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CRASHWORTHINESS OPTIMIZATION OF AN AUTOMOTIVE FRONT BUMPER

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Abstract. In automotive industry, structural optimization for crashworthiness criteria is of special importance in the early design stage. Crashing performance of structures under dynamic impact can be investigated using finite element codes. By coupling FE simulation tools with nonlinear mathematical programming procedure and statistical techniques, it is possible to optimize the design with reduced number of analytical evaluations. Optimization methods using statistical techniques are widely used in engineering applications to utilize estimated models which are often referred to metamodels. Meta-modeling optimization is performed through construction of objective functions, design of experiment (DOE) and modeling. Various types of meta-modeling techniques were used for crashworthiness optimization.
In this paper the comparative study of Kriging and Radial Basis Function Network (RBFN) was performed in order to improve the crashworthiness effects of a front bumper subsystem subjected to impact. The objective function is the maximization of the specif energy absorption (SEA) and the design variables are geometrical parameters subjected to some design constraints. The optimized solution was achieved interfacing LS-DYNA codes with LS-OPT and using a domain reduction strategy.

1 INTRODUCTION

During the past decades passive safety is treated as an attribute with increased importance in automotive industry. Bumper systems play an important role in the energy management of vehicles during accidents. Structural optimization for crashworthiness criteria is therefore of special importance in the early design stage. Crashing performance of structures under dynamic impact can be investigated using finite element codes. By coupling FE simulation tools with nonlinear mathematical programming procedure and statistical techniques, it is possible to optimize the design with reduced number of analytical evaluations [1]. Optimization methods using statistical techniques are widely used in engineering applications to utilize estimated models which are often referred to metamodels. Meta-modeling optimization is performed through construction of objective functions, design of experiment

(DOE) and modeling. Various types of meta-modeling techniques were used for crashworthiness optimization [2-6].

In this paper the comparative study of Kriging and Radial Basis Function Network (RBFN) was performed in order to improve the crashworthiness effects of a front bumper subsystem subjected to impact. The objective function is the maximization of the specific energy absorption (SEA) and the design variables are geometrical parameters subjected to some design constraints. The optimized solution was achieved interfacing LS-DYNA codes with LS-OPT and using a domain reduction strategy. At first some numerical simulations were conducted in order to find the best solution in terms of section profile and curvature of the beam. Only after, the chosen configuration was implemented in the iterative optimization process. From the obtained results, it is evident how both metamodels are able to improve the crushing performance of the basic system up to 21% in SEA value, giving comparable solutions.

2 METAMODELS

In crashworthiness optimization, direct coupling method may be inefficient and sometimes impossible since iterative non-linear FEA during optimization usually require enormous computational efforts and take the high risk of premature simulation failure prior to a proper convergence. As a result, surrogate models or metamodels are more often used as an alternative for formulating the design criteria in terms of an explicit function of design variables in advance of optimization, which has proven an effective and sometimes a unique approach [7-9].

In this study comparative analysis of Radial Basis Function Network and Kriging metamodels were carried out using Space Filling design of experiment; approximated functions were created using seven simulation points and fifteen iterations with sequential domain reduction strategy [10]. Below a brief description of such models is presented.

2.1 Radial Basis Function Network model

A radial basis function neural network has a distinct 3-layer topology. The input layer is linear. The hidden layer consists of non-linear radial units, each responding to only a local region of input space. The output layer performs a biased weighted sum of these units and creates an approximation of the input-output mapping over the entire space. The most common basis function is Hardy's formula [11], given as:

$$g_h(x_1,...,x_k) = \sqrt{1+\frac{r^2}{\sigma_h^2}} \tag{1}$$

The activation of the h-th radial basis function is determined by the Euclidean distance $r = \sqrt{\sum_{k=1}^{K}(x_k - W_{hk})^2}$ between the input vector $x = (x_1,...,x_K)$ and RBF center $W_h = (W_{h1},...,W_{hk})$ in K-dimensional space. Parameter σ_h controls the smoothness properties of the RBF unit. For a given input vector x the output of RBF network with K inputs and a hidden layer with H basis function units is given by:

$$Y(x,W) = W_0 + \sum_{h=1}^{H} W_h f(\rho_h) \quad (2)$$

where W_0 includes the polynomial terms, W_h is the weighted coefficient for the term of the h-th variable, ρ_h is the Euclidean distance and f is the radial basis function.

2.2 Kriging model

In recent years, the Kriging method has found wider application as a spatial prediction method in engineering design. The basic postulate of this formulation, given by Simpson [12], is:

$$y(x) = f(x) + Z(x) \quad (3)$$

where y(x) is the unknown function of interest, f(x) models the global trend of the function of interest and Z(x) models the correlation between the points by a stochastic process whose mean is zero and variance is σ^2. Z(x) provides local deviations and the covariance between different points is modelled as:

$$Cov(Z(x_i), Z(x_j)) = \sigma^2 \bar{R}([R(x_i, x_j)]) \quad (4)$$

With L the number of sampling points, $\bar{R}$ is the LxL correlation matrix defined by Gaussian correlation function $R(x_i,x_j)$ as follows:

$$R(x_i, x_j) = \prod_{k=1}^{n} \exp\left[-\theta_k (x_i^k - x_j^k)^2\right] \quad (5)$$

where n is the number of variables, θ_k is the unknown correlation parameter to determine and x_i^k is the k-th component of sample point x_i.

3 BUMPER SUBSYSTEM OPTIMIZATION STUDY

To apply the methodologies described in the section above, an optimization study on an automotive CAD bumper subsystem for a race car is performed.

3.1 Bumper subsystem

The bumper geometry has been taken from an automotive design practice with a mesh density that is both acceptable for the predictions of interest and also feasible in terms of computational effort. The geometry consists of a cross-section made of a one chamber that represents the transverse bumper and two longitudinal crash boxes (Figure 1). Given the symmetry of the system respect to y-axis, only half structure has been modelled constraining the right degrees of freedom in the reflection plane. Moreover the right end of the longitudinal crash box is rigidly fixed to the frame. The bumper has been realized with an high strength steel.

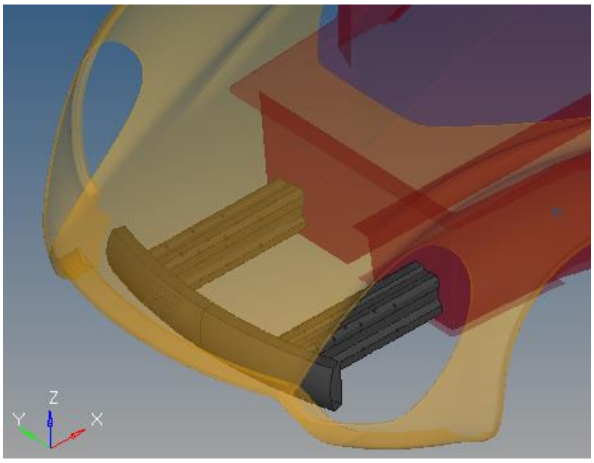

Figure 1: CAD assembly of the bumper subsystem

As regards the initial condition, instead of IIHS low velocity impact [13], Allianz crash repair test and the impact to pole test [14], a full width front impact against a flat rigid barrier at a speed of 56 km/h has been used. In such case, in fact, the bumper subsystem, designed for a race car, must be able to absorb all the kinetic energy during a frontal collision.

3.2 Optimization definition

The optimization process has been conducted through three different approaches. Firstly, an optimized cross section of the transverse beam has been identified. Secondly, a change into the beam curvature has been analyzed and finally, the best configuration has been used for an iterative model in LS-OPT (Figure 2) using two different metamodels, such as Radial Basis Function Network and Kriging.

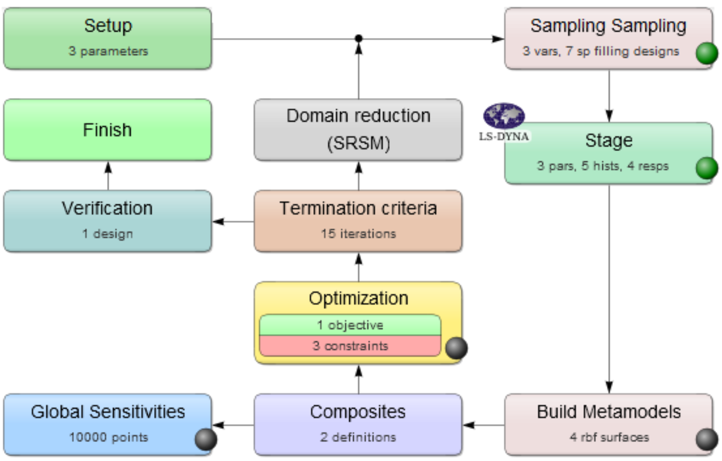

Figure 2: Iterative model in LS-OPT

3.2.1 Section profile optimization

At first, profile optimization was conducted changing the cross section of the transverse beam. In particular, the work of Belingardi *et al.* [13] showed that the best cross section profile for a bumper, able to guarantee a progressive deformation, was that with a series of internal hinges. Therefore, such configuration was compared with the basic CAD model (Figure 3) in order to identify the best configuration to adopt in terms of section.

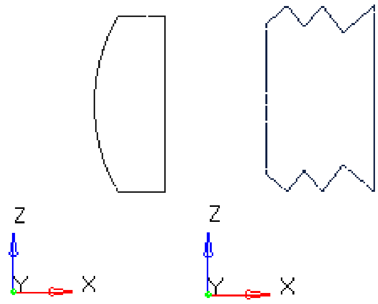

Figure 3: Profile geometries taken into account

The diagram below (Figure 4) shows the force trends vs. displacement for both configurations. Moreover, in table 1 the respective values of maximum and average deceleration, maximum stroke and specific energy absorption (SEA) were compared.

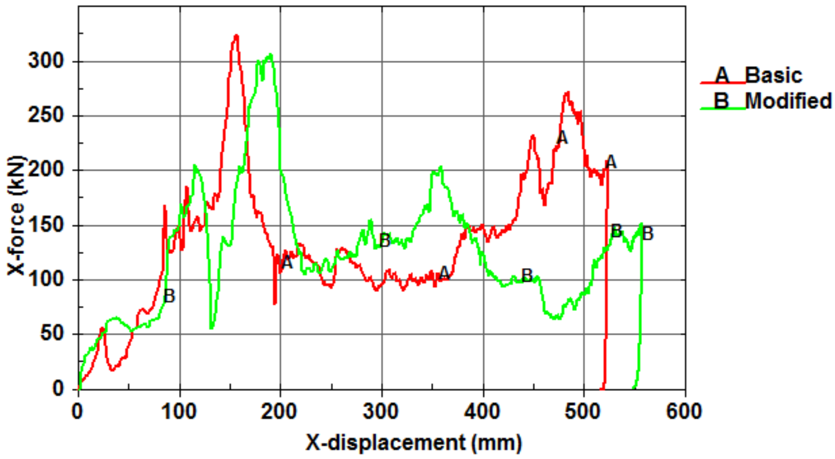

Figure 4: Force vs. Displacement for both section profiles

Table 1: Crash characteristics for both configurations

Configuration	Max deceleration (g)	Average deceleration (g)	Max stroke (mm)	SEA (kJ/kg)
Basic	55.34	25.27	523.28	8.95
Modified	52.36	19.60	557.60	7.77

As mentioned in previous research [13], the modified profile, with a series of hinges, is able to reduce the peak value and guarantee a more stable and progressive deformation, even if it tends to weigh more and absorbs less energy than the basic profile. Therefore the basic configuration seems to be very attractive from the point of view of future optimization, that will tend to maximize the specific energy absorption.

3.2.2 Beam curvature optimization

Another analyzed change was the beam curvature. In particular the modified profile was tested into three different cases: straight, medium radius and maximum one (Figure 5).

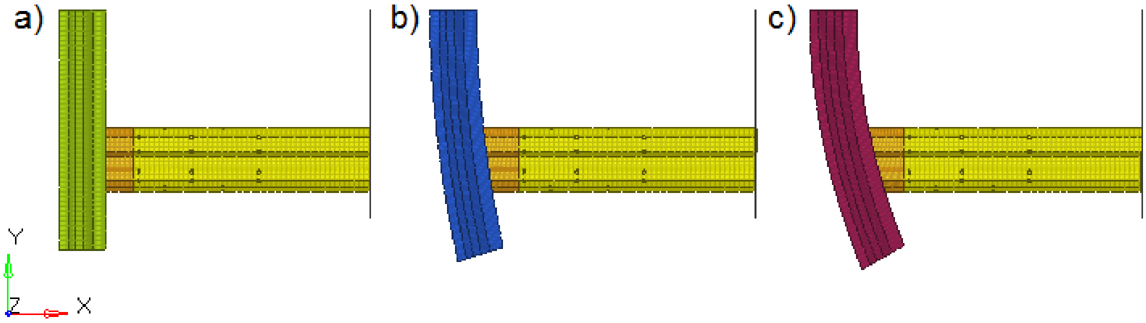

Figure 5: Beam curvature cases: a) straight, b) medium radius, c) maximum radius

The diagram below (Figure 6) shows the force trends vs. displacement for the three configurations. Moreover, in table 2 the respective values of maximum and average deceleration, maximum stroke and SEA were compared.

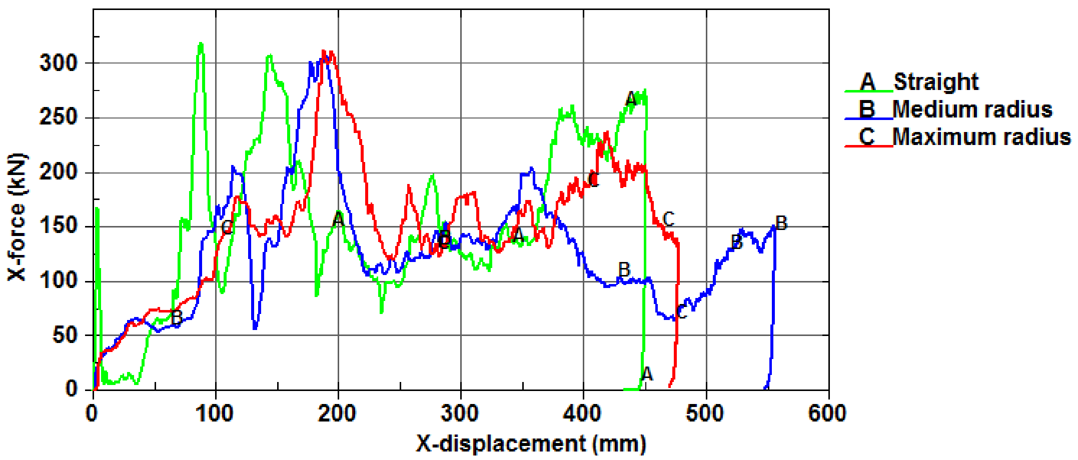

Figure 6: Force vs. Displacement for the three beam curvatures

Table 2: Crash characteristics for the three configurations

Configuration	Max deceleration (g)	Average deceleration (g)	Max stroke (mm)	SEA (kJ/kg)
Straight	54.69	27.85	452.21	7.88
Medium radius	52.36	19.60	557.60	7.77
Maximum radius	53.34	23.84	478.60	7.68

Even if the straight configuration reaches a value of SEA greater than the other, the best behavior seems to be reached by the medium radius. From Figure 6 it is in fact evident how, unlike other cases, the first configuration generates an initial peak load also in the first time instants due to the contact with a larger area since the beginning of impact. Moreover in such case the absorbed energy from the only bumper is very low respect to the presence of a certain level of curvature and the beam tends to slip into high during crush causing a not progressive deformation with a series of peaks (Figure 7). In terms of deformation trend, deceleration values and specific energy absorption the medium radius has the best data and therefore, for the next optimization procedure, the bumper with the basic section profile and a medium curvature will be considered.

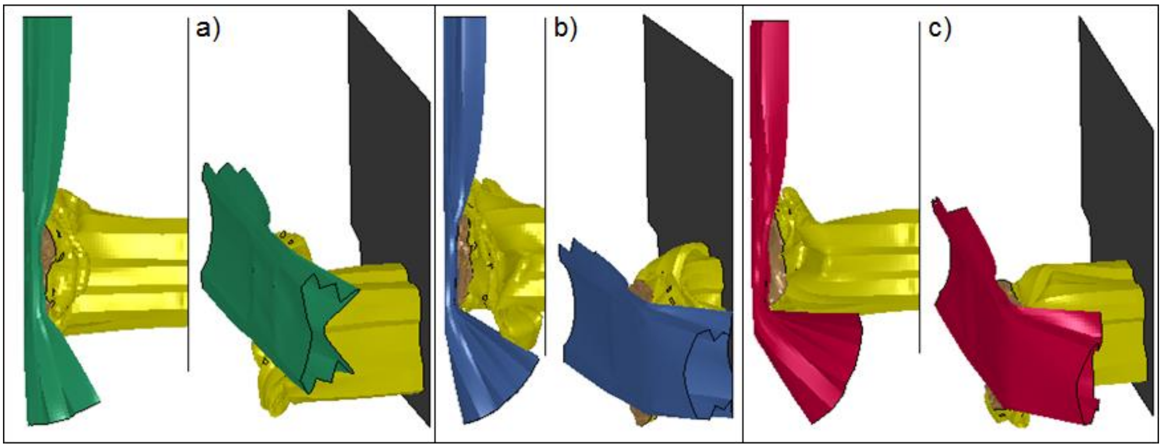

Figure 7: Side and isometric view of the final deformation for each case:
a) straight, b) medium radius and c) maximum radius

3.2.3 Optimization through the iterative models in LS-OPT

Nowadays, with the increasing awareness of the environmental footprint of the vehicle, mass reduction of the different vehicle subcomponents is mandatory. Meanwhile a high level of energy absorption must be guarantee maintaining a deformation level as close as possible to an ideal absorber, without high peaks of deceleration. Therefore, the goal of the optimization process is to obtain an optimized bumper profile in terms of specific energy absorption (SEA), while satisfying a set of design constraints [15].

In order to optimize the bumper, three parameters are considered that correspond to the shell thickness values of the three parts (red, green and blue) in which the bumper subsystem was divided (Figure 8). The parameter ranges and the nominal values are represented in Table 3. From previous numerical simulations, it was noted that the subdivision, in terms of shell thickness, of the longitudinal crash box into two parts is able to guarantee a reduction of the load peak and the introduction of some alternated hole allows to obtain a progressive and controlled deformation during crushing.

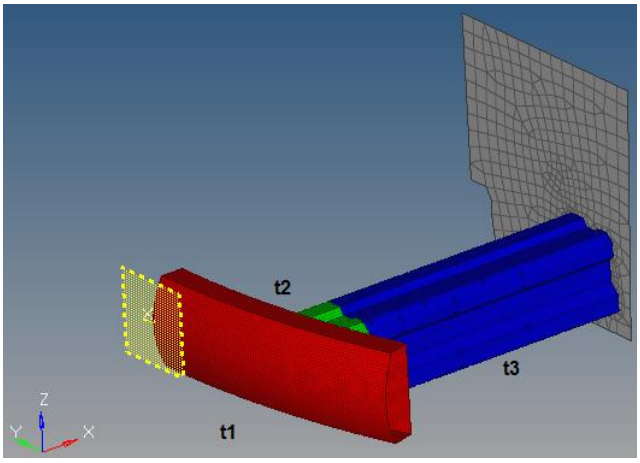

Figure 8: Bumper parameters

Table 3: Design parameters

Parameter	t1	t2	t3
Min (mm)	1	1	1
Max (mm)	3	3	3
Nom (mm)	2	1.5	2

Therefore, the mathematical model for the structural optimization is as follows:

$$\max SEA(t1,t2,t3)$$
$$\text{subject to}\begin{cases}\text{Max\_acceleration}<50\text{ m/s}^2\\ \text{Average\_acceleration}<25\text{ m/s}^2\\ \text{Max\_stroke}<550\text{ mm}\end{cases} \tag{6}$$

As mentioned before, such optimization procedure has been implemented in LS-OPT using two different metamodels, such as Radial Basis Function Network and Kriging. At each iteration step, each metamodel evaluates, taking into account also the previous DOE experiments, the best solution to adopt until get to convergence.

4 RESULTS AND DISCUSSION

Table 4 shows the optimal values of thickness for RBFN and Kriging metamodel, respectively. It is evident how different surrogates give feasible and very comparable solutions.

Table 4: Variables optimal values for both surrogates

Metamodel	Design variables		
	t1	t2	t3
RBFN	1.14	1.36	1.99
Kriging	1.21	1.42	1.91

In terms of objective and constraints values it is possible to note how both metamodels are able to improve the basic configuration (Table 5).

Table 5: Optimum results of RBFN and Kriging metamodel

	Basic	RBFN	Kriging
SEA (kJ/kg)	8.94	10.82	10.67
Max_acc (g)	55.02	45.97	46.12
Average_acc (g)	23.39	22.55	21.86
Max_stroke (mm)	521.06	540.21	539.35

Figure 9 shows the optimization history for variables and objective varying iteration step. It is evident how the domain of each thickness tends to reduce in time up to converge to the optimal solution. Moreover also the SEA value tends to stabilize around a value of about 11 kJ/kg.

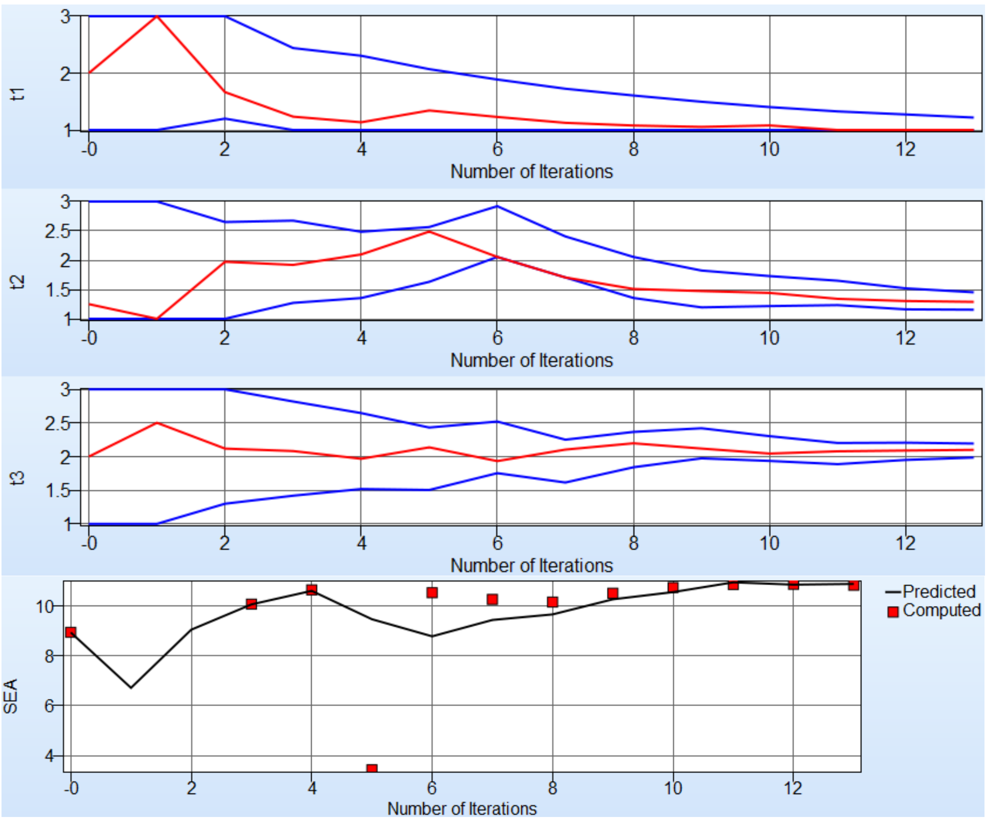

Figure 9: Optimization history for the design variables and objective

Sensitivity analysis allows to determine the significance of the design variables. In LS-OPT two sensitivity measures are implemented: Linear ANOVA and GSA/Sobol. ANOVA depicts positive or negative influence, while Sobol just shows the normalized absolute value and guarantees an easier comprehension (Figure 10). It is evident how the t3 variable, that depicts the thickness of the last zone of the longitudinal crash box, is the most influential parameter for each responses.

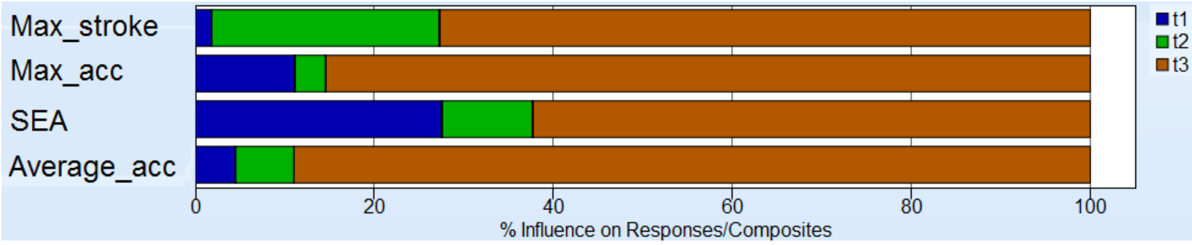

Figure 10: Sobol values for multiple responses

The three dimensional response surfaces obtained from the RBFN and Kriging models and simulation points were plotted for the SEA objective vs. two design variables (Figure 11). It is evident how the Kriging metamodel tends to approximate the DOE experiments (green and red points correspond to feasible and unfeasible solution, respectively) with a more complex surface.

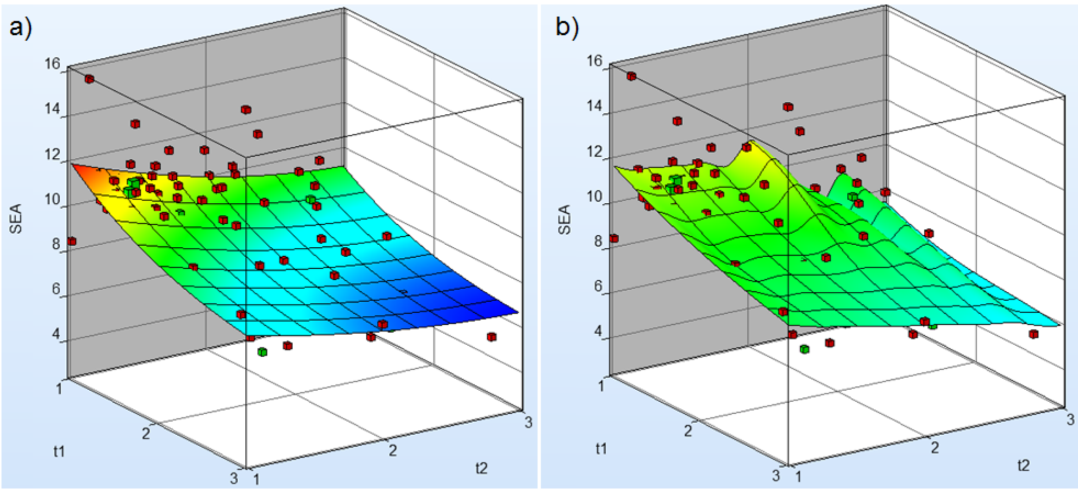

Figure 11: Response surfaces of SEA for RBFN (a) and Kriging (b) metamodels

5 CONCLUSIONS

This paper presents the application of two metamodels, such as Radial Basis Function Network and Kriging, in the context of crashworthiness. In particular the work is dedicated to the development of a front race car bumper subsystem in conventional material with the aim to improve its energy absorption capability. At first the basic configuration has been compared with other solutions, in terms of section profile and beam curvature. Only after, the chosen solution has been analyzed with an optimization process using LS-OPT tool, by considering as design variables the wall thicknesses of the beam and of the longitudinal crash boxes. For this objective, numerical simulations have been conducted through explicit solver LS-DYNA and structural results for the bumper have been compared. The following conclusions can be drawn:

- The adoption of a bumper with internal folds into the profile seems to be best in terms of progressive deformation, even if this implies an higher weigh and a lower SEA value.

- It is not convenient to realize a bumper using a straight curvature, because it generates initial peaks and lower energy absorption level as well as a not uniform crushing process.
- After the initial deformation, where the only bumper is involved, the energy absorption is guarantee from the longitudinal crash boxes and therefore it seems suitable to divide such structure at least in two zones at different thicknesses and insert some hole to reduce the peaks and guarantee a progressive and controlled deformation.
- Implementation of an optimization process through RBFN and Kriging methods demonstrated that the crushing performance, in term of SEA, of the bumper system can be improved by 21% and 19%, respectively.
- No great differences can be observed from the point of view of the design variables values between the considered surrogates.

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