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IDENTIFICATION OF OPTIMAL MULTIBODY VEHICLE MODELS FOR CRASH ANALYSIS[1]

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This work proposes an optimization methodology for the identification of vehicle multibody models for crashworthiness analysis based on the use of plastic hinge approach. The multiple objective functions for the optimal problem are built as the deviation of the model behavior from the required crash responses. The design variables of the problem are the plastic hinge constitutive relations. The constraints are set not only as technological side constraints but also as some of the deviation functions of selected crash responses that would, otherwise, be used as objective functions. The vehicle model identification methodology is demonstrated by its application to the construction of virtual vehicle models, designated as the generic car model, for which the reference is available as a detailed finite element model.

Key words: multibody vehicle models, optimization, crashworthiness, plastic hinge

1. Introduction

The construction of computational models of vehicles for crashworthiness studies requires the knowledge of most of its construction details being the outcome of the analysis, generally, very sensitive in the quality of the model. When a detailed geometric model of the vehicle is available, the software tools existing today allows for the automatic construction of very detailed finite element models suitable for crash analysis. But, even when such automatic model generation tools exist for the building of multibody models, the necessary information on the vehicle may not be disclosed to the analyst, even if

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a commercial partner of the automaker. This is, generally, the case either because such aspects may be confidential by the vehicle developer, representing technological advances or simply due to legal reasons that are associated to liability and, therefore, they cannot be disclosed even to commercial or development partners. A solution to this problem is the construction of virtual vehicle models that have the same crash response of the detailed models for selected crash scenarios studies, but that are not an exact match of the original vehicles (Sousa *et al.*, 2008). Such a crash response can be measured in terms of accelerations of given points in the vehicle structure or the anthropometric testing devices, energy absorption characteristics of the vehicle subsystems, intrusion measures or by any other measurable characteristic of the vehicle behavior in the crash scenario. Therefore, it is convenient to develop vehicle models that can be used at the conceptual design development stage, for quick analysis and redesign. These models may include, or not, all structural and mechanical features of the real vehicle but they must provide high quality crash responses for the selected scenarios. As an example of application of this virtual model, a developer would be able to tackle the task of devising a subcomponent or protective system for a selected part of the vehicle being assured that the overall behavior of the vehicle model is validated against some reference performance.

The generic multibody vehicle model can also be used in the design of new vehicles from scratch. Since the vehicle model has all structural characteristics of a real vehicle, it can be modified to present an improved crash performance. In the context of a new design, such a reference crash response can be defined as a functional objective. The generic model can be used to devise which parts of its structure should be modified in order to match the targeted crash performance. The next stage on the use of the new vehicle model would be the identification of real structural components or mechanical systems for which the multibody model would be valid, using inverse engineering methodologies.

The most important outcomes on the simulations of crash events that require analysis are the mechanisms of deformation of the structural components to identify intrusions, the amount of energy absorption due to the structural deformation of the vehicle and its subsystems and the acceleration level of vehicle structural components and occupants (Ambrósio and Pereira, 1997). With these crash responses, it is possible to evaluate most of the structural integrity and biomechanical injury indexes (Ambrósio, 2010). Therefore, rather detailed information is required on deformation mechanisms of the structural components and on surface contact forces that are associated to the impact of the substructures of the vehicle. The vehicle model developed must include the possibility for the development of such mechanisms of deformation on the structural components and on the structural regions where deformation energy has to be controlled.

The vehicle multibody model, suitable for crashworthiness application, uses the plastic hinge approach (Nikravesh *et al.*, 1983; Ambrósio, 2001), in which localized areas of the structural component experience the plastic deformations. The first step of the model construction methodology is to identify the potential location of the plastic hinges well in advance of the simulation. Usually, the plastic hinges occur near the joints of the member, weak areas of the element and load application points. A plastic hinge is modeled by a kinematic joint, describing the kinematics of the deformation and a generalized spring element which is used to represent the constitutive characteristics of deformation. Such a constitutive spring element represents the elastic-plastic stiffness of the member and the energy absorption characteristics when plastic deformations occur (Nikravesh *et al.*, 1983). The spring that represents the plastic hinge constitutive relation can be applied with any common type of joint used in multibody modeling, as those depicted in Fig. 1a-d, for one axis bending, two axis bending; torsion and axial loading (Ambrósio, 2001). Then, the structural component is modeled as a collection of rigid bodies connected by plastic hinges, such as in Fig. 1e. Depending on the particular location of the component and the joint, the choice of each joint type is required and relevant for the deformation mechanism.

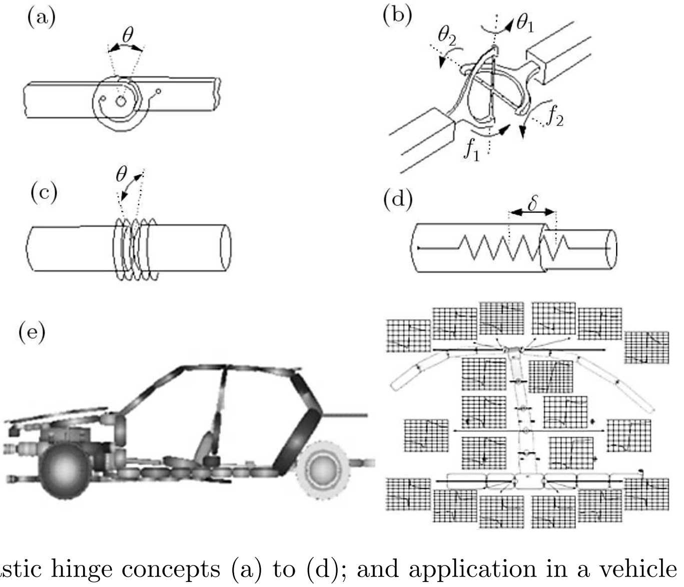

Fig. 1. Plastic hinge concepts (a) to (d); and application in a vehicle model (e)

After devising the topological structure of the multibody system that represents the structural vehicle components that describe the most relevant mechanisms of deformation, it is necessary to identify the constitutive behavior of the plastic hinges and adjust the vehicle response to that of a reference vehicle. This task is actually done by using a trial and error procedure. However, the improvement of the model predictability, or its validation, can be done by using an optimization procedure based on the minimization of deviation between the observed response of the vehicle model and the reference response. The reference data is obtained by simulating crash tests of a validated FE model of the vehicle or by using data directly obtained in an experimental EuroNCAP test. Such a procedure is outlined in Fig. 2, deemed as the methodology used to validation of the MB models. The vehicle model obtained is said to be validated and constitutes a virtual model of the reference vehicle (Carvalho, 2009).

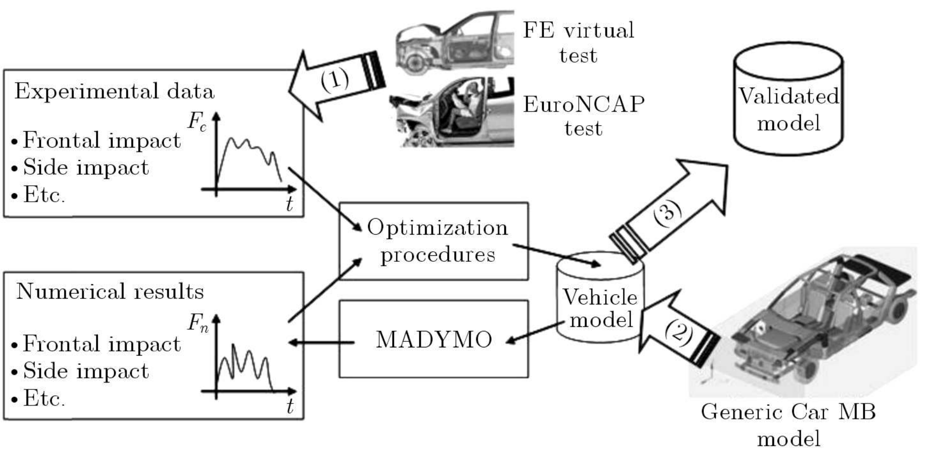

Fig. 2. Scheme of the methodology for validation of MB vehicle models

Different optimization procedures can be used to solve the problem. In this work, the multibody dynamic analysis code is linked with general optimization algorithms included in the MATLAB Optimization Toolbox (MATLAB, 2008). After an evaluation of the most suitable optimization algorithm to handle this type of problems, the choice is the Sequential Quadratic Programming. Note that the use of genetic or swarm optimization (Eberhard *et al.*, 2003; Sedlaczek and Eberhard, 2006; Ambrósio and Eberhard, 2009) has not been investigated. The optimization methodology requires the evaluation of the sensitivities of the problem. The simplest procedure to calculate the sensitivity derivatives is the finite-difference approximation (Adelman and Haftka, 1986). However, small perturbations may result in errors in the derivative due to the limited accuracy of the dynamic response variation, while large perturbations can lead to truncation errors (Greene and Haftka, 1989). Analytical sensitivities, obtained either by direct implementation (Neto *et al.*, 2009) or by using automatic differentiation tools (Bischof *et al.*, 1992) are preferred if access to the source analysis code is possible (Neto *et al.*, 2009). However, when using a commercial code, their use in not an option and, consequently, numerical sensitivities are the only option that can be used, regardless of the drawback of this method related to the additional analysis required (Dias and Pereira, 1997).

The identification of the design variables and the objective function and constraints are of extremely importance for the resolution of the optimization problem. In this work, the objective is to identify a vehicle multibody model that has prescribed crash responses, in which each response is associated to accelerations, velocity and intrusion histories of different pick-up points of the structure and, eventually, with energy absorption ability of several structural regions of the vehicle. The problem can be defined as being multiple objective optimization or by summing the different objectives in a single function (Ambrósio and Eberhard, 2009). In this work, the time interval of the analysis is discretized into time points and the objective functions are evaluated as the sum of the square deviations at such points. Some of the objective functions are used as constraints in the optimal problem instead of using a procedure similar to that described by Gonçalves and Ambrósio (2005) for the optimization of road vehicle suspensions. The choice of the design variables to be used in the identification of the vehicle multibody model is the final step required by the procedure. The potential design variables include the location of the plastic hinges, as in reference (Pereira and Ambrósio, 1997), the shape of the curves that make the plastic hinges constitutive relations, or the scaling of selected plastic hinge relations. Due to the ability to change the model crash behavior demonstrated by the scaling of the plastic hinge constitutive relation (Sousa *et al.*, 2008) and to the complexity of the vehicle multibody models (Ambrósio and Dias, 2005); the design variables used in this work are the scaling factors of selected plastic hinge relations.

The methodology here proposed is suitable to be used with any multibody dynamics approach or code, but it is demonstrated by its application to the identification of the vehicle multibody model of a large family car by using the MADYMO multibody code as solver (MADYMO, 2004). It is foreseen that the use of optimization procedures can lead to more robust models obtained in a shorter development time. The selection of the optimization methodologies used and the strategies used to avoid premature convergence or instability problems in the optimal problem are discussed herein and the procedure envisaged is demonstrated by an application to the identification of a vehicle multibody model of a large family car (GCM3 MB model) based on the reference crash response obtained from a detailed vehicle finite element model (GCM3 FE model).

2. Vehicle multibody models: matching reference models

2.1. Motivation

The generic car model is to be used in crash test scenarios described by the regulations approved in Europe. Of particular relevance are the ECE regulations for frontal and side impacts that must be fulfilled by any new vehicle that seeks approval for release in the EU countries. In the application described here, the GCM3 MB model is tested according to the ECE R33 European Regulation for full frontal rigid barrier impact (1995). The same frontal crash test is conducted with the GCM3 FE model. Due to the easy access to finite element models, these are used here as reference vehicles. This MB model has been validated for frontal impact according to the procedure reported by Puppini *et al.* (2005). However, note that real vehicle data can be used as reference data with the proposed procedure when available. In agreement with the regulation, the impact speed is 48.3 Km/h.

The crash response of the vehicle is measured by accelerations, velocities and intrusions in selected points of the structure, shown in Fig. 3. It should be noticed that the acceleration signals are filtered with CFC 60, the velocities and displacements signals are filtered with CFC 180 in both FE models and MB models.

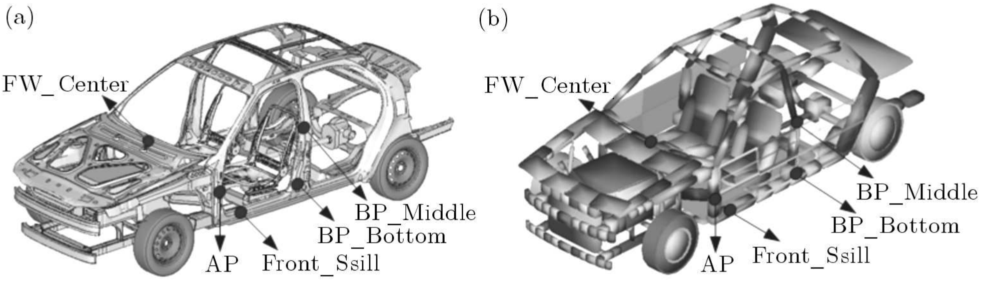

Fig. 3. Accelerometers position in GCM3 model: (a) FE model; (b) MB model

Frames showing the deformations of the simulations results of the initial MB and FE models, for the ECE R33 crash scenario, are presented in Fig. 4.

With the dynamic response and deformations shown, these results suggest that the initial MB model is too stiff when compared with the reference model. In particular, some plastic hinges have constitutive functions, which cause rotation in the longitudinal bars of the frame instead of allowing for the deformation of the crash box. The plastic hinge approach disregards the generalized elastic deformation of the structural members and considers the plastic deformation region as represented by a single point. Two corrective measures can be applied to the MB models, one is to increase the number of plastic hinges in each structural member, the second, which is used in what follows, is to decrease the stiffness of some plastic hinges constitutive functions.

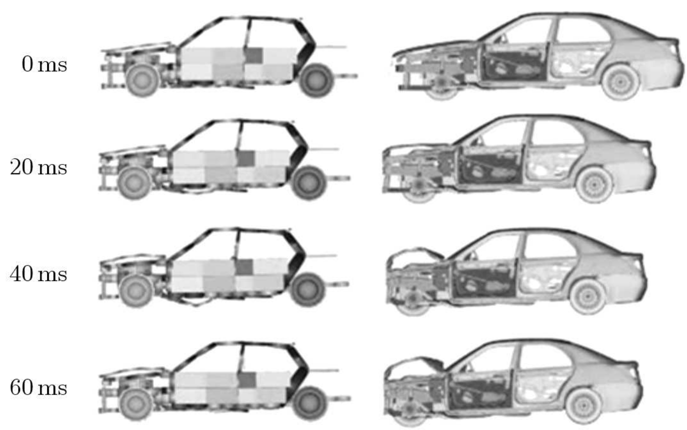

Fig. 4. Sequence of deformation of GCM3 MB and FE models in ECE R33 test

The objective is to correlate the displacement, velocity and acceleration in the five accelerometers displayed in Fig. 3 of the MB model with the FE model, which is the reference. In the first approach considered, the usual trial and error procedure used in industrial applications, the correlation between the MB and FE models is attempted.

The strategy pursued consists in scaling the stiffness of the constitutive functions of all plastic hinges in each subcomponent. Several simulations are performed attempting different scaling factors for the constitutive functions. The results that lead to the best correlation between the MB model response and the FE model are achieved by using different scaling factors for different subsystems. The scaling factors are the following (Sousa *et al.*, 2008):

- Forces on the plastic hinges of the body structure are scaled by $x_1 = 0.1$.
- Forces on the plastic hinges of the frame are scaled by $x_2 = 0.2$.
- Forces on the plastic hinges of the bumper frame are scaled by $x_3 = 0.35$.

- Forces on the plastic hinges of the sub-frame are scaled by $x_4 = 0.45$.
- Forces in the plastic hinges of the bumper sub-frame are scaled by $x_5 = 0.65$.

The location of the kinematic joints with plastic hinges referred is represented for the left side of the car in Fig. 5, being symmetrically located for the right side of the vehicle.

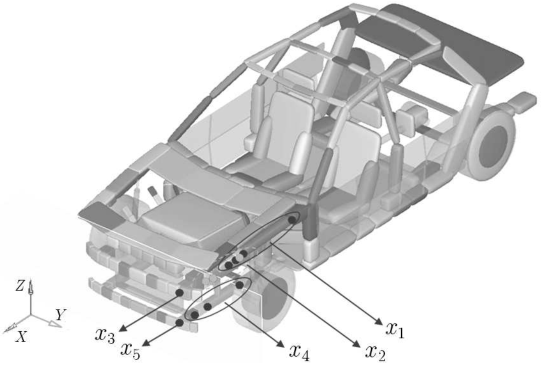

Fig. 5. Joints localization and respective design variables for the GCM3-MB model

All responses measured in terms of accelerations, velocities and displacements of the improved model show a better correlation with the reference response than the original model. This improvement is measured with the error function defined by Eq. (2.1), and in Table 1 the error for the initial and for the improved MB model is listed

$$f_i(x) = \sum_{i=1}^{N} \sqrt{(R_{ref}(i) - R_n(x,i))^2} \tag{2.1}$$

Table 1. Measure of the error for the initial and improved MB model calculated with Eq. (2.1)

Accelerometer i	$f_{i,acc_{(\times 10^4)}}$		$f_{i,vel_{(\times 10^2)}}$		$f_{i,disp}$	
	Initial	Improved	Initial	Improved	Initial	Improved
A-Pillar	1.64	0.72	2.57	0.36	5.45	0.33
FW Center	1.49	1.40	2.47	0.48	5.14	0.21
Front Sill	1.59	0.77	2.56	0.41	5.23	0.54
B-Pillar (middle)	1.52	0.47	2.86	0.50	5.24	0.47
B-Pillar (bottom)	1.50	0.73	2.59	0.39	5.25	0.44

The response of the initial and improved multibody and reference finite element models are presented in Fig. 6 for accelerations, velocities and displacements measured in the sensor located in the bottom B-Pillar. All acceleration, velocity and displacement responses of the improved model show good correlations with the reference responses as depicted in Table 1.

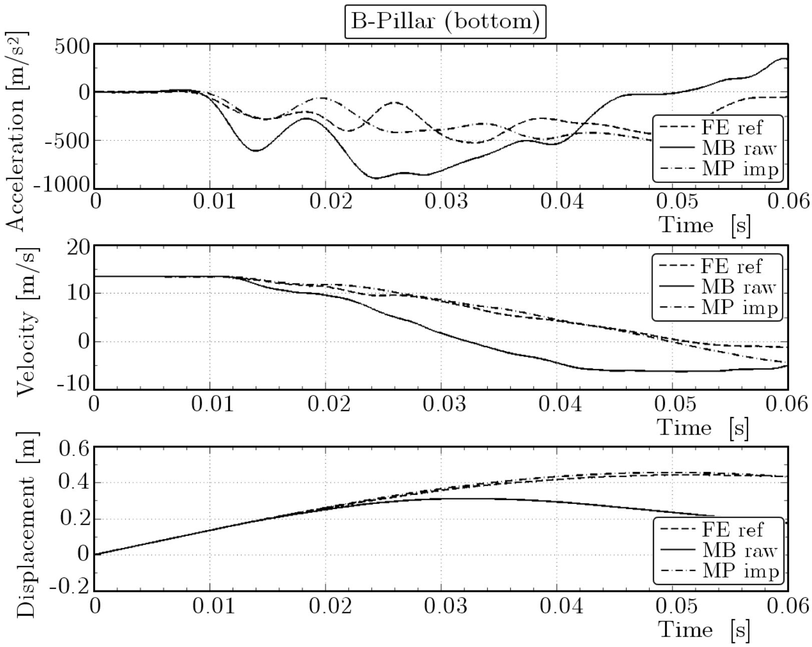

Fig. 6. Dynamic responses for the initial and improved MB model versus the FE model in the front impact test measured in the sensor located in the left BP bottom

3. Identification of the multibody vehicle models

The improvement of the vehicle multibody model is obtained at the cost of the constitutive equations and location of the plastic hinges and the potential mechanisms of deformation, which are modified within a given range of variation. This has been the procedure used by other researchers as well, see Mooi *et al.* (1999), Gielen *et al.* (2000), Zweep *et al.* (2005). The acceptable range of variation of the model data in the validation step is related to the approximations made when defining the discretization of the model and the constitutive equations of the plastic hinges. These ranges are represented as corridors inside which different force-displacement characteristics are accepted. The validation process includes:

1) Collect the dynamic responses of the reference vehicle as intrusions, velocities and accelerations of selected points of the body structure or occupant models.
2) For the MB model, define which parameters are allowed to vary and identify their variation range. The constitutive relation for a particular plastic hinge is shown in Fig. 7.
3) For each of the dynamic responses considered in step 1 calculate the error between the reference response and the actual response of the model at a finite number of instants.

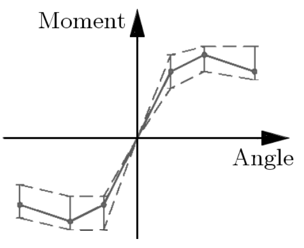

Fig. 7. Constitutive relation for a generic plastic hinge and variation corridor

3.1. Formulation of the optimization problem

Although the trial and error procedure leads to a better correlated MB model, the outlined procedure constitutes in fact an optimization process to identify the MB model that best represents the reference vehicle. Sequential Quadratic Programming (SQP) methods are the recommended optimization methods for this type of problems (Schittkowski, 1985). The `fmincon`, which is the SQP method, implemented in MATLAB Optimization Toolbox (MATLAB, 2008) is used in this work. In this method, the function solves a quadratic programming (QP) subproblem at each iteration. First, an estimate of the Hessian of the Lagrangian is updated using the BFGS (Fletcher and Powell, 1963; Goldfarb, 1970), which is used to generate a QP subproblem that is solved using an active set strategy similar to that described in Gill *et al.* (1981). The solution of this problem is used to form a search direction for a line search procedure. The line search is performed using a merit function similar to that proposed by Gill *et al.* (1981), Han (1977) and Powell (1978a,b). This gradient based optimization algorithm can achieve fast convergence requiring less function evaluations when compared with the genetic algorithms.

However, this algorithm is heavily dependent on the initial design and requires accurate gradient information for the iterative approximation of the design space. In this case, the gradient is obtained with the forward finite difference formula, which requires $n+1$ function evaluations, being n the number of design variables. If the updating of the Hessian matrix is deemed inefficient, $n+1$ extra function evaluations are needed.

The gradient information is severely affected by numerical noise that is normally inherent to the nonlinear simulation of complex numerical models, such as the full vehicle models used in this application. The success of the implementation of the SQP algorithm to solve the present optimization problem is affected not only by the initial design but is also conditioned to the constraints imposed, limiting the feasible region for search and avoiding the lack of precision of the gradient information.

The objective of the model validation is described by a scalar optimization problem defined by

$$\min_x F(x) = \sum_{i=1}^{n} w_i f_{i,acc}(x) = \sum_{i=1}^{5}\sum_{t=1}^{N} \sqrt{\Big(acc^i_{ref}(t) - acc^i_n(x,t)\Big)^2} \cdot 10^{-4} \tag{3.1}$$

subject to: $0.1 \leqslant x_j \leqslant 2$, $j = 1,\dots,5$ and

$$\begin{aligned} f_{i,vel}(x) &= \sum_{t=1}^{n_t} \sqrt{\Big(vel^i_{ref}(t) - vel^i_n(x,t)\Big)^2} \leqslant f^*_{i,vel} \\ \boldsymbol{f}^*_{vel} &= [40, 50, 45, 55, 40] \end{aligned}$$

where the objective function is defined as the sum of the mean square error of the accelerations, represented in Fig. 8, measured in different points of the vehicle, represented in Fig. 5, and sampled for the duration of the crash event. The design variables x_j, $j = 1,\dots,5$, are the same defined for the improvement made by the trial and error process previously described, which are the scale factors for the plastic hinge forces of the constitutive relations for the body structure, frame, bumper, sub-frame and bumper sub-frame hinges.

The error in the intrusion velocity profile of the vehicle is used as a constraint rather than in the objective functions, being the total mean square deviation between the model and the goal velocities given by f^*_{vel}. These values are chosen based in the values obtained for the improved MB model (Table 1), in order to obtain models by an optimization algorithm with better or similar correlations than this one.

The maximum number of iterations allowed and tolerances used for the convergence criteria of the SQP algorithm used is listed in Table 2.

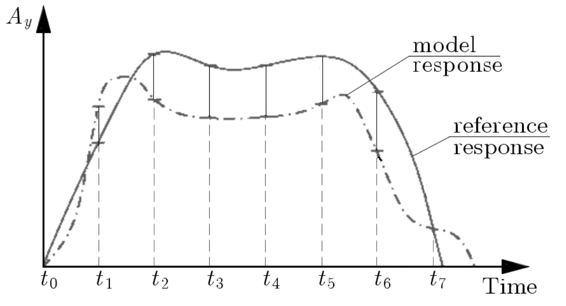

Fig. 8. Model and reference responses for a selected point of the vehicle

Table 2. Stopping criteria used in `fmincon`

Options	Description	Set values
MaxFunEval	Maximum number of function evaluations allowed	default {100*numberOfVariables}
MaxIter	Maximum number of iterations allowed	default {400}
TolFun	Termination tolerance on the function value	0.01
TolCon	Termination tolerance on the constraint violation	default $\{10^{-6}\}$
TolX	Termination tolerance on x	0.1

3.2. Results of the application

Starting from the raw model, $x_{0j} = 1$, $j = 1, \ldots, 5$, the optimum design is achieved for the 14th iteration, with an optimum objective function value of 3.72 and with the design variable $x_{opt} = [0.1, 0.22771, 0.32932, 0.11232, 0.18595]$. The iterations history is represented in Fig. 9 and listed in Table 3.

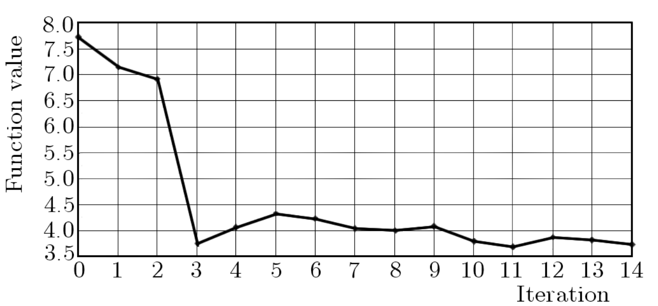

Fig. 9. History of the value of the objective function

Table 3. History of SQP iterations of the vehicle model optimization

	x_1	x_2	x_3	x_4	x_5	$f(x)$
0	1.00000	1.00000	1.00000	1.00000	1.00000	7.73
1	0.80555	0.68728	1.90560	1.81640	0.14442	7.15
2	2.00000	0.10000	0.10000	1.68070	0.35768	6.92
3	0.15989	0.10000	0.64067	0.79964	0.10000	3.74
4	0.29380	0.10000	0.10000	0.10000	0.10000	4.07
5	0.33259	0.23192	0.10000	0.10000	0.25839	4.33
6	0.30370	0.19192	0.29173	0.10000	0.13880	4.23
7	0.30372	0.19184	0.29340	0.10000	0.13888	4.04
8	0.30371	0.19182	0.29340	0.10001	0.13888	3.99
9	0.33662	0.19616	0.29471	0.11049	0.13672	4.07
10	0.14522	0.22951	0.32976	0.10000	0.18649	3.79
11	0.10000	0.23157	0.32915	0.11539	0.19119	3.70
12	0.10000	0.22536	0.32988	0.12794	0.19057	3.86
13	0.10000	0.22741	0.32877	0.11518	0.18403	3.82
14	0.10000	0.22771	0.32932	0.11232	0.18595	3.72

Table 4 shows the objective function, i.e., the error measure between the reference and MB crash response for the initial and optimal MB models. The results show an improvement of all dynamic responses as shown in Fig. 10.

Table 4. Measure of the criterion for the optimized MB model

Accelerometer i	$f_{i,acc_{(\times 10^4)}}$		$f_{i,vel_{(\times 10^2)}}$		$f_{i,disp}$	
	Initial	Optim.	Initial	Optim.	Initial	Optim.
A-Pillar	1.64	0.66	2.57	0.35	5.45	0.28
FW Center	1.49	1.24	2.47	0.44	5.14	0.17
Front Sill	1.59	0.70	2.56	0.40	5.23	0.47
B-Pillar (middle)	1.52	0.44	2.86	0.54	5.24	0.54
B-Pillar (bottom)	1.50	0.68	2.59	0.38	5.25	0.38

Though the results show an improvement of the correlations, with gradient based algorithms, no guarantee exists that the global minimum is reached. With a grid of initial designs, it is possible to look for the lowest objective function value, but always without being able to ensure that it is the global minimum. The design obtained by the trial and error procedure, which shows also a satisfactory correlation with the reference response, is a good candidate for the initial design in this methodology.

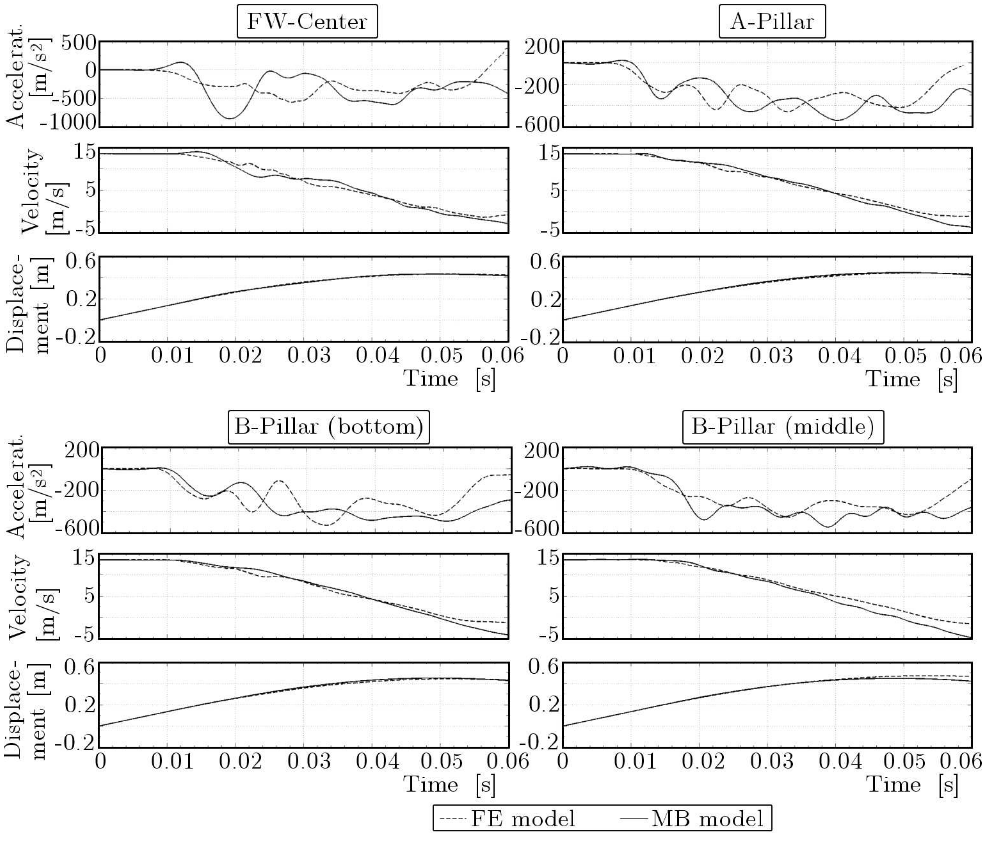

Fig. 10. Dynamic response for the optimized MB model versus the FE model in the front impact test

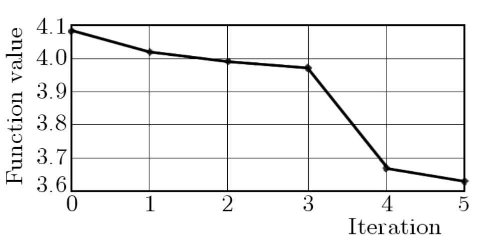

Fig. 11. History of the value of the objective function

Starting from the improved model, the optimum design is achieved for the 5th iteration, with an optimal function value of 3.63. The iterations history is listed in Table 5 and represented in Fig. 11. The optimum design is defined by the plastic hinge scale factors shown in the vector $\boldsymbol{x}_{opt} = [0.13199, 0.13782, 0.22923, 0.59378, 0.42484]$.

Table 5. History of SQP iterations

	x_1	x_2	x_3	x_4	x_5	$f(x)$
0	1.00000	0.20000	0.35000	0.45000	0.65000	4.08
1	0.10587	0.20163	0.37578	0.47422	0.67109	4.02
2	0.10604	0.20124	0.37470	0.48018	0.67289	3.99
3	0.10648	0.20084	0.37363	0.48372	0.67354	3.97
4	0.14023	0.15042	0.23682	0.57870	0.38677	3.67
5	0.13199	0.13782	0.22923	0.59378	0.42484	3.63

Table 6 shows the error measure for the optimized and improved by trial and error MB models. The results show an improvement in almost all dynamic responses considered, as shown in Fig. 12.

Table 6. Measure of the criterion for the optimized MB model

Accelerometer i	$f_{i,acc}{}_{(\times 10^4)}$		$f_{i,vel}{}_{(\times 10^2)}$		$f_{i,disp}$	
	Initial	Optim.	Initial	Optim.	Initial	Optim.
A-Pillar	0.72	0.59	0.36	0.20	0.33	0.07
FW Center	1.40	1.38	0.48	0.49	0.21	0.21
Front Sill	0.77	0.58	0.41	0.24	0.54	0.21
B-Pillar (middle)	0.47	0.65	0.50	0.52	0.47	0.94
B-Pillar (bottom)	0.73	0.59	0.39	0.22	0.44	0.14

The optimization problem is formulated as the minimization of an objective function, described by the sum of the mean square error of the vehicle accelerations measured in different points of the structure and sampled for the duration of the crash event. The error of the intrusion velocity profile of the vehicle is used as a non-linear constraint. Table 7 contains a summary of the results obtained in the application with the two initial designs: the first concerns the raw model and the second is the model improved by trial and error.

Starting from the raw MB model, the SQP algorithm took 14 iterations to obtain an optimal design, being the minima basically reached in three iterations. However, there appear numerical problems with the gradients and, consequently, with the Hessian matrix update, which lead to oscillations of the iterative optimization procedure about the local minima until convergence is obtained without constraint violations. This optimization problem takes about 5 CPU hours to reach the minimum which improves all crash responses, when comparing with the initial design.

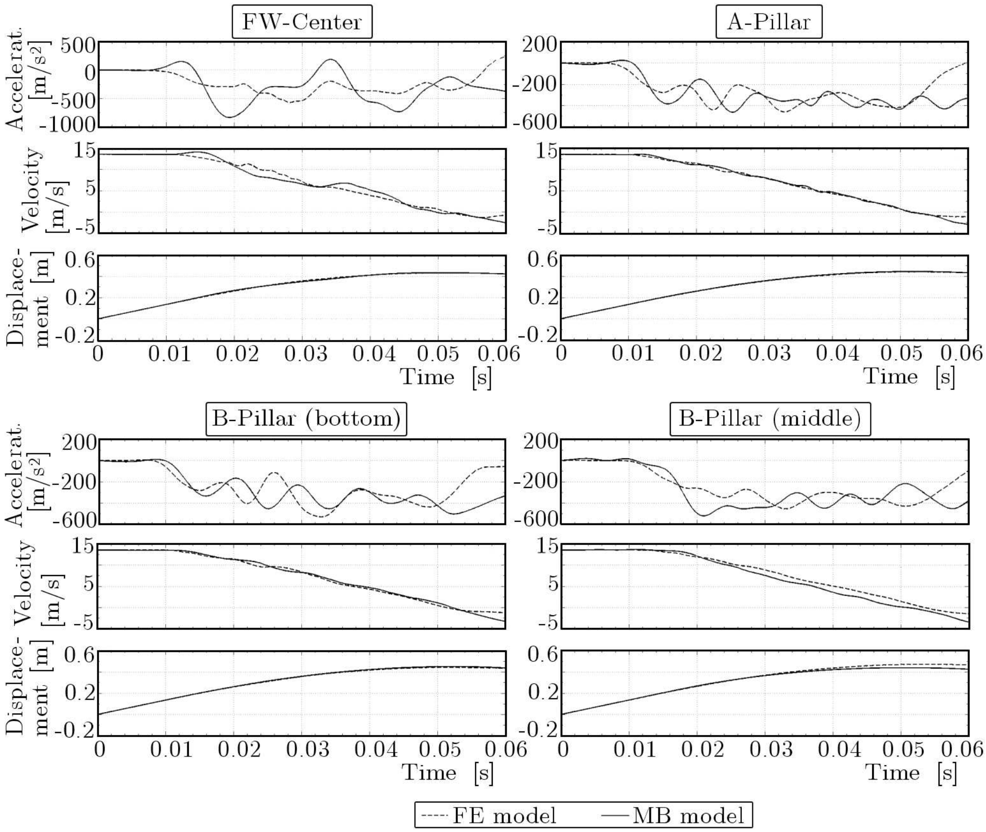

Fig. 12. Dynamic response for the optimized MB model versus the FE model in the front impact test

Based on the knowledge of a good design, the second optimization run used the improved MB model by trial and error. Because this design is close to the minimum, in this optimization the convergence was reached in five iterations only. Furthermore, the velocity non-linear constraints are the upper limits for this initial design. This design leads to the lowest value of the objective function. All crash responses of the optimal problem are better correlated with the reference response than the model improved by trial and error, with the exception of the acceleration, velocity and displacement in the middle of B-Pillar. The crash responses of the validated and reference vehicles are shown in Fig. 12 showing that a good predictability of the model has been achieved.

Notice that the deformations of the optimized and FE model are very similar for the frontal crash test, as shown in Fig. 13, which confirms the results obtained through the crash response.

Table 7. Measures of the criteria for the optimized MB model

		Initial model	Opt. 1 model	Improved model	Opt. 2 model
Iterations		–	14	–	5
$f(x)$		7.73	3.72	4.08	3.63
x	$x(1)$	1	0.10000	0.1	0.13199
	$x(2)$	1	0.22771	0.2	0.13782
	$x(3)$	1	0.32932	0.35	0.22923
	$x(4)$	1	0.11232	0.45	0.59378
	$x(5)$	1	0.18595	0.65	0.42484
$f_{i,acc_{(\times 10^4)}}$	AP	1.64	0.66	0.72	0.59
	FW_Ctr	1.49	1.24	1.40	1.38
	F_Sill	1.59	0.70	0.77	0.58
	BP_mid	1.52	0.44	0.47	0.65
	BP_bot	1.50	0.68	0.73	0.59
$f_{i,vel_{(\times 10^2)}}$	AP	2.57	0.35	0.36	0.20
	FW_Ctr	2.47	0.44	0.48	0.49
	F_Sill	2.56	0.40	0.41	0.24
	BP_mid	2.86	0.54	0.50	0.52
	BP_bot	2.59	0.38	0.39	0.22
$f_{i,disp}$	AP	5.45	0.28	0.33	0.07
	FW_Ctr	5.14	0.17	0.21	0.21
	F_Sill	5.23	0.47	0.54	0.21
	BP_mid	5.24	0.54	0.47	0.94
	BP_bot	5.25	0.38	0.44	0.14

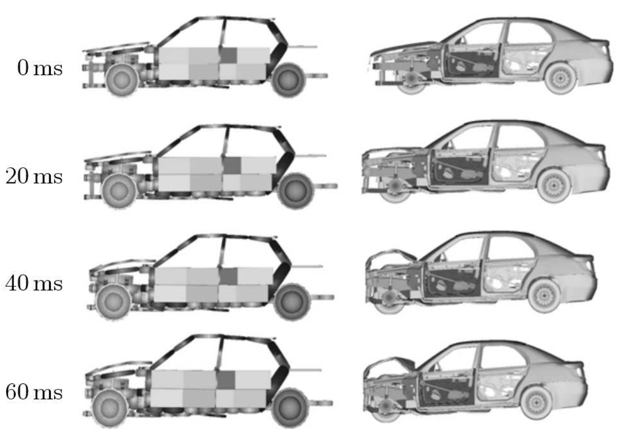

Fig. 13. Sequence of deformation of the improved MB model versus the FE model in the front impact test

4. Conclusions

The methodology proposed here is demonstrated by its application to the identification of the vehicle multibody model of a large family car for which the reference crash behavior is available. It is foreseen that the use of optimization procedures can lead to more robust models than those commonly obtained by trial and error approaches. The identification of the design variables and the objective function and constraints are of extreme importance for the resolution of the optimization problem.

The multiple objectives, represented by the mean square errors of the difference between the multibody model and reference crash responses, measured in several points of the vehicle, are reduced to a single objective function obtained as a weighted sum of the individual error accelerations. The main difficulty of this approach is the choice of the initial designs and of the values for the weights w_i, which has influence on the optimization results. In this application, the optimization results for two initial designs, the raw model and the improved model, being assumed that all acceleration criteria in the objective function are equally important, are compared. The function that evaluates the velocity error, defined by the vector $\boldsymbol{f}^*_{vel}$ is introduced in the optimal problem as constraints and kept below specified values. This approach allows reducing the design feasible region, leading to a better convergence. The disadvantage of this approach is that the solutions to the optimal problem depend on the values of the non-linear constraint vector. Overall, a large improvement of the vehicle multibody model is observed as the acceleration errors have been greatly minimized and the velocity and intrusion errors basically eliminated. In an industrial application, the methodology proposed in this work is suitable to lead to better vehicle designs, satisfying a large number of the requirements imposed by regulations restrictions, project goals, thus shortening the development time and reducing the inherent costs. The designs obtained with the optimization methodology presented in this framework are suitable to serve as the basis for a detailed design of the vehicle with improved crashworthiness characteristics.

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Identyfikacja optymalnych modeli wielobryłowych pojazdów samochodowych dla celów analizy testów zderzeniowych

Streszczenie

Praca prezentuje metodologię optymalizacji identyfikacji wielobryłowych modeli pojazdów samochodowych pod kątem ich przydatności do symulacyjnych badań zderzeniowych opartych na koncepcji plastycznych połączeń międzybryłowych. Funkcje celu w omawianym zagadnieniu polioptymalizacji sformułowano na podstawie odchyleń odpowiedzi dynamicznych w stosunku do wymaganych przebiegów obserwowanych podczas testów zderzeniowych. Dobieranymi funkcjami modelu są równania konstytutywne plastycznych połączeń międzybryłowych. Przyjęto, że więzy wynikają nie tylko ze względów technologicznych, ale także są funkcjami odchyleń w rejestrowanych odpowiedziach dynamicznych układu przy zderzeniu, które w przeciwnym razie same byłyby użyte jako funkcje celu. Metodologia identyfikacji została zaprezentowana na przykładzie jej aplikacji do budowy wirtualnych modeli samochodów, zwanych modelami generycznymi, dla których układami odniesienia są modele szczegółowo przeanalizowane za pomocą Metody Elementów Skończonych.

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