference response that acquired through experiment testing. It shows that the optimization method is required to get a similar result with the experimental data.

The aim of this study is to develop a mathematical model based on a spring-mass-damper approach to predict a vehicle's behavior after a collision. This model can help reduce the need for expensive experimental work while also providing accurate predictions of vehicle behavior during collisions. In this paper, a single Kelvin model is used as a modelling benchmark to develop seven lumped masses vehicle structure for analyzing the

vehicle crash tests during frontal collisions. A modified Kelvin model with multiple mass-spring-damper arrangements namely Multiple Kelvin Model (MKM) is proposed and derived from the Lagrange equation. The overall mass of the MKM is referred to Malaysia Nasional car namely Perodua Myvi [11] and the initial values of *k* and *c* parameters of the springs and dampers are obtained from Kelvin model [12]. Finally, *k* and *c* values of each mass are optimized with Particle Swarm Optimization (PSO) to obtain the accurate response as Actual Crash Data (ACD) in terms of body acceleration and deformation of the crumple zone [13,14].

PSO is a computational optimization method that draws inspiration from the collective behaviour of social creatures such as groups of fish and colonies of birds [15]. This optimization method is a population-based metaheuristic method that is employed to solve the optimization issues. In PSO, a set of particles navigates through a search space to identify the optimal solution by adjusting the positions based on the best performing particles in the swarm [16]. The technique starts by randomly initializing the locations and speed of the particles within the search region. Every particle maintains the global best-known position denoted as (G_{best}) which is the best solution that any particle in the swarm has discovered, and tracks its personal best-known position, denoted as P_{best} [17,18]. During each iteration, the particles modifying their locations and speed according to the mathematical formulation that mix their social and cognitive impacts to reach the best-known position where it also influences the particle to the global best-known position. As iterations progress, particles explore the search space and through interactions with each other, converge towards the global optimum or near-optimal solutions. The algorithm continues to function until a predetermined threshold is reached, such as completing a specified number of iterations or accomplishing a desired level for the response. In order to obtain the accurate response that closely the Accident Crash Data (ACD), PSO is implemented by varying the optimization parameters including the iteration number (N_i), dimension number (N_d) and inertia weight (i_w). Thus, the contribution of this study is modeling of crumple zone behavior using optimized MKM that can be used to represent the actual collision dynamic response.

The arrangement of this paper is organized as follows. Section one introduces previous vehicle modeling and optimization methods for frontal collision studies. Section two explains the methodology of this study which consists of MKM modeling approach using Lagrange equation, optimization process and followed by validation of the model against the ACD result. Finally, section four presents the conclusion of this study.

2.0 METHODOLOGY

The methodology of this study starts with the introduction of single Kelvin model, MKM modeling approach and PSO method used to determine the optimum parameters for the model in order to achieve the minimum error against the ACD.

2.1 Single Kelvin Crash Model

The single Kelvin model or also known as Kelvin-Voigt model is a mathematical model that is used for vehicle collision analysis to describe behavior of the vehicle crumple zone. The mathematical model consists of a mass linked to a spring and damper in parallel arrangement where the spring represents the elastic behavior while damper represents viscous behavior as shown in Figure 1. When a force is introduced at the frontal crumple zone, the spring and damper will absorb the impact energy of the vehicle collisions. Therefore, this single Kelvin model can be used to simulate the frontal vehicle collision by using appropriate spring and damper parameters to predict the deformation and acceleration response of the frontal collisions.

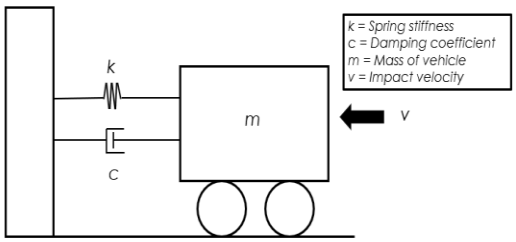


Figure 1 Single Kelvin Model [2]

2.2 Seven Lumped Masses of Multiple Kelvin Model (MKM)

Previous study by Munyazikwiye *et al*. [19] has developed a 2-DOF model, where the double spring-mass-damper model managed to produce a similar response as compared to actual crash result. Therefore, in this study a simple mass Kelvin model is developed into seven lumped masses known as Multiple Kelvin model (MKM). The MKM mathematical is divided into seven layers of the spring and damper components that connected in parallel arrangement as shown in Figure 2.

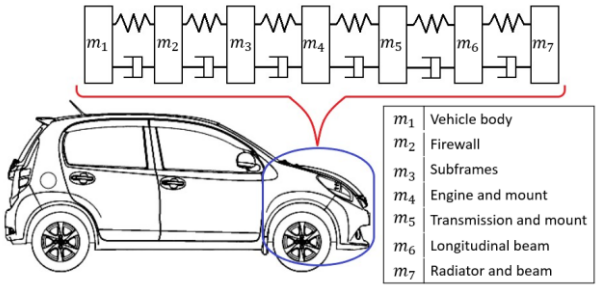


Figure 2 The Seven Lumped Masses of Multiple Kelvin Model

The modelling of MKM is developed using a Lagrange formulation comprising the vehicle body (m_1), firewall (m_2), subframes (m_3), engine and mount (m_4), transmission and mount (m_5), longitudinal beam (m_6) as well as radiator and bumper (m_7) that represents the seven lumped masses. The Langrage formulation in equation (1) is derived to three energy equations namely kinetic (T), dissipative (Q) and potential (K) energies as shows in equation (2) to (4) respectively [20].

$$\frac{d}{dt}\left(\frac{\partial T}{\partial \dot{x}_i}\right) - \left(\frac{\partial T}{\partial x_i}\right) + \left(\frac{\partial Q}{\partial x_i}\right) + \left(\frac{\partial K}{\partial x_i}\right) = F_i \tag{1}$$

$$T = \frac{m_1\dot{x}_1^2}{2} + \frac{m_2\dot{x}_2^2}{2} + \frac{m_3\dot{x}_3^2}{2} + \frac{m_4\dot{x}_4^2}{2} + \frac{m_5\dot{x}_5^2}{2} + \frac{m_6\dot{x}_6^2}{2} + \frac{m_7\dot{x}_7^2}{2} \tag{2}$$

$$Q = \frac{1}{2}c_1(\dot{x}_2 - \dot{x}_1) + \frac{1}{2}c_2(\dot{x}_3 - \dot{x}_2) + \frac{1}{2}c_3(\dot{x}_4 - \dot{x}_3) + \frac{1}{2}c_4(\dot{x}_5 - \dot{x}_4) + \frac{1}{2}c_5(\dot{x}_6 - \dot{x}_5) + \frac{1}{2}c_6(\dot{x}_7 - \dot{x}_6) \tag{3}$$

$$K = \frac{1}{2}k_1(x_2 - x_1)^2 + \frac{1}{2}k_2(x_3 - x_2)^2 + \frac{1}{2}k_3(x_4 - x_3)^2 + \frac{1}{2}k_4(x_5 - x_4)^2 + \frac{1}{2}k_5(x_6 - x_5)^2 + \frac{1}{2}k_6(x_7 - x_6)^2 \tag{4}$$

Based on the seven lumped masses of the Multiple Kelvin model shown in Figure 2, the dissipative and potential energies are differentiated with respect to velocity and displacement for mass 1 as written in equations (5) and (6).

$$\frac{dT}{d\dot{x}_1} = m_1\ddot{x}_1, \frac{dQ}{d\dot{x}_1} = -c_1(\dot{x}_2 - \dot{x}_1) \tag{5}$$

$$\frac{dT}{dx_1} = 0, \frac{dK}{dx_1} = -k_1(x_2 - x_1) \tag{6}$$

The derived equations in (5) and (6) are then used to obtain the acceleration based on Lagrange formulation as written in equation (7).

$$\ddot{x}_1 = \frac{1}{m_1}\left(c_1(\dot{x}_2 - \dot{x}_1) + k_1(x_2 - x_1)\right) \tag{7}$$

Similarly, the acceleration equations for masses 2, 3, 4, 5, 6, and 7 are obtained using the total kinetic, dissipative, and potential energies of the respective mass.

$$\ddot{x}_2 = \frac{1}{m_2}\left(c_2(\dot{x}_3 - \dot{x}_2) - c_1(\dot{x}_2 - \dot{x}_1) + k_2(x_3 - x_2) - k_1(x_2 - x_1)\right) \tag{8}$$

$$\ddot{x}_3 = \frac{1}{m_3}\left(c_3(\dot{x}_4 - \dot{x}_3) - c_2(\dot{x}_3 - \dot{x}_2) + k_3(x_4 - x_3) - k_2(x_3 - x_2)\right) \tag{9}$$

$$\ddot{x}_4 = \frac{1}{m_4}\left(c_4(\dot{x}_5 - \dot{x}_4) - c_3(\dot{x}_4 - \dot{x}_3) + k_4(x_5 - x_4) - k_3(x_4 - x_3)\right) \tag{10}$$

$$\ddot{x}_5 = \frac{1}{m_5}\left(c_5(\dot{x}_6 - \dot{x}_5) - c_4(\dot{x}_5 - \dot{x}_4) + k_5(x_6 - x_5) - k_4(x_5 - x_4)\right) \tag{11}$$

$$\ddot{x}_6 = \frac{1}{m_6}\left(c_6(\dot{x}_7 - \dot{x}_6) - c_5(\dot{x}_6 - \dot{x}_5) + k_6(x_7 - x_6) - k_5(x_6 - x_5)\right) \tag{12}$$

$$\ddot{x}_7 = \frac{1}{m_7}\left(F - c_6(\dot{x}_7 - \dot{x}_6) - k_6(x_7 - x_6)\right) \tag{13}$$

Where:

$m_1, m_2, m_3, m_4, m_5, m_6, m_7$	=	mass for component 1,2, 3,4,5, 6 and 7
$x_1, x_2, x_3, x_4, x_5, x_6, x_7$	=	displacement of mass 1, 2, 3, 4, 5, and 6
$\dot{x}_1, \dot{x}_2, \dot{x}_3, \dot{x}_4, \dot{x}_5, \dot{x}_6, \dot{x}_7$	=	velocity of mass 1, 2, 3, 4, 5, 6, and 7
$\ddot{x}_1, \ddot{x}_2, \ddot{x}_3, \ddot{x}_4, \ddot{x}_5, \ddot{x}_6, \ddot{x}_7$	=	acceleration of mass 1, 2, 3, 4, 5, 6, and 7
$c_1, c_2, c_3, c_4, c_5, c_6$	=	damping coefficient of dampers 1, 2, 3, 4, 5, and 6
$k_1, k_2, k_3, k_4, k_5, k_6$	=	stiffness of springs 1, 2, 3, 4, 5, and 6

2.3 Development and Optimization of Multiple Kelvin Model

This section presents the procedure used to select the initial values of k and c of Multiple Kelvin model. Equations (1) to (13) are utilized to develop the model using MATLAB-Simulink based on the Lagrange equation for seven lumped masses. The model is subjected to collision force input (F_c) and resulting in the output responses of displacement, velocity and acceleration to the respective masses. A 50 kN impact force is applied to m_7 to observe the vehicle response during the crash test. The acceleration and deformation responses of m_1 are

recorded after the collision and the translational motions of each mass are represented using a block diagram representation in MATLAB-Simulink as illustrated in Figure 3.

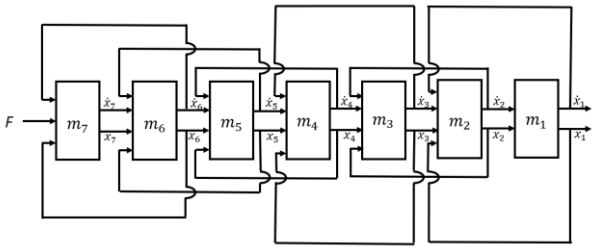


Figure 3 Schematic Diagram of Multiple Kelvin Model

The MKM configuration parameters in the software is set to step-size of 0.001 using solver ODE 14x (extrapolation) and the simulation is run for 0.5 seconds. The overall mass of the model is referred to Myvi car as well as *k* and c parameters for the model are obtained from [11, 12]. These parameters are then set as the initial parameters for the mathematical model at the workspace as presented in Table 1 before the optimization process is conducted. In this study, PSO is utilized to optimize the parameters of the Multiple Kelvin model namely spring constants k_1, k_2, k_3, k_4, k_5, k_6 and damping coefficients c_1, c_2, c_3, c_4, c_5, c_6. In PSO, the initial values of the upper boundary (UB) and lower boundary (LB) in the coding process are established using estimated parameters specific to an actual vehicle.

Table 1 The Initial Parameters of Mass, Spring and Damper

Parameter		Value
Mass of the vehicle, *m* (kg)	m_1	900
	m_2	100
	m_3	50
	m_4	180
	m_5	40
	m_6	45
	m_7	5
Spring constant, *k* (kN/m)	k_1	30
	k_2	600
	k_3	800
	k_4	100
	k_5	500
	k_6	90
Damping coefficient, c (kNs/m)	c_1	70
	c_2	10
	c_3	6
	c_4	10
	c_5	80
	c_6	70

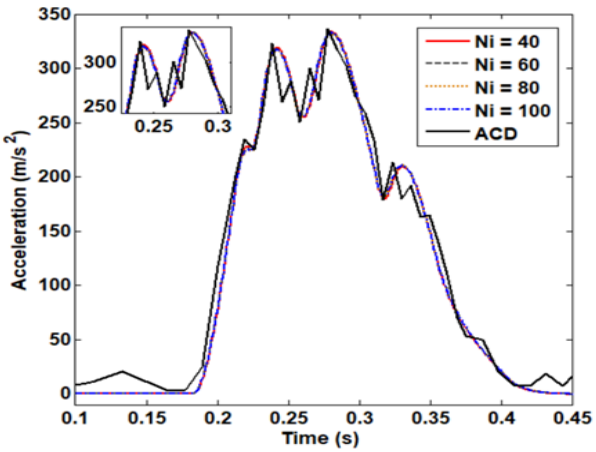
Next, the parameters in PSO are adjusted repeatedly until the simulations' deformation and acceleration responses with the desired result matched. Additionally, PSO is investigated by varying the iteration numbers (N_i), dimension numbers (N_d) and inertia weight (i_w) on the overall optimization results that contribute to improve the modelling results [21-23].

3.0 RESULTS AND DISCUSSION

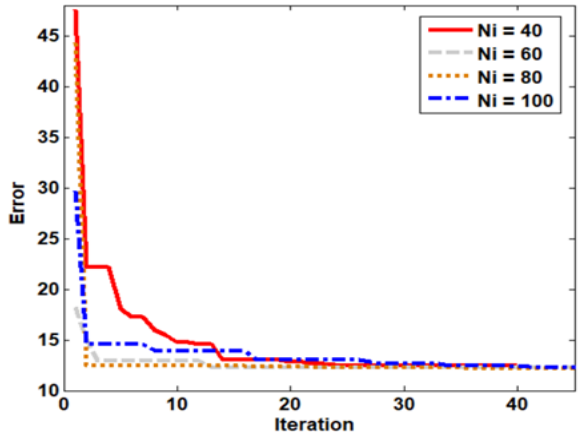
3.1 Impacts of Modifying the Iterations Numbers (N_i)

The iteration numbers, N_i is one of the important parameters in PSO as it determines the duration of the particles explore for the optimal solution [24]. In general, increasing the iteration numbers will produce the least error value because the particles are provided with extra time to navigate the search space and get to the optimal response. In this section, N_i are selected at different cases namely 40, 60, 80 and 100 where then the result is compared with the response of acceleration from the previous ACD. From Figure 4(a), the acceleration response shows that the model closely follows the trend of real crash vehicle data when the iterations number increased.

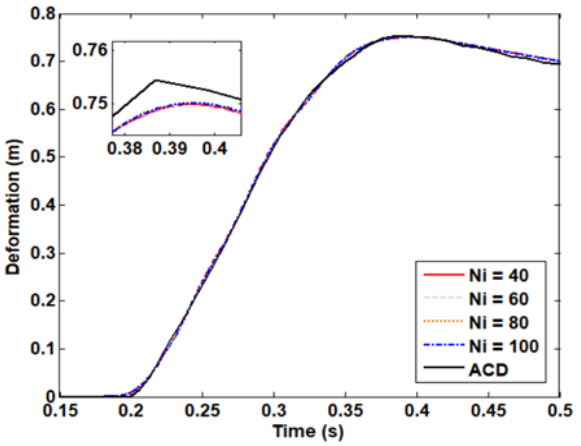
Due to the small distinction for each case of N_i, their values of error are analysed to find the optimal parameter. In Figure 4(b), the minimum value of error (12.15) is already achieved at N_i = 80. Therefore, it is not necessary to iterate until N_i =100 because it will only increase the error value to 12.19. These findings show that the particles have already converged to a local optimum at the number of iterations N_i = 80 as shown in Appendix A. Moreover, the response of deformation that illustrated in Figure 4(c) also produced results that align with the ACD with the increasing number of iterations.



(a) Acceleration Response



(b) Number of Iteration Error



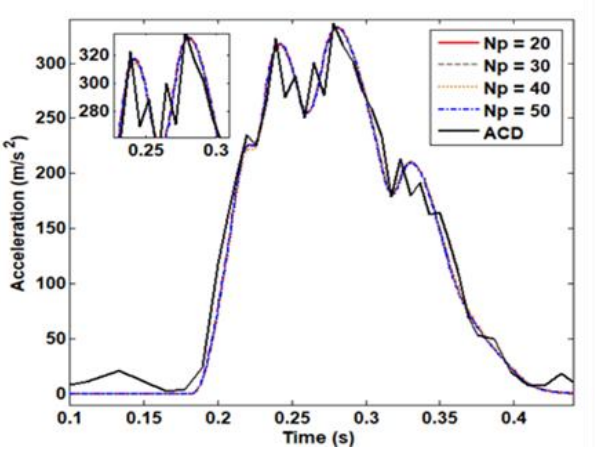
(c) Deformation Response

Figure 4 The Results of Changing Iteration Numbers, N_i.

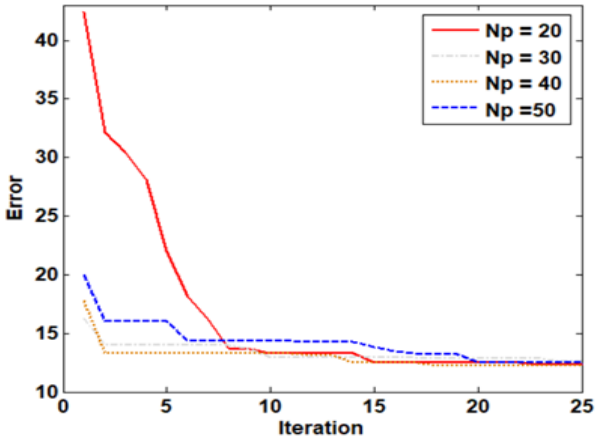
3.2 Impacts of Modifying the Particles Numbers (N_P)

The number of particles, N_p in PSO has a significant impact on performance and behavior of the algorithm. As the number of particles grows, search space becomes larger and more complex due to the exploration of the particles at the entire search space which led to less convergence and increase the difficulty in finding the global optimum [25]. Increasing the number of particles will give a better result. Nevertheless, it may decrease the diversity of the swarm and can lead to premature convergence and suboptimal solutions.

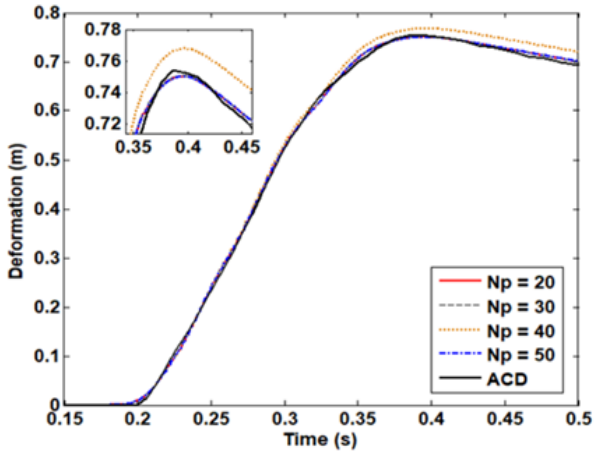
Referring to Figure 5(a), the number of particles N_p is optimized at 4 different samples namely 20, 30, 40 and 50 where the acceleration responses are compared with ACD and show a similar correlation. According to Figure 5(b), there are 3 potential parameters to be chosen as the optimal parameter for their fast rate of convergence at the number of particles 30, 40 and 50. However, considering the lowest value of error based on Appendix B, N_p = 40 is chosen instead for producing the least error value at 12.19. On top of that, the deformation response also closely fits with the ACD as number of particles increased based on Figure 5(c).



(a) Acceleration Response



(b) Particle Numbers Error



(c) Deformation Response

Figure 5 The Results of Changing Particle Numbers, N_p

3.3 Impacts of Modifying Inertia Weight (i_w)

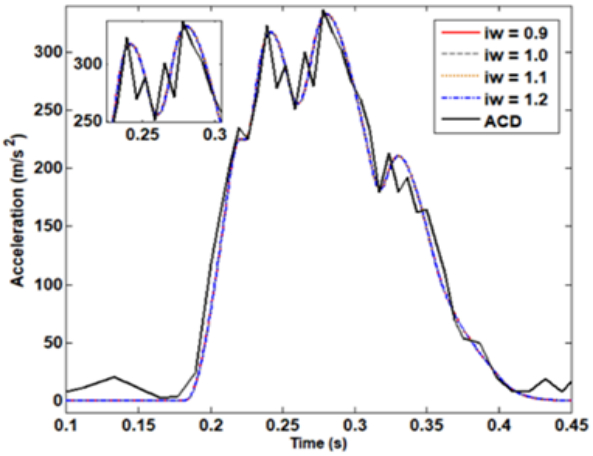
The following assessment analysed the impact of inertia weight on the PSO algorithm by determining the balance between exploitation and exploration. A higher inertia weight emphasizes exploration by

allowing particles to move more extensively throughout the search area in order to speed up the rate to find new and better solutions [26]. In this section, different value of inertia weights namely 0.9, 1.0, 1.1, and 1.2 are selected for the acceleration and deformation response that are compared with the previous experimental data. As depicted in Figure 6(a), the acceleration response closely aligns with the trend in real crash test data with the smallest value of inertia weight.

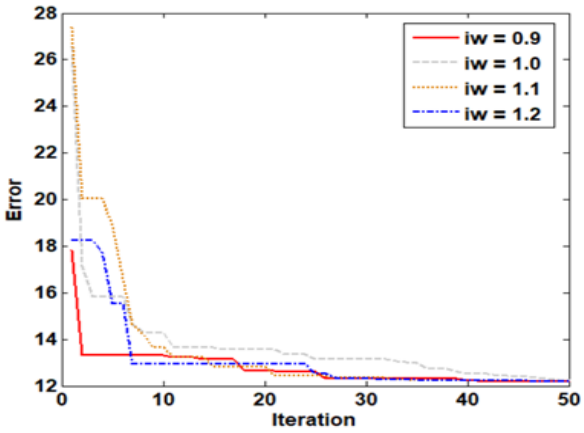
Based on Figure 6(b), the optimum inertia weight rated at i_w = 0.9 closely tracks the desired trend of experimental results with the minimum error value of 12.15 that shown in Appendix C. For other cases of inertia weight at 1.0, 1.1 and 1.2, a minimally increased error values obtained at 12.21, 12.18 and 12.19 respectively. This shows that a smaller value of i_w leads to a better rate of convergence and stability of the PSO algorithm, resulting in less error. Furthermore, the deformation response follows the trend of the ACD as illustrated in Figure 6(c).

3.4 Optimized Simulations Results

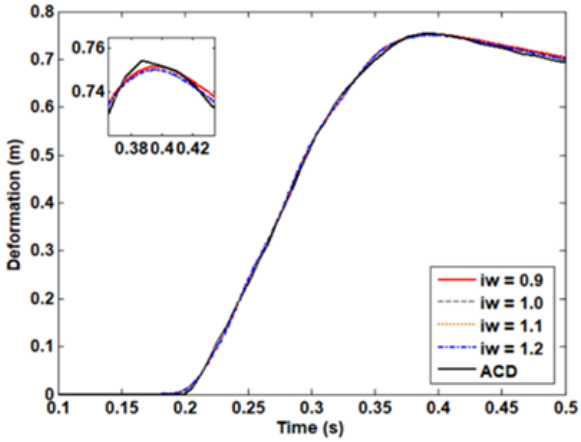
After successfully conducting the optimization process, the seven lumped masses of MKM parameters are replaced the optimized model parameters which are damping coefficient and spring stiffness based on the least error value for each case. Thus, the optimum parameters for this mathematical model that shown in Table 2 demonstrated the best fit for deformation and acceleration responses with the previous study from ACD. This model produces 12.10 of error for the vehicle crash analysis by varying the parameter N_i = 80, N_p = 40 and i_w =0.9 as illustrated in Figure 7.



(a) Acceleration Response



(b) Inertia Weight Error

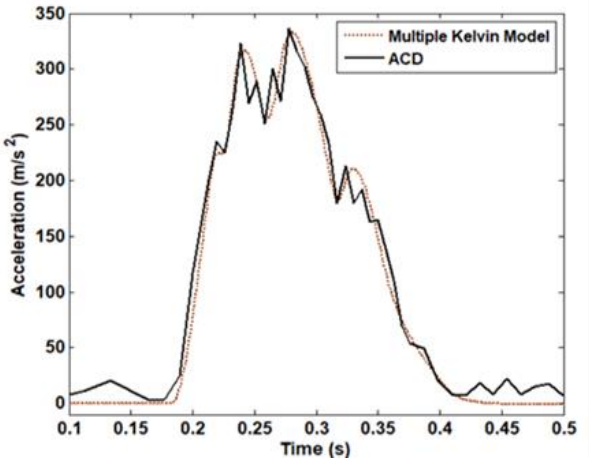


(c) Deformation Response

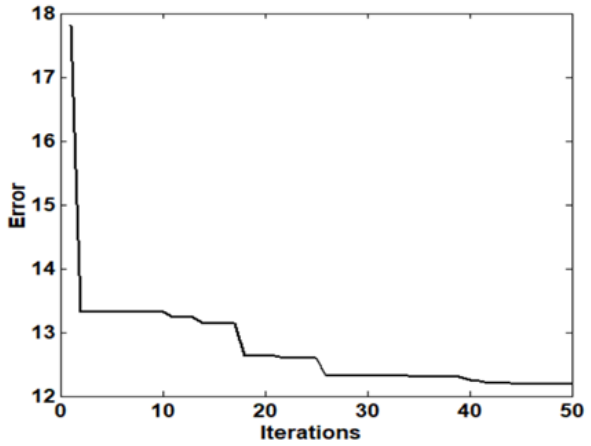
Figure 6 The Results of Changing Inertia Weights, i_w

Table 2 The Optimal k and c values

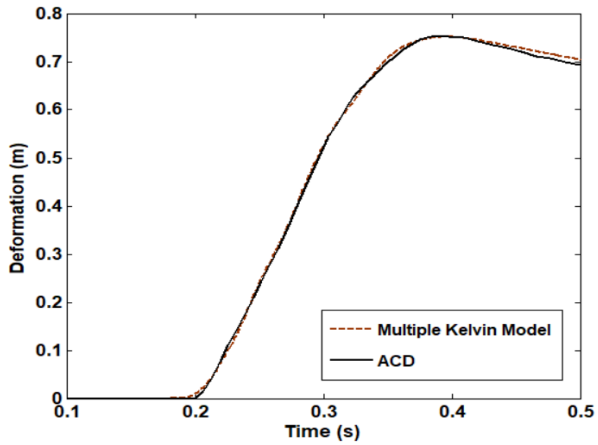
Parameters		Value
Spring constant, *k* (kN/m)	k_1	33.27
	k_2	93.63
	k_3	99.78
	k_4	50.00
	k_5	95.92
	k_6	93.14
Damping coefficient, *c* (kNs/m)	c_1	44.36
	c_2	89.25
	c_3	62.55
	c_4	50.00
	c_5	50.00
	c_6	100.00



(a) Acceleration Response



(b) Error Between MKM response and ACD

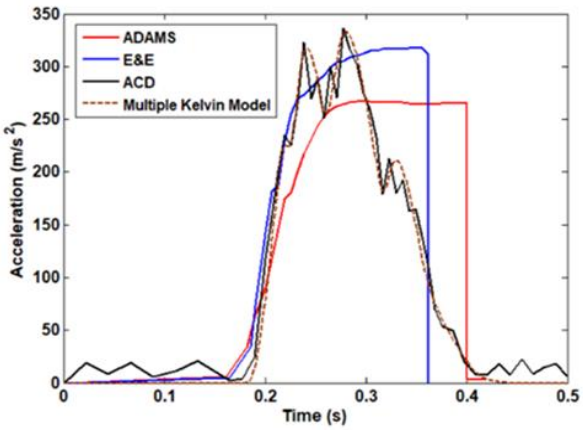


(c) Deformation Response

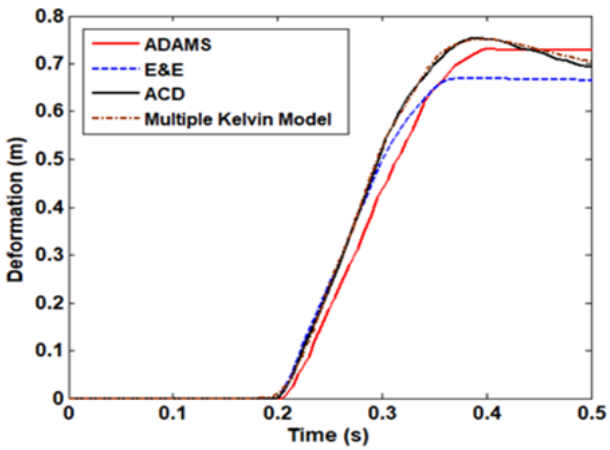
Figure 7 The Optimized Model Parameters for Multiple Kelvin Model

Additionally, in order to demonstrate the accuracy of the MKM, its deformation and acceleration responses are compared with the previous models by [27-29], where (Accident Crash Data) ACD serving as the benchmark for the performance evaluation. The E&E model in [27] and [28] introduced a front-end structure for passenger vehicle model characterized by four non-linear springs with stiffness k_s. These springs delineate the upper (rails) and lower members of the vehicle's frontal structure, with two springs allocated to each. The vehicle's bumper is represented by a lumped mass m_b, capable of longitudinal motion along the x-axis and rotational motion on the non-impacted side of each bumper. Meanwhile, the ADAMS model in [29] presents a passenger vehicle model that integrated with a fully independent suspension system merged with Fiala tyre model. This model incorporates four sets of non-linear spring-damper pairs, which are interconnected with rigid cross members to the vehicle's cabin.

To validate these models, ACD obtained from published source under free-rolling conditions with a frontal impact speed of 16.1 m/s, serves as the benchmark. For the comparison process, it needs to be noted that all the MKM, E&E and ADAMS models are within the same vehicle specification category namely passenger vehicles. Figure 8 shows the validation results of the proposed MKM against the E&E and ADAM models in terms of both acceleration and deformation responses, surpassing the performance of other models. This seems to indicate that developed model can give a precise outcome where the results are similar to the benchmark and produce least error as outlined in Table 3.



(a) Acceleration Response



(b) Deformation Response

Figure 8 Validation Results with E&E and ADAMS Models

Table 3 Percentage Error of Each Model Based on Peak Value

Acceleration Response		
Simulated model	**Acceleration Peak Value(m/s²)**	**Percentage Error (%)**
E&E	317.80	5.52
ADAMS	265.70	21.01
MKM	332.75	1.08
Deformation Response		
Simulated model	**Deformation Peak Value(m/s²)**	**Percentage Error (%)**
E&E	0.67	11.04
ADAMS	0.73	3.18
MKM	0.75	0.37

4.0 CONCLUSION

This paper presented a comprehensive study on vehicle crash model based on mass-spring-damper system to represent the real vehicle body components in order to analyze the collisions impact of a vehicle crumple zone. The Multiple Kelvin model was developed and optimized using PSO algorithm to obtain the similar acceleration response at the vehicle body and bumper deformation against the experimental data. In order to obtain the better modelling responses, three important parameters in PSO namely the iteration numbers (N_i), the particle numbers (N_p) and the inertia weight (i_w) were varied. Overall, the findings of this study managed to identify the optimized PSO parameters and next able to further improve the Multiple Kelvin model responses with minimum error as well as able to follow the experimental data with an acceptable percentage error of peak value which are 1.08 % for acceleration and 0.37 % for deformation response. It is also proven that the Multiple Kelvin model produced lowest percentage of peak value error as compared to the established of crash models namely E&E and ADAMS models.

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Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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Appendix A

The optimized parameters for different number of iterations

Parameters	Number of iterations (Ni)			
	40	60	80	100
c_1	44.40	44.39	44.29	44.34
k_1	32.74	33.13	33.41	33.33
c_2	99.57	84.84	60.30	85.32
k_2	94.16	74.62	100.00	84.00
c_3	99.30	66.66	100.00	65.17
k_3	57.50	88.37	53.02	98.19
c_4	27.46	50.00	50.00	50.00
k_4	50.04	100.00	50.00	64.77
c_5	50.00	50.00	50.00	50.00
k_5	67.28	99.87	51.25	81.45
c_6	100.00	50.56	100.00	100.00
k_6	91.45	50.27	63.68	61.39
Error	12.41	12.22	12.15	12.19

Appendix B

The optimized data for different number of particles

Parameters	Number of particles (Np)			
	20	30	40	50
c_1	44.38	44.17	43.52	44.30
k_1	32.98	33.33	30.77	32.71
c_2	72.33	73.62	63.78	74.72
k_2	100.00	50.46	76.17	50.00
c_3	88.87	88.26	75.95	99.37
k_3	50.00	51.74	76.07	54.51
c_4	42.57	43.16	49.84	36.70
k_4	100.00	50.00	87.98	50.10
c_5	50.00	50.00	50.00	50.00
k_5	54.29	71.99	54.59	80.57
c_6	68.03	59.10	77.09	54.60
k_6	50.00	73.89	96.76	100.00
Error	12.24	12.26	12.19	12.34

Appendix C

The optimized data for different inertia weights

Parameters	Inertia Weight(iw)			
	0.9	1.0	1.1	1.2
c_1	44.46	44.23	43.44	44.36
k_1	31.70	33.44	33.06	32.27
c_2	63.00	95.67	80.01	89.26
k_2	74.54	50.00	100.00	93.63
c_3	92.64	59.47	69.16	62.55
k_3	100.00	71.49	95.98	99.78
c_4	50.00	50.00	50.00	50.00
k_4	99.63	67.74	100.00	50.00
c_5	48.20	50.00	50.00	50.00
k_5	96.59	50.13	100.00	95.92
c_6	87.55	100.00	100.00	100.00
k_6	96.74	66.74	100.00	93.14
Error	12.15	12.21	12.18	12.20