A Simulation-Driven System Design Methodology with Manufacturing Constraints

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Abstract

This paper presents a holistic simulation-driven system design methodology considering multiple performance objectives, performance constraints including formability criterion defined herein, using a genetic algorithm based multi-objective optimization software GDOT, developed in-house. This tool treats multiple objective functions separately without combining them in any form. A decision-making criterion is subsequently invoked to select the "best" subset of solutions from the obtained non-dominated Pareto optimal solutions under multiple performance constraints along with a formability index. Geometric properties, associated material properties (yield strength / plastic strain to failure) are considered as design variables.

An example involving the frontal impact on a rail section is used to demonstrate the methodology. This process can further suggest requirements for synthesizing new materials that will result in optimal product performance.
The objective of this study is to establish an 'optimized' set of design parameters with the dual aim of (i) minimizing the structural weight and (ii) maximizing energy absorption efficiency of the front rail system during frontal impact. The performance constraints being maximum transmitted force, maximum intrusion, pulse efficiency and formability criterion. This study also looks at the effect of parameter uncertainty on the optimal design. This study is composed in two stages. The first stage attempts to solve the multi-objective optimization problem, which is attempted using proprietary GDOT optimization code. Stage two performs reliability-based multi-objective optimization to generate a 'reliable' pareto optimal front.

A 2nd order meta model is developed using responses, including formability index, computed from physics-based finite element models using LS-DYNA^{TM} analysis code.

Looking at a broader picture, this methodology can potentially fill the gap between numerically optimized system development and simulation-driven digital product development. This, in turn, will help realize numerical simulation-driven product development process by aiming to achieve designs that are "first time right".

Keywords*: Simulation-driven design, multi-objective optimization, GDOT, non-dominated point, pareto-optimal solution, impact, formability criterion, manufacturing constrain, reliability-based multi-objective optimization.*

1. Introduction

The highly competitive nature of the automotive industry demands continuous product innovation and reduction in product development cycle time while satisfying ever-increasing performance and regulatory requirements. Numerical design optimization, embedded in a simulation-driven product development framework, provides a scientific approach to automatically determine the most efficient designs under the target operating environment.

Application of numerical optimization to crashworthiness assessment, which is a highly nonlinear phenomenon, is still an evolving discipline. Reduction in structural weight to improve fuel economy is a never-ending task and at the same time, crashworthiness is one of the most critical performance requirements of the vehicle body. Techniques that can achieve both enhanced crashworthiness performance and weight reduction simultaneously are therefore key body technologies of the future. In general, enhanced crashworthiness performance is associated with increased energy absorption efficiency. A major candidate that can have a big impact on achieving this is an application-specific, “synthesized” material with “optimal” mechanical properties [1].

The objective of this study is to establish an ‘optimized’ set of design parameters with the dual aim of (i) minimizing the structural weight and (ii) maximizing energy absorption efficiency of the front rail system during frontal impact. The performance constraints being maximum transmitted force, maximum intrusion, pulse efficiency and formability criterion. The design parameters chosen for this study are panel thickness of ‘double-hat’ type rail cross-section and representative material properties affecting mainly the plastic deformation stage. This study also looks at the effect of parameter uncertainty on the optimal design. This study is composed in two stages. The first stage attempts to solve the multi-objective optimization problem, which is attempted using proprietary GDOT optimization code. Stage two performs reliability-based multi-objective optimization to generate a ‘*reliable*’ pareto optimal front.

Meta models of 2nd order are developed using responses computed from physics-based finite element models using LS-DYNA™ analysis code.

2. Problem Definition

This study considers a box-shaped, energy-absorbing front-end rail structure (refer Fig. 1). Crashworthiness is studied by crashing the rail-section into a rigid wall with a collision velocity of 6.67 m/sec. The rail section is fixed at the base and 4-noded linear elements are used with spot-welds connecting the top and bottom sections (refer Fig. 1). The finite element models developed is solved using LS-DYNA with piecewise linear plastic material model (MAT 24) with fully integrated linear shell element (ELFORM = 16 in LS-DYNA). Failure plastic strain is specified in the material model for all models, but no strain-rate sensitivity is considered. All models are run for 36 milliseconds to balance computational requirements to a minimum and still achieve representative results. The design variables considered are top and bottom thickness (t_1 and t_2) and material yield strength (σ_y). There is another linked design parameter in material young’s modulus (E).

Thickness parameters are considered continuous while the material yield strength can attain a discrete set of values. The material young’s modulus is related to its yield strength using the following relation:

$$E = E_0 + \Delta * (\sigma_y - \sigma_{y,l}) / (\sigma_{y,u} - \sigma_{y,l}) \quad \ldots\ldots\ldots \quad (1)$$

Where,

E_0 = base value of young’s modulus (190 GPa in this study)

Δ = Range of permitted young’s modulus (30 GPa in this study)

σ_y = Yield strength of the material in GPa

$\sigma_{y,u}$ = Upper value of yield strength (0.7 GPa in this study)

$\sigma_{y,l}$ = Lower value of yield strength (0.2 GPa in this study)

This linking relation ensures that Young's Modulus can take only discrete values.

The responses considered for meta model development are structural weight, maximum transmitted force (using SAE 1000 filter), maximum intrusion, internal energy, crash pulse efficiency and energy absorption efficiency. The pulse efficiency and energy absorption efficiency are derived measures (composite function involving two primary responses) and computed as:

Pulse efficiency (%),

$P = 100 * \text{Area under force-displacement curve} / (F_{max} * D_{max})$ ……….. (2)

where, F_{max} = maximum transmitted force
D_{max} = maximum intrusion

Energy absorption efficiency (%),

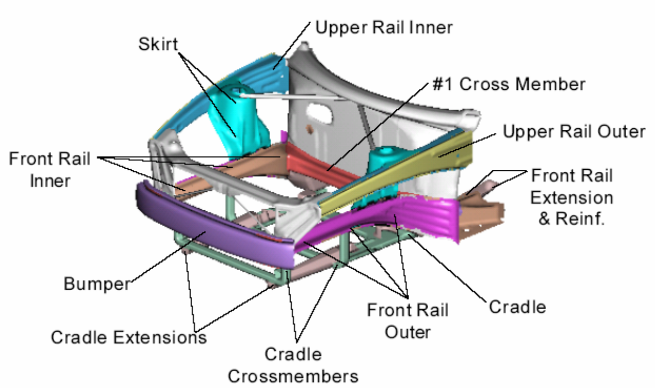
$E = 100 * \text{Area under force-displacement curve} / \text{Initial Kinetic energy}$ ……….. (3)

Formability indicator = 1 - indicates feasible design
= 0 – infeasible design …(4)

In subsequent sections, design exploration is performed using Latin hypercube technique for selection of design points where numerical experiments are performed using finite element models, followed by numerical design optimization studies using multiple objectives respectively. In this study, structural weight and energy absorption efficiency are treated as objectives with pulse efficiency as a constraint, in addition to constraints on maximum force, intrusion and formability.

Formability indicator attains a value of 1 if all measured points in the strain space lie below the forming limit curve (FLC) for that material by a certain threshold distance. The FLC's are generated using Keeler's method.

Please note that the numerical values presented here are only illustrative and may NOT be assignable to real crash simulation.



Length of the rail → 600 mm;
Section at tip→ 260 mm x 120 mm;
Taper → 0.0733 in 1;
Flange width → 25 mm

Fig.1:- Representative front end (ULSAB) and Rail section

Meta model development is a very important step in the whole study and it can be used as a design guide later on by design engineers and also used for optimization and uncertainty analysis. This step is also referred to as “design exploration” in the literature. Response surface models up to 2^{nd} order (quadratic) are considered in this study. This approximate model is defined only within the specified design space. In all, 32 points are generated using Latin Hypercube technique with three design variables for conducting “numerical experiments”. The Latin Hypercube technique is chosen because it covers the whole design space and is reported to have performed better than other techniques while modeling highly non-linear responses [2]. The permissible values of material yield strength variable are {0.20, 0.30, 0.35, 0.40, 0.45, 0.50, 0.55, 0.60, 0.65, 0.70}.

3. Multi-Objective Optimization

The multi-objective optimization study is performed using GDOT multi-objective code, based on evolutionary computing principles. It treats multiple objectives in their virgin form, without combining them. The output is not a single optimal design point, but a set of optimal designs representing ‘optimal’ compromises. The details about multi-objective optimization methods and algorithms can be found in the reference [4].

Here the structural weight (W) is minimized along with maximization of energy absorption efficiency (E). The constraints are on maximum transmitted force (F_{max}) and maximum intrusion (D_{max}) and crash pulse efficiency (P). The problem is formulated as follows:

Minimize Structural weight (W)
Maximize energy absorption efficiency (E) ……. (5)

Such that,

$\mathbf{F_{max} \leq 200.0}$ **kN**
$\mathbf{D_{max} \leq 190.0}$ **mm**
$\mathbf{P \geq 18}$ **%**
$\mathbf{0.50 \leq t_1, t_2 \leq 2.0}$
σ_y ***-> {0.20, 0.30, 0.35, 0.40, 0.45, 0.50,0.55, 0.60, 0.65, 0.70}***
Formability indicator = 1

The output of the multi-objective optimization process is a set of pareto-optimal points. These points are called *non-dominated* and represent the ‘optimal’ compromises. One has to select one pareto optimal point instead of many and this requires a *higher level, user-specified* information. Mathematically, this operation converts a partial order relation (pareto optimal set) to a total order relation to enable comparison.

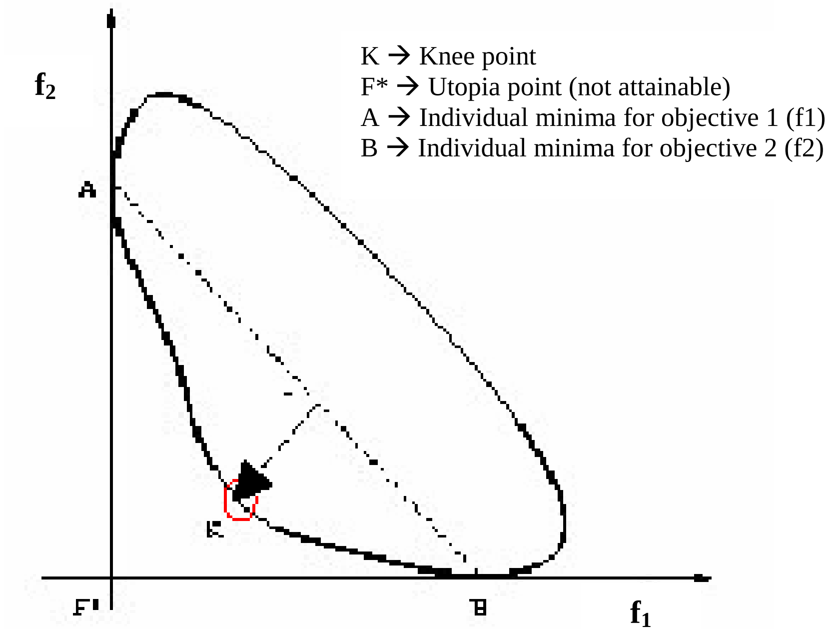


Fig. 2:- The point (K) on the pareto-front having largest distance from line AB, connecting individual minima, is termed *knee point*

Most of the time, the chosen point belongs to a region in the pareto optimal front that '*bulges*' out the most and lie somewhat '*in the middle*' of the front. This point is termed as the '*knee point*'. This '*knee point'* is characterized by a point that lies farthest from the surface connecting each individual optimal point for each objective (refer Fig. 2). A point given by the optimal values of each individual objective is termed as the '*utopia point*'. This point cannot be attained in practice in the presence of conflicting objectives.

The *knee point* design is verified using LS-DYNA simulation.

The manufacturability criterion used in this work is introduced by means of formability. Formability of a design is quantified using the forming limit diagram (FLD). The distance of measured points in the strain space from the corresponding points on the forming limit curve is taken as the formability metric in this study. The greater the distance, better is the formability.

4. Reliability Based Multi-Objective Optimization Formulation

In system parameter design, the reliability-based multi-objective design optimization (RBMODO) problem can be stated as:

Minimize $f(X) = (f_1(X), f_2(X), \ldots, f_M(X))$
Subject to:

$$P(G_i(X) \geq 0) \leq \Phi(-\beta_{ti}) \text{ where, } i = 1,.., p$$

$\Phi(.)$ represents the cumulative distribution function of standard normal distribution with β_{ti} being the prescribed reliability target corresponding to i^{th} constraint. The constraints can also be cast in another format relating safety reliability index β_{si} to prescribed reliability target such that $\beta_{si} \geq \beta_{ti}$. This formulation is used for all reliability constraint formulations in this work. One striking difference between the deterministic and reliability based optimization is that, in the reliability based optimization, the optimized parameters are the "mean" optimal values rather than "the" optimal values. This is because, reliability based optimization formulation assumes variation about "mean" values and makes sure that the optimal design thus arrived do not fail in any performance criteria (e.g., constraints) due to these variations.

In reliability based optimization approaches, the additional computation step is computation of safety reliability index β_{si}. The reliability-index [5] approach (RIA) is used for computation of β_{si}. In this case, the analysis is performed in two different random spaces: the original random design variable space (X-space) for design optimization and the independent standard normal space (U-space) for reliability analysis [5, 6]. A transformation between X and U space at design points must be carried out for estimating the probabilistic constraints. The transformation between two different random spaces at the design point d^k is defined as:

$$U = T(X) \text{ where } d^k = \mu^k(X)$$

It is assumed that, no correlation exists among the design variables. This requires probability distribution information for each input random variable. Most of the transformations from X to U-space are nonlinear, except the normal distribution.

In RIA, the first-order safety reliability index is obtained by formulating an optimization problem with an equality constraint in U-space, which is the failure surface, as

$$\begin{array}{ll} \text{minimize} & \|U\| \\ \text{subject to} & G(U) = 0 \end{array}$$

The minimum point on the failure surface is called the Most Probable Point (MPP) $u^*_{G(u)=0}$ and the safety reliability index is defined by $\beta_s = \| u^*_{G(u)=0} \|$. To find the solution to either an MPP search algorithm that has been specifically developed for the first-order reliability analysis or a general optimization algorithm can be used. Due to its simplicity and efficiency, the HL-RF method is a popular choice for conducting a reliability analysis in RIA, and the same has been used in this work.

The iterative algorithm of the HL-RF method is,

$$u^{(k+1)} = (u^{(k)}.n^{(k)})n^{(k)} + \frac{\nabla G(u^{(k)})}{\| \nabla G(u^{(k)}) \|} n^{(k)}$$

where,

$$n^{(k)} = -\frac{\nabla G(u^{(k)})}{\| \nabla G(u^{(k)}) \|}$$

is the steepest descent direction of the performance function $G(u)$ at $u^{(k)}$. The first term on the right side of the iterative relation above finds a direction with the shortest distance to the failure surface, and the second term is a correction term to reach *G* (**U**).

Post optimization, the probability of failure (P_f) is computed using the following formulae:

$$P_f = \Phi(-\beta) = \frac{1}{2}[1 + erf(-\beta/\sqrt{2})] \text{ for } \beta \le 8.0$$

$$= \frac{1}{\beta\sqrt{2\pi}} e^{-\frac{\beta^2}{2}} \text{ for } \beta > 8.0$$

In this case, all the design variables are assumed to be normally distributed with coefficient of variation of 0.05 (5%) for the purpose of reliability-based multi-objective optimization process. The target reliability indices (β_{ti}) for first two constraints are set to 6.0 while the third constraint has a beta target value of 3. The reliability based multi-objective design optimization (RBMODO) statement becomes:

Minimize Structural weight (W)
Maximize energy absorption efficiency (E)... *(14A)*

Such that,

$\beta_{t1} \ge 6.0$ **----- Constraint on max. Force**

$\beta_{t2} \ge 6.0$ **----- Constraint on max. Intrusion**

$\beta_{t3} \ge 3.0$ **----- Constraint on pulse efficiency (%)**

Formability indicator = 1

$0.50 \le t_1, t_2 \le 2.0$

$0.20 \le \sigma_y \le 0.70$

5. Results and Discussions

For multi-objective optimization, GDOT multi-objective optimizer is used. The problem statement is given in (5). The two objectives are not combined in any form and the output is set of optimal points called ‘pareto-optimal’ front (refer Fig. 3). A pareto optimal solution, that is better with respect to one objective, requires a compromise in at least one other objective [3].

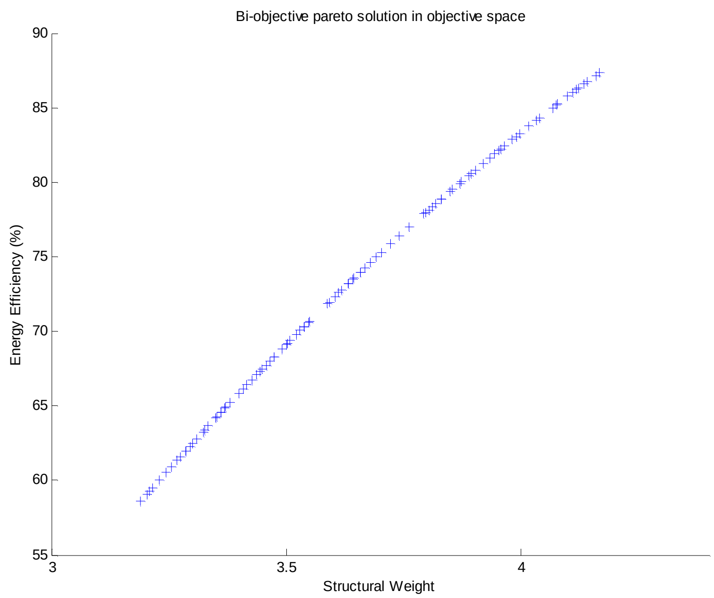


Fig. 3:- Optimal Pareto front for deterministic formulation

The results of multi-objective optimization are summarized below:

Table 1:- Summary of results for multi-objective optimization

Pareto point	t_1	t_2	σ_y	W	E	F_{max}	D_{max}	P
Knee point	1.185	0.507	0.70	3.6792 [1](3.679)	74.61 (74.36)	161.37 (161.2)	166.67 (166.2)	19.26 (19.38)
Minima W	0.95	0.505	0.70	3.19	58.61	126.37	179.9	**18.09**
Maxima E	1.42	0.5	0.70	4.165	87.33	**196.9**	156.33	19.89

As can be seen, the crash pulse efficiency is relatively close to the constraint boundary in majority of the cases. At knee point, the design is not very close to any constraint boundary. Maximum force constraint is active when maximizing for energy absorption only. This design indicates higher structural weight, but crash pulse efficiency is also improved. Similarly, the design for minimum structural weight indicates constraint activity for pulse efficiency constraint. The reduced panel thickness values seem to lower the pulse energy efficiency and therefore '*pushing*' it to the boundary. This behaviour is expected and probably, it is the higher material yield stress that keeps this minimum weight design just within the constraint boundary. Another interesting observation is that, different thickness for the two panels with higher yield strength steel (AHSS) is advocated for optimal performance. Higher yield strength seems better from energy absorption viewpoint.

In this study, the material yield stress value is indicated to be 0.70 GPa (700 MPa) for knee design point. The possible choices available from AHSS family are CP (complex phase), DP (dual phase) and TRIP steels. The formability criterion is used to select a material out of these

[1] Quantities in brackets indicate analysis results obtained from LS-DYNA simulation.

choices. It can be observed that the computed strains for DP 700 grade steel are very close to the FLC and therefore termed infeasible. CP 700 grade steel is chosen since the computed strains are away from the FLC and is cheaper than TRIP steel (refer to Fig. 4 and 5).

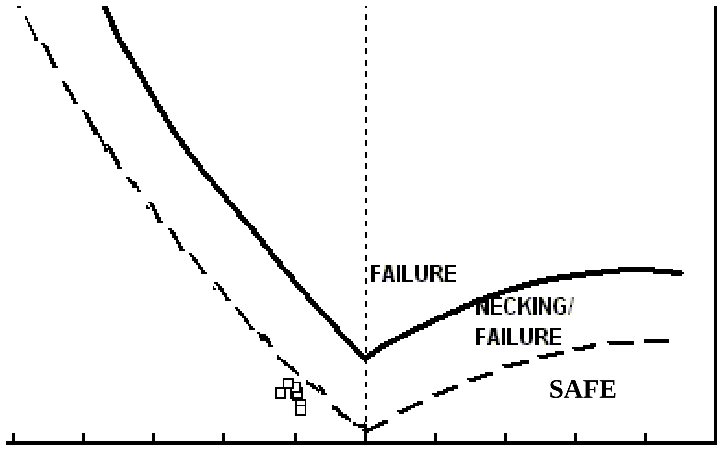


Fig. 4:- FLD for DP 700/1000 grade AHSS

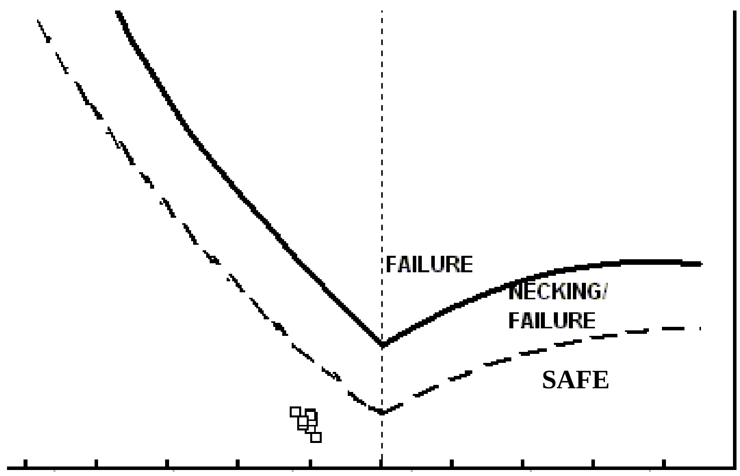


Fig. 5:- FLD for CP 700/1000 grade AHSS

The weldability aspects of this complex phase steel needs to be studied in some detail to finalize the manufacturing aspects for the suggested rail section. Inclusion of strain-rate sensitivity effects in the material model used will further enhance the energy absorption capability.
Now, in order to look at the '*reliability*' of the 'optimal' design, the design variables are assumed to follow normal distribution with standard deviation of 5% about the mean. While using reliability based optimization, the "optimal" pareto front shifts from that of deterministic version and depends on the target reliability indices used (refer Fig. 7).

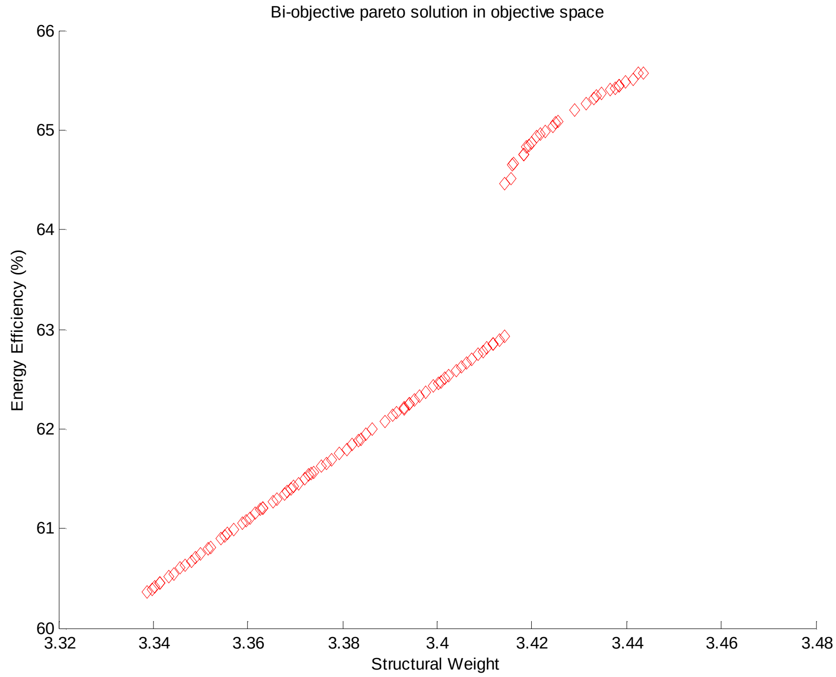


Fig. 6:- Optimal Pareto front for reliability-based formulation

Table 2a - b:- Summary of results for reliability-based multi-objective optimization using RIA

Pareto point	t_1	t_2	σ_y	*W*	*E (%)*
Knee point	1.012	0.546	0.65	3.4142 [2](3.414)	64.46 (64.58)
Minima W	1.021	0.5	0.60	3.3387	60.364
Maxima E	1.052	0.52	0.65	3.4435	65.558
Significant point **	1.056	0.501	0.60	3.41418	62.932

Pareto point	β_1	β_2	β_3
Knee point	6.543	7.212	**3.001**
Minima W	6.848	**6.048**	3.344
Maxima E	**6.028**	7.432	3.11
Significant point **	**6.021**	6.40	3.775

[2] Quantities in brackets indicate analysis results obtained from LS-DYNA simulation.

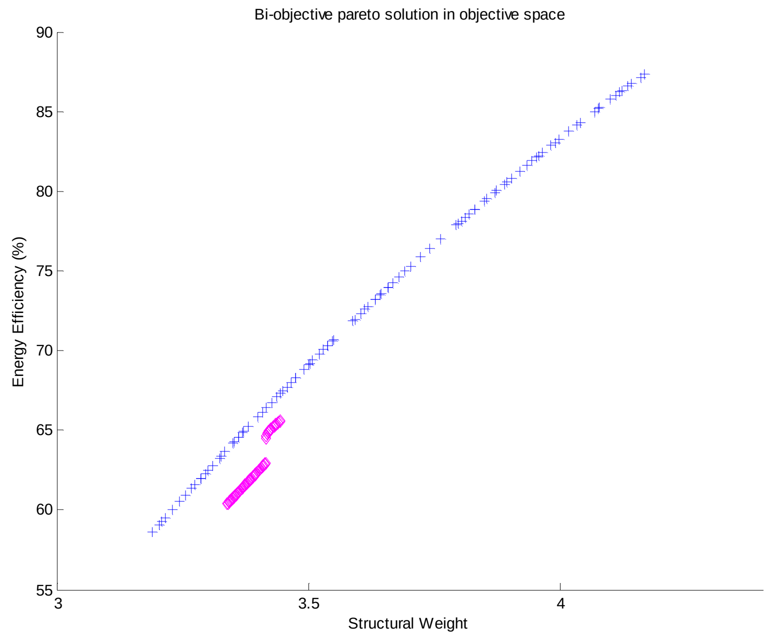


Fig. 7:- Pareto optimal front obtained using deterministic and reliability-based (RIA) approaches

It is observed from the results that the reliability based pareto optimal fronts and also the robust pareto optimal front have shifted below the corresponding deterministic pareto optimal front. This result is along expected lines, but another observation is that of a 'jump' in the pareto optimal front (see Fig. 6). The same problem was run with increased number of generations (200 and 400 generations) to check if it has really converged and make sure that such behaviour is not due to algorithmic issues. This discontinuity is observed in terms of energy absorption efficiency. For two pareto optimal points with very close structural weight gives a very different energy absorption efficiency (marked as '*knee point*' and '*significant point*' in table 2a-b). This 'jump' seem to be controlled by the constraint activity and material yield stress property (material yield stress does not appear in structural weight calculation so long as unit weight remains the same). Higher yield AHSS gives better energy absorption while satisfying all reliability constraints with pulse efficiency being very close to constraint boundary. The 'reliability-based' solutions indicate the 'optimal' material for this application, in terms of the material yield stress value of 0.65 GPa. This maps to AHSS and CP650/1000 grade is chosen for this application based on the formability criterion.

6. Conclusion

A response surface based design optimization methodology is presented here. This illustrates use of numerical simulation code with an integrated design optimization framework consisting of multiple optimizers capable of supporting multi-disciplinary, multi-objective optimization process. This theme is central to any simulation based design synthesis approach. Evolutionary computing based optimizer GDOT is used for multi-objective optimization involving minimization of structural weight and maximization of energy efficiency. The optimal pareto-front is obtained and important points on the front are characterized, including the '*knee point*'.
This study indicates the 'optimal' material for this application, in terms of the material yield stress value of 0.70 GPa. This maps to AHSS and CP700/1000 grade is chosen for this application based on the formability criterion.

When uncertainty is taken into consideration, the “optimal” pareto front shifts towards a “safer” region where parameter uncertainties no longer impact the feasibility of the optimal design solutions. As a preliminary observation, it can be seen that robustness based “optimal” front is more “conservative”, that is, it is further away from the deterministic “optimal” front. But this is still initial days and more numerical investigation for varying categories of problems are required before we can make a “strong” claim. Results obtained suggest different panel thickness for double-hat type rail section and higher yield strength material perform better from energy absorption viewpoint (for the same structural weight) for materials having similar plastic strain to failure. In future, studies will include strain-rate sensitivity of the material to take further advantages in terns of energy absorption capability. Looking at a broader picture, this methodology can potentially fill the gap between numerically optimized system development and simulation-driven digital product development. This, in turn, will help realize numerical simulation-driven product development process by aiming to achieve designs that are “first time right”.

Acknowledgments

The authors wish to express their appreciation for the encouragement given by Dr. Roland Haas, MD, DaimlerChrysler Research and Technology, India during the course of this study and subsequent publication of results.

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Definitions, Acronyms and Abbreviations

AHSS: Advanced High Strength Steel

DP: Dual Phase

CP: Complex Phase

TRIP: Transformation Induced Plasticity

GDOT: Generic Design Optimization toolkit

FLD: Forming Limit Diagram