Design Optimization of Vehicle Structures for Crashworthiness Using Equivalent Mechanism Approximations

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A new method for crashworthiness optimization of vehicle structures is presented, where an early design exploration is done by the optimization of an "equivalent" mechanism approximating a vehicle structure. An equivalent mechanism is a network of rigid links with lumped mass connected by prismatic and revolute joints with nonlinear springs approximating aggregated behaviors of structural members. A number of finite element (FE) models of the thin-walled beams with typical cross sections and wall thicknesses are analyzed to build a surrogate model that maps a property of nonlinear spring to the corresponding FE model. Using the surrogate model, an equivalent mechanism is optimized for given design objectives by selecting the properties of the nonlinear springs among the values that can be realized by an FE model. After the optimization, the component FE models corresponding to the optimal spring properties are "assembled" into a FE model of an entire structure, which is further modified for final tuning. Two case studies of a vehicle front substructure are presented, which demonstrate the approach can help obtain a better design with far less computational resources than the direct optimization of a FE model. [DOI: 10.1115/1.1862680]

1 Introduction

Passenger vehicle crashworthiness is one of the essential vehicle attributes. According to the National Highway Traffic Safety Administration (NHTSA), there were over six million vehicle crashes in the United States in the year 2000, which claimed the lives of more than 40,000 people. As part of their responsibility for safety, to meet standard tests and to gain better customer attractiveness, automotive designers strive to improve the crashworthiness of the vehicle structures.

While protection against excessive deformation generally favors a stiff structure, excessive stiffness also reduces crashworthiness due to the increased risk of occupant injury during severe impacts. As such, a crashworthy structure should be stiff in some portions to prevent intrusions into sensitive areas such as the passenger cabin and fuel system, but soft in other portions to absorb the impact energy before reaching to the stiff regions. Optimization of structural crashworthiness is a challenging task due to the highly nonlinear relationship between the allocations of stiffness in substructures and the overall crush behavior of a structure. Full exploration of the design space during optimization is practically hindered by the heavy computational resources required for nonlinear dynamic finite element analyses and the associated numerical noises.

This paper presents a new method for crashworthiness optimization of vehicle structures, where an early design exploration is done by the optimization of an "equivalent" mechanism approximating a vehicle structure. An equivalent mechanism is a network of rigid beams joined by prismatic and revolute joints with special nonlinear springs. These springs are designed to mimic the force-displacement characteristics of thin-walled beams often found in the vehicle body structures, subject to axial crash and transversal bending. Dissimilar to the conventional lumped parameter and surrogate models, the EM model is capable of capturing the geometry of crash modes during structural collapse, providing an essential clue to the designer during conceptual design phases.

A number of finite element (FE) models of the thin-walled beams with typical cross sections and wall thicknesses are analyzed to build a surrogate model that maps a property of nonlinear spring to the corresponding FE model. Using the surrogate model, an equivalent mechanism is optimized for given design objectives by selecting the properties of the nonlinear springs among the values that can be realized by an FE model. After the optimization, the component FE models corresponding to the optimal spring properties are "assembled" into a FE model of an entire structure, which is further modified for final tuning. Two case studies of a vehicle front substructure are presented, which demonstrate the approach can help obtain a better design with far less computational resources than the direct optimization of a FE model.

The following sections provides a review of relevant literature, the description of each step in the proposed EM-based approach including the details of the EM models, and two case studies on vehicle frontal rail substructures. The paper then concludes with the discussion and future work.

2 Related Work

The main difficulties in automated design for crashworthiness are the computational resources required for finite element crash simulations and the associated numerical noises. Therefore, the dominant approach is to use a surrogate model within the optimization loop, which helps to smooth out the numerical noise and reduce the number of expensive crash simulations.

Among many variants of surrogate models, the most popular seems to be the response surface method (RSM) [1–5]. The RMS builds an algebraic function capturing the input-output relationship of a complex function (e.g., finite element crash simulation) based on a finite (hopefully small) number of sample pairs of an input and an output. While the RMS and other surrogate models have been successfully applied to parametric optimization for crashworthiness [6–8], the ranges of design variables are often

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fairly limited in order to build an accurate model with a small number of samples, each of which takes a crash simulation.

For this reason, the success of the surrogate model is severely limited when full vehicles are considered. Mase et al. [9] considered a full vehicle optimization under a low speed test (5 mph), where the structural parts unlikely to deform during crash were removed to reduce the size of the finite element model. Without such model reduction, Yang et al. [10] reported the use of 512 processors running in parallel for 72 h to perform only two local optimization iterations. In addition to this scaling problem, surrogate models can be an over-abstraction in crashworthiness design, which often requires the designer to check the crash mode (a sequence of crushing events) during the optimization cycle.

As a more physically oriented approximation, coarse mesh, lumped parameter, and lattice models [11–15] have been used in crashworthiness optimization. While these models can be computationally inexpensive and also bear some physical roots in underlying crash phenomena, a difficulty arises after the optimized model is obtained: designing a detailed FE model that realizes the behavior of the optimized model is an optimization problem by itself, involving expensive crash simulations.

Some attempts have been made in the application of conventional structural topology optimization methods to crashworthiness design [16–22], while other approaches extend these methods to utilize lumped parameter models and/or reduced order lattice models [11,12]. However, the application has been limited to very simple structures due to a large number of design variables involved in topology optimization. Furthermore, topology optimization in vehicle structure generally provides a concept, not a final design.

In summary, the current difficulties in crashworthiness optimization are the following.

- Crash simulations with FE models are computationally too expensive and noisy.
- Building accurate surrogate models covering a large design space requires many samples of crash simulation results, and is also computationally very expensive.
- To build an approximated model (surrogate or others), a FE model must be constructed first.
- Approximate models are too abstract to simulate *crash modes* (CM), a sequence of axial crushing, twisting, and transversal bending during a crash event, essential to the physical understanding of the designs.
- Realization of a reduced model (coarse mesh, lumped parameter, etc.) as a detailed FE model is not easy.

The approach presented in this paper attempts to overcome these difficulties with an equivalent mechanism (EM) model—a physically oriented abstraction of structures that (1) is inexpensive to simulate, (2) can be constructed without a FE model, (3) is capable of simulating crash modes, and (4) can easily be realized to a FE model. Figure 1 shows the comparison of a FE model, a lumped parameter model, and an EM model of a vehicle front substructure. In lumped models (Fig. 1(*b*)), entire zones of the structure are lumped into equivalent springs and only the main masses (e.g., for the engine and the passenger compartment) are considered. In EM models (Fig. 1(*c*)), each main structural member is represented by a set of rigid masses connected by prismatic and revolute joints. These joints have special nonlinear springs that are tuned to mimic the collapse behavior of the structural members. By performing most optimizations on the EM model rather than the FE model, quick design insight and considerable savings on computational time can be achieved.

3 Crashworthiness Optimization with Equivalent Mechanism Models

3.1 Overview. The proposed method utilizes a database of *preanalyzed* FE models of the thin-walled beams with typical

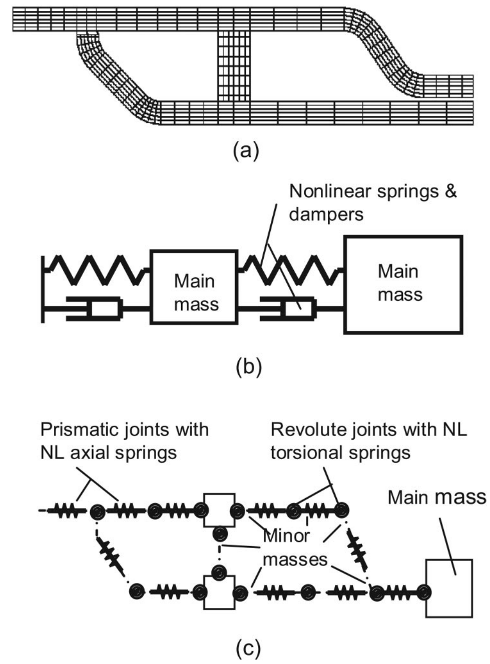


Fig. 1 (*a*) finite element, (*b*) lumped parameter, and (*c*) equivalent mechanism models of a vehicle substructure

cross sections and wall thicknesses. The database is implemented as a surrogate model that maps the cross-sectional dimensions and wall thicknesses of these preanalyzed FE component models to the corresponding property of the nonlinear spring of the joints in an EM. Given such a database, the method consists of the following two steps:

(1) Optimization of EM model with FE component database [Fig. 2(*a*)] by selecting the properties of the nonlinear springs among the values found in the FE component database. After the optimization, the component FE models corresponding to the optimal spring properties are "assembled" into a FE model of an entire structure.
(2) Tuning of assembled FE model (Fig. 2(*b*)) by manually altering its geometry to match its *crush mode* (CM)—a sequence of axial crushing, twisting, and transversal bending during a crash event—with the one of the optimal EM.

Note that the FE component database, constructed off-line prior to step 1, is reusable to solve different problems. Step 2 is an emulation of a process commonly known as "crush

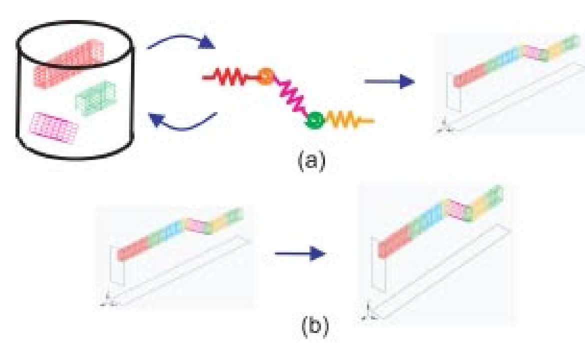
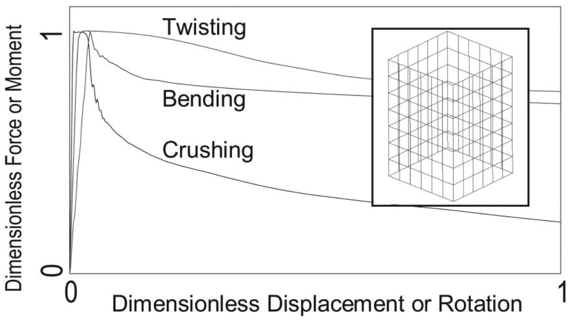
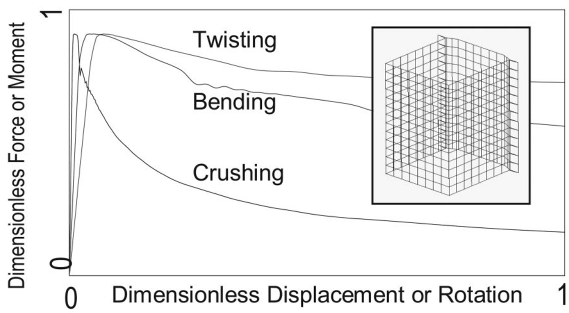


Fig. 2 Crashworthiness optimization with equivalent mechanism (EM) models: (*a*) optimization of EM model with FE component database and (*b*) tuning of the obtained FE model by matching crush mode (CM) with the optimal EM



(a)



(b)

Fig. 3 Typical deformation resistance curves for (*a*) box section and (*b*) hat section

mode matching" among experienced vehicle designers, where the crash performance of a structure is improved by manually modifying the design until its CM matches the one the designers deem as optimal (in this case the CM of the optimal EM). While empirical, the following case studies indicated that the process converges to higher quality designs with significantly fewer number of FE simulations than a numerical optimization of the FE model. The following subsections describe more details of the EM model and the crush mode matching.

3.2 Equivalent Mechanism Models. The idea in the equivalent mechanism (EM) approximations is that the main structural members of the vehicle frame, which are typically modeled using plate or shell elements in finite element (FE) models, can be approximated as sets of rigid masses connected by prismatic and revolute joints that have special nonlinear springs (Fig. 1). The deformation resistance behavior of the springs is chosen to capture the behavior of the structural members. The EM models are then solved using a conventional dynamic simulation algorithm, thereby providing an efficient estimation of the vehicle structure behavior.

To characterize the nonlinear springs, a study of the deformation resistance forces and moments of thin-walled structural members is conducted [23]. The study involved many nonlinear FE simulations of axial crushing, bending, and twisting of thin-walled box and hat sections using the LS-DYNA software [24]. Typical deformation resistance curves for box and hat sections are provided in Fig. 3. It is observed that the overall deformation resistance behavior of thin-walled structural members is similar in pattern and is characterized by the following

- Deformation resistance rises quickly while still in the elastic stage (small deformation).
- Deformation resistance reaches a peak (usually near the onset of plate buckling) and then collapses.
- Deformation resistance approaches a steady value as deformation keeps progressing.

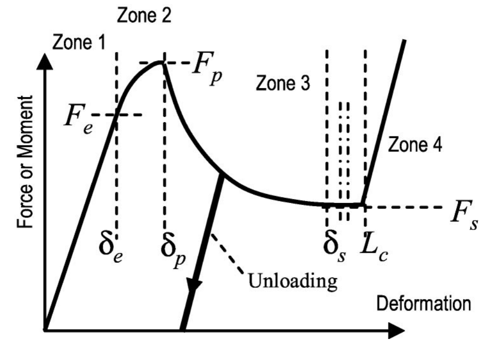


Fig. 4 EM nonlinear spring behavior and main curve parameters

These characteristics that are observed in nonlinear FE simulations are also in agreement with reported experimental observations [6,25] as long as the considered members are short enough so that no multiple folds of the sheet metal are formed, which would then result in a secondary peak force.

Based on these observations, the nonlinear spring equation is made up of four regions (Fig. 4), blended together using a sigmoid function [26]. The total spring force (or moment) F_k is expressed as

$$F_k = sig_1 F_1 + sig_2 F_2 + sig_3 F_3 + sig_4 F_4 \tag{1}$$

where F_1, F_2, F_3, and F_4 are the force values, and sig_1, sig_2, sig_3, and sig_4 are the sigmoid functions for zones 1, 2, 3, and 4, respectively. The sigmoid function has a value equal to 1.0 within its zone, which decreases to 0.5 at the transition point to another zone and goes quickly to zero outside the zone. A sigmoid function provides a smooth differentiable transition between any continuous curves it is used to blend [26].

Zone 1 represents the linear elastic behavior observed for small deformations. Zone 2 represents a quadratic approximation of the peak deformation resistance, and zone 3 represents an exponential collapse in the deformation resistance that approaches a steady state value. Zone 4 represents the high stiffness after crushing the full deformable length. The behavior during unloading is assumed to go parallel to the elastic zone starting from the maximum deformation that had occurred (Fig. 4). This manner of unloading mimics the energy loss due to plastic deformation and removes the need for explicit dampers to be added in the EM model. The equations of the forces in zones 1–4 are given as

$$F_1 = \frac{F_e}{\delta_e}\delta \tag{2}$$

$$F_2 = F_p - \frac{(F_p - F_e)}{(\delta_p - \delta_e)^2}(\delta_p - \delta)^2 \tag{3}$$

$$F_3 = F_s + (F_p - F_s)e^{[-4/(\delta_s - \delta_p)](\delta - \delta_p)} \tag{4}$$

$$F_4 = F_s + \frac{F_e}{\delta_e}(\delta - L_c) \tag{5}$$

where

δ = the instantaneous amount of deformation, referenced to the un-deformed length of the spring
F_e = the maximum elastic force (or moment)
δ_e = the maximum elastic deformation occurring at the transition from zones 1 to 2
F_p = the peak deformation resistance force

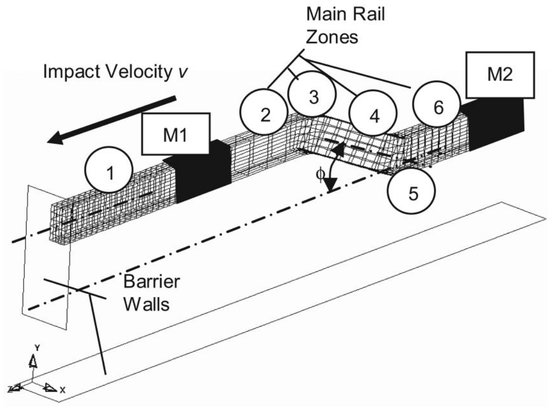


Fig. 5 Finite element model of a vehicle mid rail

δ_p = the deformation at which the peak deformation resistance occurs at the transition from zones 2 to 3
F_s = the steady state resistance force after collapse
δ_s = the deformation at which the resistance falls within 2% of the steady state value
L_c = the maximum deformable length (or angle) occurring at the transition from zones 3 to 4

The maximum deformable length L_c is estimated from the length, geometry, and connectivity of the represented structural member. The estimation of the other tuning parameters (F_e, δ_e, F_p, δ_p, F_s, and δ_s) is done by referring to the databases of *preanalyzed* FE models of the short, thin-walled beams with different sizes of box and hat sections and wall thicknesses. Different sets of the tuning parameters are identified for different directions of deformation of the nonlinear spring, in order to better represent the difference in behavior between tension and compression as well as bending in unsymmetric sections.

The database is implemented as a surrogate model (radial basis neural network [26]), whose inputs are the cross-sectional dimensions and wall thicknesses, and outputs are the corresponding values of nonlinear spring parameters F_e, δ_e, F_p, δ_p, F_s, and δ_s [23]. It is thus possible to quickly estimate the values of the nonlinear spring parameters once the physical dimensions of the structural member are known. While building the FE component database takes upfront computational efforts, it is easy to automate the building process and also the resulting database is reusable and easily updatable with additional data.

3.3 Validation of Equivalent Mechanism Models. In this subsection, the performances of FE models of the vehicle main rail with a uniform box section (Fig. 5) are compared to the corresponding EM models (Fig. 6). For each FE model with a different geometry in Table 1, an EM model is constructed with five prismatic joints PJ1–PJ5, six revolute joints RJ1–RJ6, and lumped masses M_1 and M_2, at the locations corresponding to an engine and a passenger cabin as shown in Fig. 5.

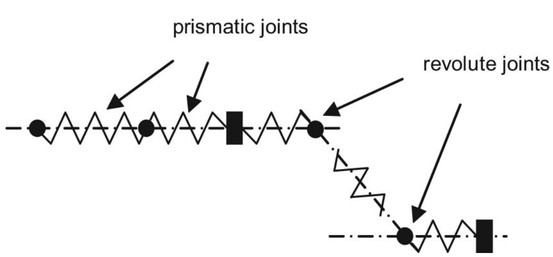


Fig. 6 EM model of the main rail

Table 1 Parameter values of three test main rails

	Test 1	Test 2	Test 3
M_1 [kg]	58.0	58.0	60.0
M_2 [kg]	130.0	130.0	130.0
v_o [m/s]	15.0	15.0	15.0
ϕ [rad]	0.451	0.451	0.451
h [mm]	50.0	50.0	50.0
b [mm]	50.0	50.0	80.0
t_1 [mm]	1.0	1.0	1.6
t_2 [mm]	1.0	1.0	1.6
t_3 [mm]	1.0	2.0	1.6
t_4 [mm]	1.0	2.0	1.6
t_5 [mm]	1.0	2.0	1.6
t_6 [mm]	1.0	2.0	1.6

Table 2 shows the values of peak force/moment and steady force/moment of each joint obtained from the FE component database. In the FE analyses, mild steel (Young's modules 207 GPa, Poisson's ratio 0.3, density 7800 kg/m^3, yield stress 240 MPa) is assumed as being linearly elastic up until yield and perfectly plastic thereafter. Since an EM model tends to behave as stiffer than the corresponding FE model in bending due to its incapability to bend at the locations other than the revolute joints, using torsional spring values 10% to 20% smaller than the values in the database seems to give better performance matches.

Figure 7 shows the comparison of the deformations of the FE and EM models, and Figs. 8 and 9 show the comparison plots of the engine and passenger cabin motion in the horizontal (x) direction. By simply using the nonlinear spring parameters obtained from the preanalyzed FE component database, the EM models can simulate a remarkably similar overall behavior at a low computational cost. Computational cost is lower because dynamic simulation of a mechanism with a few members is computationally far less expensive than a FE model with several thousand elements. It should also be emphasized that the EM model can accurately simulate overall deformation sequence (crush modes) as well as the horizontal displacements, providing a critical feedback to the designer at the early design stages.

Table 2 Nonlinear spring parameters of EM models. PJ and RJ stand for prismatic and revolute joints, respectively

	Test 1	Test 2	Test 3
PJ1 peak [kN]	50.0	50.0	105.0
PJ1 steady [kN]	10.0	10.0	14.0
PJ2 peak [kN]	50.0	50.0	105.0
PJ2 steady [kN]	10.0	10.0	14.0
PJ3 peak [kN]	50.0	50.0	105.0
PJ3 steady [kN]	10.0	10.0	14.0
PJ4 peak [kN]	50.0	100.0	105.0
PJ4 steady [kN]	10.0	15.0	14.0
PJ5 peak [kN]	50.0	100.0	105.0
PJ5 steady [kN][kN]	10.0	15.0	14.0
RJ1 peak [Nm]	800.0	800.0	1500.0
RJ1 steady [Nm]	500.0	500.0	1100.0
RJ2 peak [Nm]	800.0	800.0	1500.0
RJ2 steady [Nm]	500.0	500.0	1100.0
RJ3 peak [Nm]	800.0	800.0	1500.0
RJ3 steady [Nm]	500.0	500.0	1100.0
RJ4 peak [Nm]	800.0	800.0	1500.0
RJ4 steady [Nm]	500.0	500.0	1100.0
RJ5 peak [Nm]	800.0	1000.0	1500.0
RJ5 steady [Nm]	500.0	650.0	1100.0
RJ6 peak [Nm]	800.0	1000.0	1500.0
RJ6 steady [Nm]	500.0	650.0	1100.0

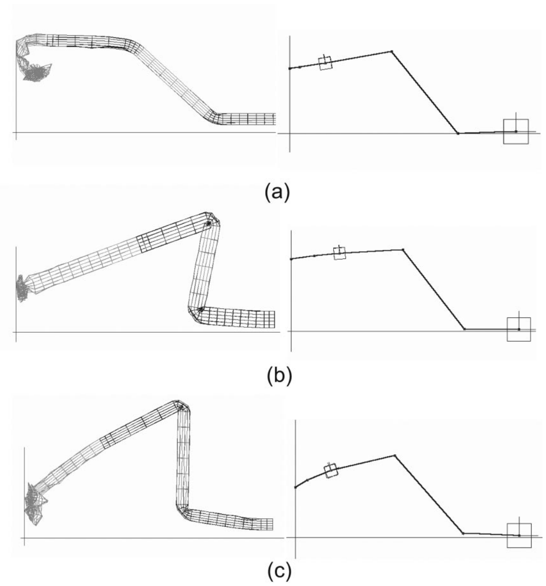


Fig. 7 Deformed shapes by FE models (left) and equivalent mechanism models (right) for (*a*) test 1, (*b*) test 2, and (*c*) test 3

3.4 Optimization of the EM Model. Based on a desired topology and deformation of the structure, the human designer constructs an initial EM model as a linkage mechanism with prismatic and revolute joints. This EM model is then optimized for given design objectives and constraints, by selecting the properties of the nonlinear springs among the values found in the FE component database. A typical design objective is the minimization of weight, subject to constraints on displacement and acceleration. The optimization of an EM model proceeds as follows

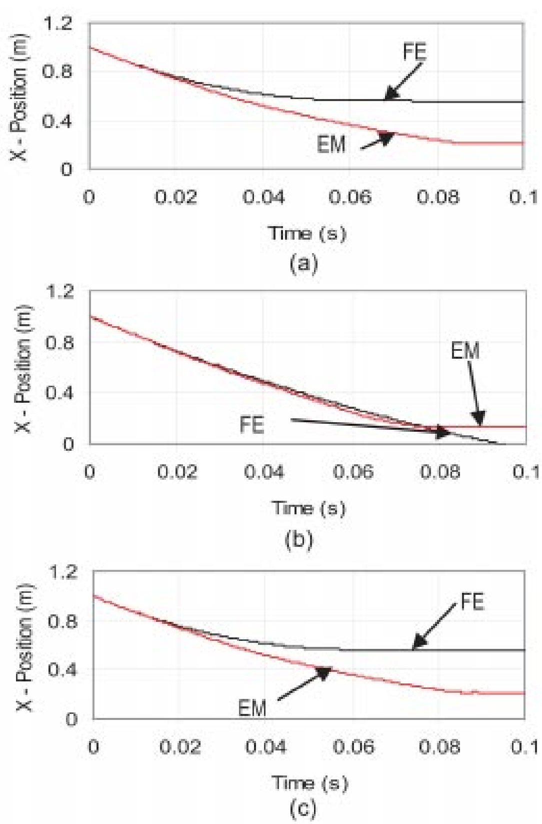


Fig. 8 Horizontal (*x*) location of engine (mass M_1) by FE and EM models for (*a*) test 1, (*b*) test 2, and (*c*) test 3

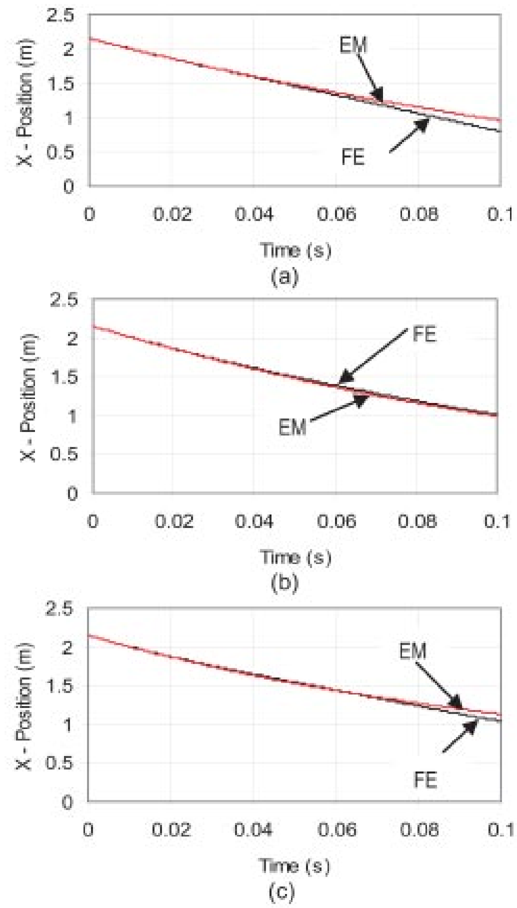


Fig. 9 Horizontal (*x*) location of passenger cabin (mass M_2) by FE and EM models for (*a*) test 1, (*b*) test 2, and (*c*) test 3

(1) *Guess* values of cross-sectional dimensions and wall thicknesses for each segment of the EM model.
(2) *Retrieve* the corresponding values of nonlinear spring parameters from the FE component database.
(3) *Evaluate* the crush performance of the EM model with the obtained nonlinear spring parameters using a dynamic simulation. If the performance is satisfactory, terminate. Otherwise go to 1.

After the termination, the component FE models corresponding to the optimal spring properties are "assembled" into a FE model of an entire structure, which is subject to further tuning as described in the next subsection. Since simulation with an EM model is mush less computationally expensive than with the corresponding FE model, a designer can examine far more design alternatives. While many numerical optimization algorithms could be adopted for the above optimization steps, the following case study utilized a genetic algorithm (GA) [27,28] for an efficient exploration of a wide range of design alternatives. Since the primal purpose of this step is the identification of a good crush mode and a starting FE model for the final tuning, the GA optimization is run for a relatively short time.

3.5 Tuning of the Assembled FE Model. The assembled FE model is manually tuned by directly altering its geometry to match its *crush mode* (CM)—a sequence of axial crushing, twisting, and

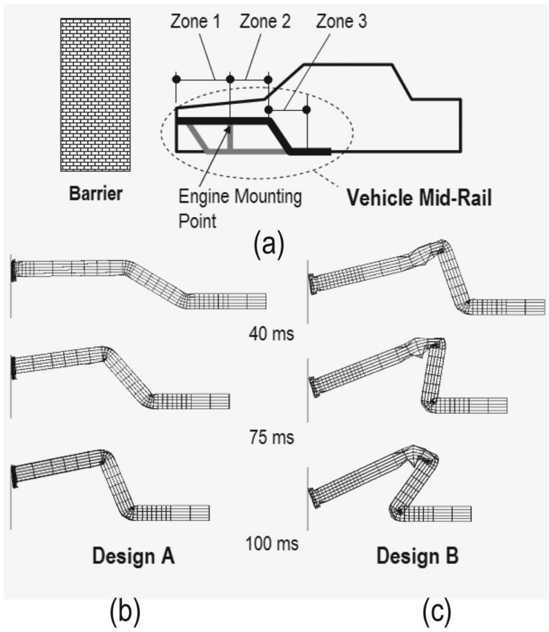


Fig. 10 Vehicle midrail subject to frontal crash: (*a*) schematic layout, (*b*) design A exhibiting one crash mode, and (*c*) design B exhibiting a different crash mode

transversal bending during a crash event—with the one of the optimal EM. This is an emulation of a process commonly called "mode matching" by experienced vehicle designers, where the crash performance of a structure is improved by manually modifying the design until its CM matches the one the designers deem as optimal (in this case the CM of the optimal EM).

Consider, for an instance, the mid-rail of a vehicle subject to frontal crash shown in Fig. 10, where crush modes of two different designs are illustrated as sequences of figures. In design A, zone 1 fully collapses first (during the first 40 ms), then zone 3 partially deforms all while zone 2 does not deform much. In design B, zone 1 only partially collapses, followed by a sever bending in zones 2 and 3. These two designs have totally different energy absorption characteristics, as indicated by the differences in their crush modes. Further, one can guess design A is better, i.e., absorbs more energy with less intrusion at zone 3, than design B due to the occurrence of an axial crushing (which tends to absorb more energy than twisting or transversal bending) immediately after the impact. To match the crash mode of design B to the one of design A, an experienced designer would reduce the stiffness of zone 1 so it would crush easily, and then increase the stiffness of zones 2 and 3 so they would not bend as much.

While such a manual tuning of the design via crush mode matching is empirical and can be potentially computationally expensive, the following case studies indicated that the process converges to higher quality designs with *significantly* fewer number of FE simulations (20–30 folds) than a numerical optimization of the FE model. A detailed study of the crush mode matching using EM models is found in [29].

4 Case Studies

4.1 Case Study 1: Vehicle Mid-Rail Subjected to Frontal Crash. The first case study is the optimization of a vehicle mid-rail subject to frontal crash, used for the validation of EM models (Fig. 5). The design objective is to minimize weight, subject to the constraints on the displacement at the engine compartment and the passenger cabin. There are nine (9) continuous design variables:

- h [mm]=box section height, range [40.0, 150.0]
- b [mm]=box section width, range [40.0, 150.0]
- t_i [mm]; $i=1,\ldots,6$=wall thickness in zones 1–6, range [0.6, 4.6]
- π [deg]=angle of the main rail, range [25.0, 35.0]

The objective function is given as

$$f = \rho\frac{(b+h)}{2}\sum_{i=1}^{6} t_i l_i \tag{6}$$

where ρ is the material density and l_i is the length of the ith zone.

The rail is crashed against a rigid barrier at an initial velocity of 15.0 m/s, and the subsequent crash event is simulated for 100 ms. The constraints are

$$g_1 = \delta_{12} - 0.95 \leqslant 0 \tag{7}$$

$$g_2 = \delta_{36} - 0.1 \leqslant 0 \tag{8}$$

where δ_{12} and δ_{36} are the total deformations in zones 1 and 2 and in zones 3–6, respectively, along the x direction at the end of the simulation. Table 3 shows the comparison of the optimization results as follows:

Table 3 Results of case study 1

	SQP only	Optimal EM	Assembled FE	After SQP	After CM matching
h	134.38	110.93	110.93	134.38	120.00
b	97.95	51.89	51.89	97.95	40.00
t_1	1.96	2.00	2.00	2.12	2.60
t_2	1.22	1.60	1.60	2.07	1.10
t_3	3.12	4.04	4.04	2.34	3.40
t_4	2.37	4.60	4.60	2.07	3.40
t_5	3.17	2.93	2.93	2.31	4.20
t_6	2.37	2.17	2.17	2.07	3.80
ϕ	30.4	28.1	28.1	28.1	28.1
f	14.45	14.36	12.75	13.71	13.13
g_1	−289.1	−144.1	−213.8	−301.3	−147.8
g_2	−5.7	−10.9	+115.4	−1.9	−13.5
No. of FE runs	~200	...	1	~200	6

- **first column:** FE model optimized with sequential quadratic programming (SQP), starting from a feasible but overly strong (i.e., heavy) design.
- **second column:** EM model optimized with GA.
- **third column:** FE model assembled from the optimal EM model in the second column.
- **fourth column:** FE model optimized with SQP, starting from the assembled FE model in the third column.
- **fifth column:** FE model after crush mode matching, starting from the assembled FE model in the third column.

It can be seen that the FE model as assembled from the optimal EM model is ultra-light, but infeasible. While both SQP and crush mode matching starting from this design found the feasible designs, the design by crush mode matching is approximately 5% lighter than the one by SQP, with a significantly smaller number of FE simulations (approximately 200 versus 6).

4.2 Case Study 2: Vehicle Mid- and Lower Rails Subjected to Frontal Crash. The second case study is the optimization of the mid- and lower rails of a vehicle subject to frontal crush (Fig. 11). The design objective and constraints are identical to case study 1 (minimize weight without excessive deformation), as given in Eqs. (6)–(8). There are eleven (11) continuous design variables:

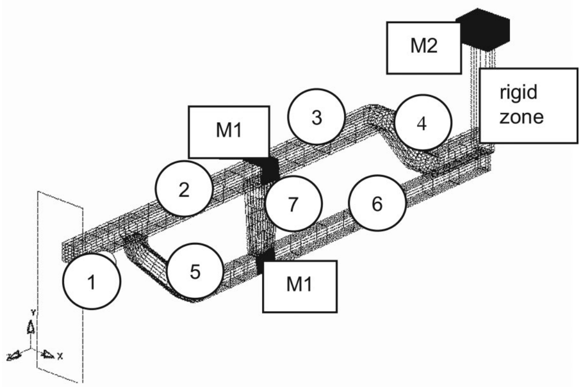


Fig. 11 Finite element model of a vehicle mid and lower rails

- h_1 [mm]=box section height in zones 1–4, range [40.0 150.0]
- b_1 [mm]=box section width in zones 1–4, range [40.0, 150.0]
- h_2 [mm]=box section height in zones 5 and 6, range [40.0, 150.0]
- b_2 [mm]=box section width in zones 5 and 6, range [40.0, 150.0]
- t_i ; $i=1,\ldots,7$=wall thickness in zones 1–7, range [0.6, 4.6]

Table 4 shows the comparison of the optimization results. Each column indicates the results in the same manner as in Table 3. Similar to case study 1, the FE model as assembled from the optimal EM model is ultra-light, but infeasible. Again, both SQP and crush mode matching starting from this design found the feasible designs, but the design by crush mode matching is approximately 18% lighter than the one by SQP, with a significantly smaller number of FE simulations (approximately 150 versus 6).

5 Discussion and Future Work

Figure 12 summarizes of the results of the two case studies. In both case studies, the EM optimization followed by crush mode matching yielded better designs with noticeably smaller numbers of FE runs than the direct optimization of FE models and the EM optimization followed by the optimization of the assembled FE models. The additional computational costs for building the FE component database can be well justified by this savings, considering that the database becomes a reusable resource once it is built.

Table 4 Results of case study 2

	SQP only	Optimal EM	Assembled FE	After SQP	After CM matching
h_1	116.12	50.00	50.00	120.94	70.00
b_1	71.28	110.70	110.70	104.69	90.00
h_2	91.29	50.00	50.00	84.38	90.00
b_1	95.51	43.70	43.70	86.88	60.00
t_1	4.35	1.78	1.78	3.03	2.20
t_2	1.69	0.60	0.60	0.93	1.40
t_3	4.53	1.01	1.01	1.74	1.10
t_4	3.67	1.73	1.73	3.90	3.60
t_5	4.48	4.60	4.60	1.89	3.60
t_6	4.50	4.60	4.60	4.04	4.20
t_7	4.60	1.20	1.20	3.52	1.40
f	35.66	17.65	15.36	27.88	22.81
g_1	−2.64	−44.70	−94.10	−31.89	−11.00
g_2	−0.23	−4.50	+360.80	2.59	−2.40
No. of FE runs	~150	...	1	~150	6

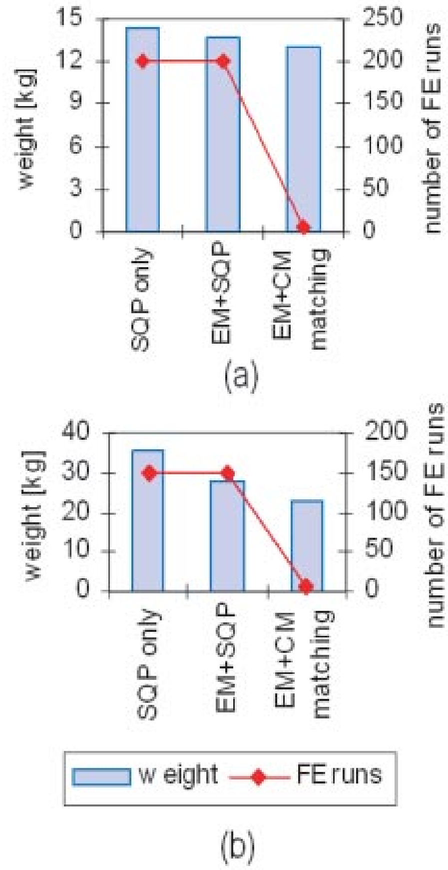


Fig. 12 Summary of the results of case studies

While a manual tuning of the FE model via crush mode matching is rather empirical and can be potentially divergent, the results clearly indicated otherwise. We conjectured this was due to the fact that (1) a crush mode of the optimal EM is also a highly effective, if not optimal, energy absorption strategy for the FE model, and (2) the assembled FE model is already quite close to the design that exhibits the crush mode of the optimal EM. Our previous work on a detailed numerical study of the crush mode matching using EM models [29] seems to confirm this conjecture. Further study is currently underway to better understand this issue. Also, the automation of the crush mode matching and the extension to three-dimensional structures will be addressed in the near future.

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