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Multidisciplinary Design Optimization of a Ground Vehicle Track for Durability and Survivability

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ABSTRACT

In this paper a Multi-Level System (MLS) optimization algorithm is presented and utilized for the multi-discipline design of a ground vehicle track. The MLS can guide the decision making process for designing a complex system where many alternatives and many mutually competing objectives and disciplines need to be considered and evaluated. Mathematical relationships between the design variables and the multiple discipline performance objectives are developed adaptively as the various design considerations are evaluated and as the design is being evolved. These relationships are employed for rewarding performance improvement during the decision making process by allocating more resources to the disciplines which exhibit the higher level of improvement. The track analysis demonstrates how a multi-discipline design approach can be pursued in ground vehicle applications. The main elements of the optimization analysis along with the results and the physical insight which can be gained from the optimal configuration are presented and discussed.

INTRODUCTION

Military vehicle design is a complex process requiring interactions and exchange of information among multiple disciplines such as fatigue, strength, propulsion, survivability, safety, thermal management, stealth, maintenance, and manufacturing. Simulation models are employed for assessing and potentially improving a vehicle's performance in individual technical areas. The vehicle's characteristics influence the performance in all of the different attributes. Challenges arise when designing a vehicle by determining a single set of values for the vehicle's characteristics for improving mutually competing objectives and satisfying constraints from multiple engineering disciplines. It is of interest to engage simulation models from the various engineering disciplines in an organized and coordinated manner for determining a design configuration that provides the best possible performance in all disciplines.

General information on engineering design optimization is presented in [1-5]. In fields in which complex engineering systems are designed – such as naval architecture [6-9], automotive engineering [10,11], mechanical engineering [12-14], and in biomedical engineering [15], it is of particular interest to automatically synthesize the conflicting objectives from several disciplines into the search for one overall, globally optimum design [16-19]. From the design optimization methods considered and proposed in the literature, Multi-discipline Design Optimization (MDO) was widely recognized at an early stage by many on the cutting edge of engineering design as the key to the future [20,21]. This recognition stems from the requirement to synthesize several complex and computationally intensive disciplines into a single resultant design that comprises the optimum from the perspective of an equally complex top-level objective function [12,22-26]. For guidance in using MDO, there are papers outlining the steps in creating an MDO frame- work [27], discussing the characteristics of existing frameworks [28,29], and applying MDO in various disciplines [18]. Multi-level optimization algorithms, like the ones presented in [30,31] provide a systematic way of organizing the solution and the flow of information between the separate multiple discipline and system level optimizations.

Multi-Level System (MLS) design comprises a revolutionary approach in guiding the decision making process for designing a complex system where many alternatives and many mutually competing objectives and disciplines need to be considered and evaluated. Mathematical relationships between the design variables and the multiple discipline performance objectives are developed adaptively as the various design considerations are evaluated and as the design evolves. These relationships are employed for rewarding performance improvement during the decision making process by allocating more resources and influence to the disciplines which exhibit the greatest improvement. The interdependency, the implied relationships, the implied variables, and the interactions which are present in a complex system are captured during the decision making process. A new MLS algorithm for coordinating operations within a network of optimizations is presented in this paper and is employed for driving the ground vehicle track design

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14. ABSTRACT

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analysis. The main differences between alternative multi-level optimization algorithms, reside in the mathematical formulation which is embedded within the system level optimization for driving and coordinating the overall decision making process.

In this paper a multi-level system design algorithm for co-coordinating mathematically the decision making process for the design of a complex system is discussed. This system analysis approach provides an organized and seamless environment that captures the implications of design changes from a particular discipline to all other disciplines. It is possible to share design variables among disciplines and thus identify the direction that design variables should follow based on objectives and constraints from multiple disciplines. The MLS algorithm is utilized for the multi-discipline analysis of a track under durability and survivability considerations. High fidelity simulations (NASTRAN and BEST/LS-DYNA) are utilized in the optimization process. Information and results from the multi-discipline design optimization analysis are presented in this paper. A generic track section is subjected to blast and dynamic loading. The blast loading simulates the event where explosive detonates directly underneath the track section while the track is bearing the full weight of a vehicle wheel (survivability analysis). The dynamic loading occurs through the cyclic pressure of a vehicle wheel on the track section as the track passes over a gap in the soil (durability type of analysis). The two loading conditions represent two distinct design disciplines, thus, a track designed for minimum weight under each discipline, will not meet performance expectations for the other discipline. A well designed track will contain the least material necessary to satisfy the requirements for both blast survivability and dynamic cyclic loading. The objective of the multi-discipline analysis is to minimize the weight of the track by balancing the two different design directions that the two discipline level optimizations direct the design. The optimal track design for each discipline is unique given the distinctly different loading and the associated performance requirements. The severity of the blast event requires fortification of certain components for ensuring survivability. Material in other components that are relatively unaffected by the blast can be removed for reducing the weight. The dynamic cyclic loading of the vehicle wheels requires strengthening the very components that the blast-based design would weaken; the cyclic loading-based design also reduces the size of components that would become thicker in the blast-based design. The competing requirements from each design discipline make the designer's job difficult. These circumstances often result in overbuilt designs that are heavier and more expensive than they need to be.

The optimization statement and the finite element models employed in the analysis are described in the paper. The design variables which are considered in each discipline and system level optimizations, the associated objective functions and constraints are presented. The physics that are manifested in the optimal solution are also identified. The optimal track design is the result of the MLS optimization algorithm used in this multi-discipline design optimization analysis. The optimal design meets the stress requirements for all components under both performance considerations while reducing total track section weight compared to the original configuration.

MUTLI-LEVEL MDO ALGORITHM

The mathematical background of the algorithm driving the MDO analysis is discussed here. It mathematically coordinates the interactions among the various discipline level optimizations and the top system level optimization. A flow chart of the optimization process is presented in Figure 1. At the beginning of every iteration of the top level optimization, the discipline level optimizations are conducted first using as starting point the values for the design variables originating from the current step of the top level optimization. The vector $DV_i^{starting}$ represents the design variables associated with optimization discipline "i". Parameters $F_1, \dots, F_{i-1}, \dots, F_{i+1}, \dots, F_N$ comprise functionals that have been computed in all other disciplines during the previous time that the discipline level computations were conducted and may be providing information needed in the computations of discipline "i". After the discipline level optimizations have been completed, the new values of the design variables $DV_i^{optimal}$ the values of the objective function at the starting point O_i^{start} and at the optimal point $O_i^{optimal}$, and the value of a functional F_i which is evaluated during the computations of discipline "i" and used in the computations of another discipline are provided back to the top level optimization. Based on the results collected at the top level from the discipline level optimizations a targeted value is computed for each design variable of each discipline using Equation (1). Since any design variable may be shared among multiple disciplines, the target values for the design variables are determined based on the improvement encountered in the discipline level objective functions during the last optimization:

$$dv_{\mathrm{j}}^{\mathrm{target}} = \frac{\sum_{i=1}^{N} \left(dv_{i,j}^{optimal} \left| O_i^{start} - O_i^{optimal} \right| \right)}{\sum_{i=1}^{N} \left| O_i^{start} - O_i^{optimal} \right|} \tag{1}$$

In Equation (1), the subscript "j" refers to the j-th design variable, N is the total number of disciplines that share this design variable, and the superscripts "*start*" and "*optimal*" indicate starting and optimal values of design variables and objective functions for the "i"

discipline. Thus, information generated in all other disciplines affects the optimization in discipline "i". In this manner if a design variable is shared by multiple disciplines, its targeted value is influenced the most by the discipline which encountered the largest improvement. The targeted values for the design variables are utilized when defining the objective function for the top level optimization. They contain the influence of the preferences from all the discipline level optimizations. The top level objective function O_T is augmented to include information about the target values of the design variables from all disciplines resulting in a minimization statement of:

$$\begin{aligned} &\min \left(O_T + \textstyle\sum_{j=1}^{J} (dv_j^{target} - dv_j)^2\right) \\ &DV_{T,}\, dv_j \quad j = 1, \dots, J \end{aligned} \tag{2}$$

where J is the total number of design variables encountered in all disciplines and DV_T are the design variables of the top, system level optimization. Any of the discipline level design variables can also be part of the vector of the system level design variables DV_T . In this manner, the influence of the discipline objective functions is considered by requiring the design variables at the top level to match the target values of the design variables which are involved in the discipline level optimizations while at the same time improving the system level objective function.

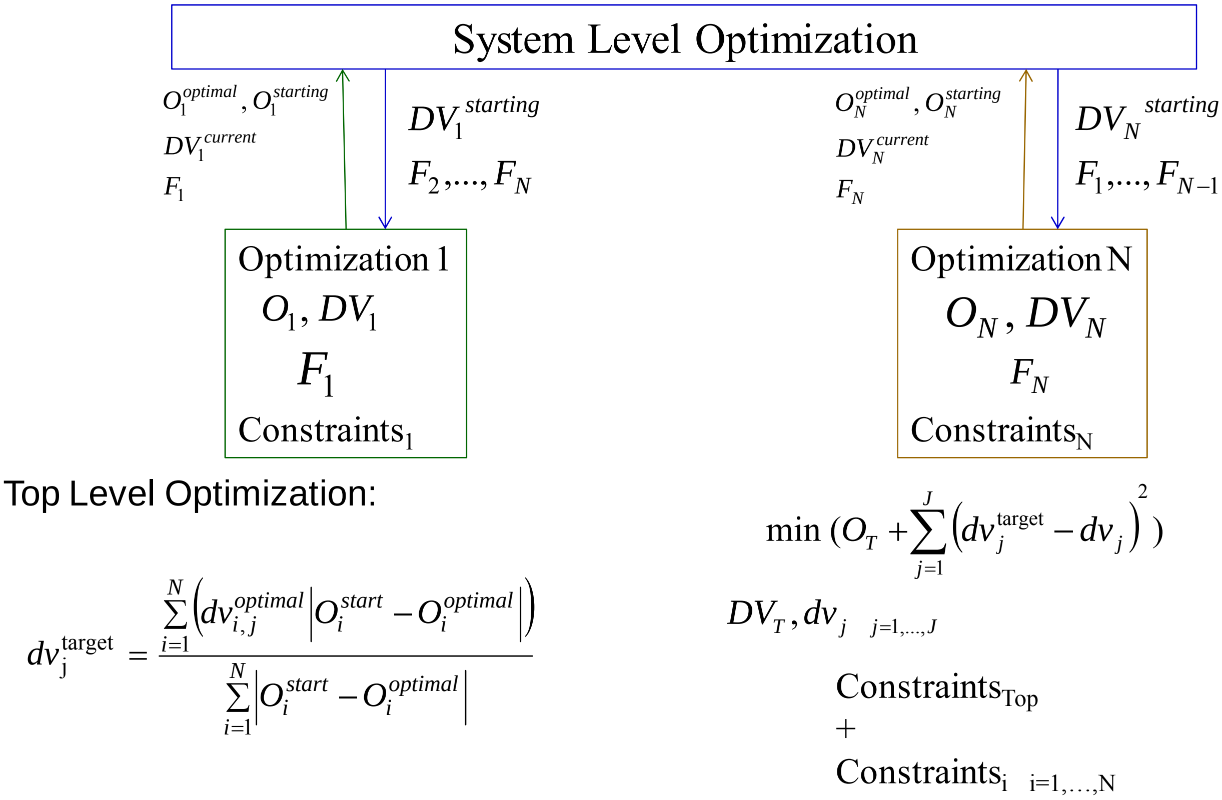

Figure 1. Flow chart of multi-level MDO algorithm

All the discipline constraints are also included in the top level optimization along with the top level constraints. In this manner the optimal point determined by the system level optimization will also be a feasible point for all disciplines.

$$\begin{gathered} g_T(DV_T) \le 0 \\ h_T(DV_T) = 0 \\ g_i(DV_i) \le 0 \\ h_i(DV_i) = 0 \end{gathered} \tag{3}$$

where $g_T(DV_T)$ and $h_T(DV_T)$ are the inequality and equality constraints for the top level, respectively, and $g_i(DV_i)$ and $h_i(DV_i)$ are the inequality and equality constraints for the "i" discipline. Interaction among multiple discipline level optimizations is coordinated through a top level optimization statement. Typically, the top level optimization addresses a global, overall system metric (such as cost, weight, etc.), while the discipline level optimizations target improvement in different performance attributes of a system. Each discipline has its own objective function, constraints, and design variables. Different disciplines can share common design variables and it is also possible for a functional evaluated within a particular discipline to influence computations in another discipline. Thus, the interaction among disciplines materializes through the functionals $F_1, \ldots, F_N$, and through the starting point and the ranges defined for the design variables from each top level iteration for all discipline level optimizations. The communication of all this information among all the disciplines is coordinated through the top level optimization. This process allows coordination of the multiple discipline optimizations by the top level and facilitates the flow of information among disciplines.

FINITE ELEMENT MODEL FOR THE TRACK

The finite element model of the generic track which is used in the MDO analysis is presented in Figure 2. It contains approximately 100,500 elements. The different colors highlight the various sections of the track which are used for defining the design variables. Specifically, six design variables are considered:

- Plate thickness of the horizontal center section (shown in green, Figure 3) – t_1
- Plate thickness of the vertical center section (shown in yellow, Figure 3) – t_2
- Plate thickness of the center section tips (shown in brown, Figure 3) – t_3
- Diameter of the track pin (shown in green, Figure 3) – t_4
- Diameter of the track ring (shown in blue, Figure 3) – t_5
- Diameter of the track rod (shown in brown, Figure 3) – t_6

Figure 2 presents the six design variables. The middle section of the track is built using shell elements. This is necessary in order to automatically recreate the finite element model during the optimization process as the design evolves. The use of shell elements for the center section of the track allows the center of the pin assembly to remain stationary when the thicknesses of the center section of the track vary. Furthermore, the thicknesses of the center section are specified by single numerical entries in the track finite element model file. As such, the optimization analysis can be automated by regenerating the finite element model for every different combination of the design variables during the optimization process. Specialized codes were developed for re-generating automatically the parts of the track modeled with solid finite elements (design variables 4 – 6). Varying thicknesses of components in the pin assembly is much more complicated, because these three components are concentric and must be in contact with each other. Solid model geometry is also much more complex to update than shell element thickness. A suite of executables that automatically scale the solid components in the pin assembly to ensure contact between them and create new FE models for both NASTRAN and LS-Dyna at every optimization step were generated. The total mass is calculated for each model file for the optimization algorithm to read in as the objective function. Other functions parse the output files from NASTRAN and LS-Dyna to identify maximum stresses for use in evaluating constraints. This level of automated model updating and assessment is critical for the optimization analysis to be possible. Without the automated finite element model generation capability the algorithm would have to pause at each iteration step, ask the user to create a new FE model given the design parameters, and ask the user to run an analysis and post-process the results. Such an approach would be tedious.

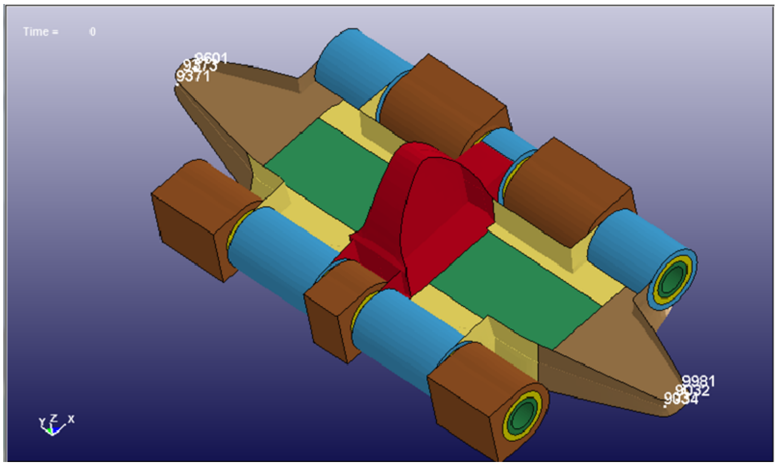

Figure 2. FEA model of the track

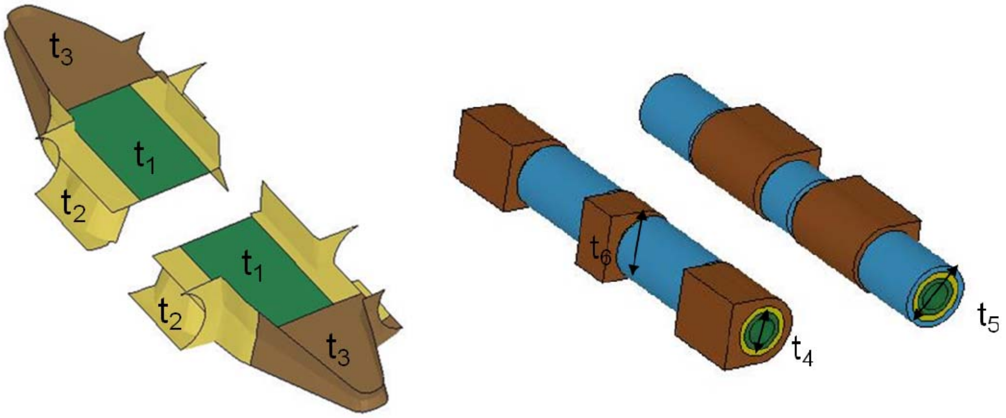

Figure 3. Design variables in the optimization analysis

Blast Analysis Simulation

The scenario simulated in this analysis is the detonation of an explosive located directly beneath a track section with the full weight of a wheel applied above it. The vehicle is considered to have twelve wheels and a mass of 27,600kg. As such, no nodes in the finite element model are constrained, rather a distributed mass equivalent to the weight transmitted through one wheel is applied to the horizontal part of the shell element model. A tensile load of 2.7E4 N is also applied on the track. The blast simulation was coordinated by the Blast Event Simulation System (BEST) [1-3]. The BEST tool manages the blast response problem with a two-step approach. An Eulerian analysis of the explosive and the soil is conducted first. The pressure histories near the structure are recorded to be used as loading in the second analysis. BEST automatically creates the Eulerian grid given a structural model and mesh shape, boundary, and grid density specifications from the user. The structural model is superimposed on the mesh and all soil cells intersecting or contained by the structural model are deleted. The LS-Dyna Eulerian solver is used for conducting the simulation and generating the loads for the Lagrangian analysis. In the second step, the structural response is calculated by applying the pressure histories from the first step as load curves on the elements composing the bottom surface of the structural model. The two step method was particularly useful for the present effort because the Eulerian analysis which determines the loading was only run once. The pressure histories are not subject to change as the structural model changes. Therefore the pressure histories are independent of any modification of the design variables and only need to be recorded once. Only the Lagrangian analysis is run repeatedly during the optimization process. The explosive used for the blast analysis is considered buried 8 cm below the surface of the soil. The Eulerian model used in this work is presented in Figure 4. The profile of the track section can be seen on the top surface of this model.

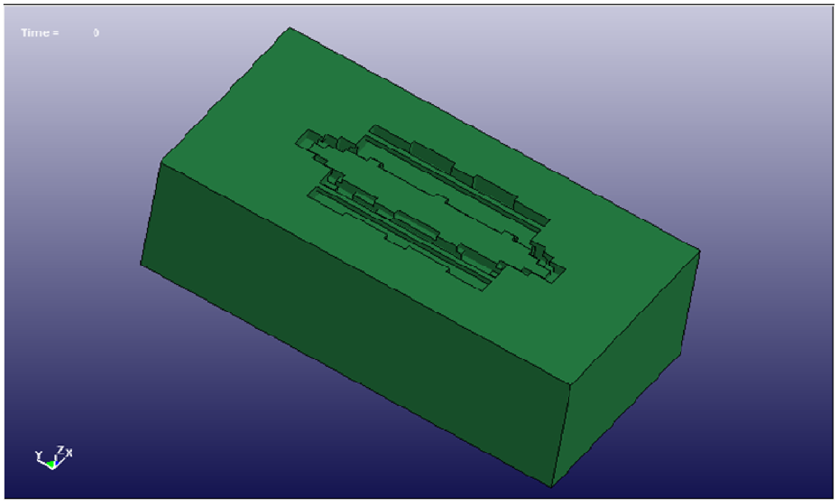

Figure 4. Explosive and Soil Model

Dynamic Simulation

The dynamic analysis is conducted using NASTRAN. A cyclic loading is applied to the track section, mimicking the weight borne by the track as the vehicle wheels roll over it. A vehicle speed of 30 mph is considered and the corresponding load profile is presented in Figure 5. Though it appears to be a step pulse, there is a short rise time and fall time. These are included in the dynamic loading model because the force from a wheel rolling onto the track section does not occur instantaneously. The loading profile in Figure 5 depicts the loading factor, which is multiplied by the vehicle weight divided by the number of wheels on the ground. This loading is applied to the horizontal section of the shell element portion of the tack model, shown in green in Figure 2. The track section is constrained so as to simulate the track rolling over a hole in the ground. To this end, three nodes are constrained at each of the tips, shown in brown in Figure 2 with the constrained nodes highlighted. As the load is applied, the pressure initiates displacement in the center of the track section, as the middle part acts like a bridge over the hole.

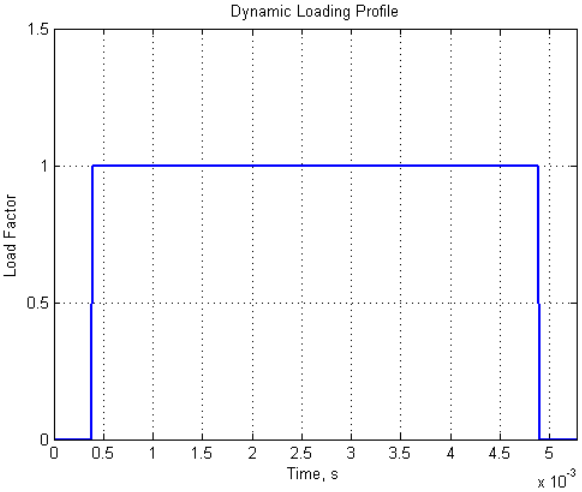

Figure 5. Dynamic Track Loading

MULTI-DISCIPLINE OPTIMIZATION ANALYSIS AND RESULTS

The objective of the optimization analysis is to reduce the mass of the track. The blast survivability and the cyclic dynamic loading design concerns comprise the discipline level optimizations. The objective function in both disciplines is to reduce mass. Each optimization is constrained by the maximum stress of the parts that make up the track section. In each discipline level optimization analysis, the optimal designs for each discipline must not exceed the maximum allowable stress for that discipline. A maximum von Mises stress of 6.4E8 Pa is considered in the optimization under blast loading and a maximum von Mises stress of 4.74E8 Pa is considered in the optimization under dynamic loading. The limiting stress under dynamic loading is a considerably lower stress because the dynamic loading will be encountered many times during the operation of the track, while the blast load is considered to be a rare event. The MLS algorithm coordinates the two single-discipline optimizations simultaneously from the top level, and the outcome is a track design that meets the performance requirements of each discipline while reducing track material from the original model. The software implementation of the MLS algorithm includes capabilities of automatically: (i) modifying the entries in the NASTRAN and the LS-Dyna data files to reflect changes introduced in the finite element models from the optimization process; (ii) launching the execution of the NASTRAN and the LS-Dyna solvers; and (iii) retrieving information from the result files in order to update the values of the constraints and the objective functions as needed. In this manner it is possible to use any solver for conducting computations during the optimization process for evaluating information relevant to the optimization statement, without the need to perform the optimization within the solver itself.

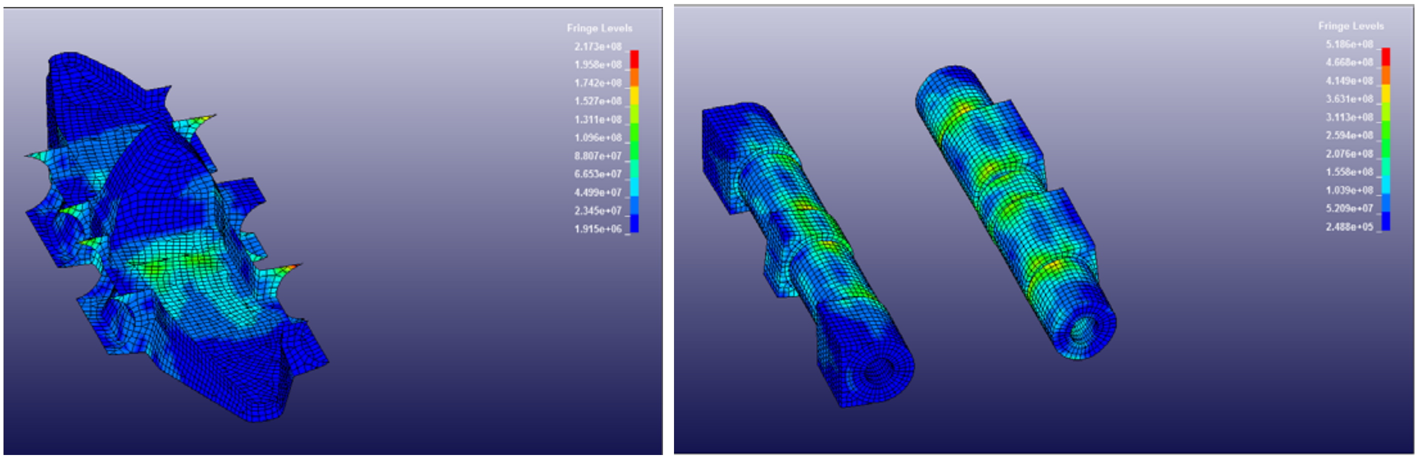

Figure 6. von Mises Stress due to Blast Loading

The physics associated with the loading in each discipline impact the direction that the design is driven towards. In the blast simulation the distributed weight of the vehicle and the load from the explosion combine to sandwich the center section of the track between them. Thus, the maximum stress is encountered at the pin assembly where such a mechanism of balancing out the loads does not exist. Figure 6 presents the distribution of the von Mises stress for a representative design at the time instance when the largest stress is encountered during the blast simulation. It can be observed that the stresses are higher in the pin assembly. The maximum von Mises stress in the pin assembly is 5.186E8 Pa, over twice the maximum value in the center section. This analysis demonstrates that the blast optimization will tend toward adding material to the pin assembly and removing material from the center section in order to reach a design that meets yield stress requirements and has the least material.

In the dynamic analysis the center portion of the track is subject to much higher stresses than the pin assembly because it acts like a bridge over the 'hole' that is simulated in the problem definition. A representative distribution of the von Mises stress is presented in Figure 7. The results correspond to the time instance when the maximum stress is encountered. These physics drive the pin assembly to reduce thickness more than the center portion of the track during the cyclic loading discipline optimization. Therefore the two discipline optimizations drive the design towards different directions due to the physics of the associated loading.

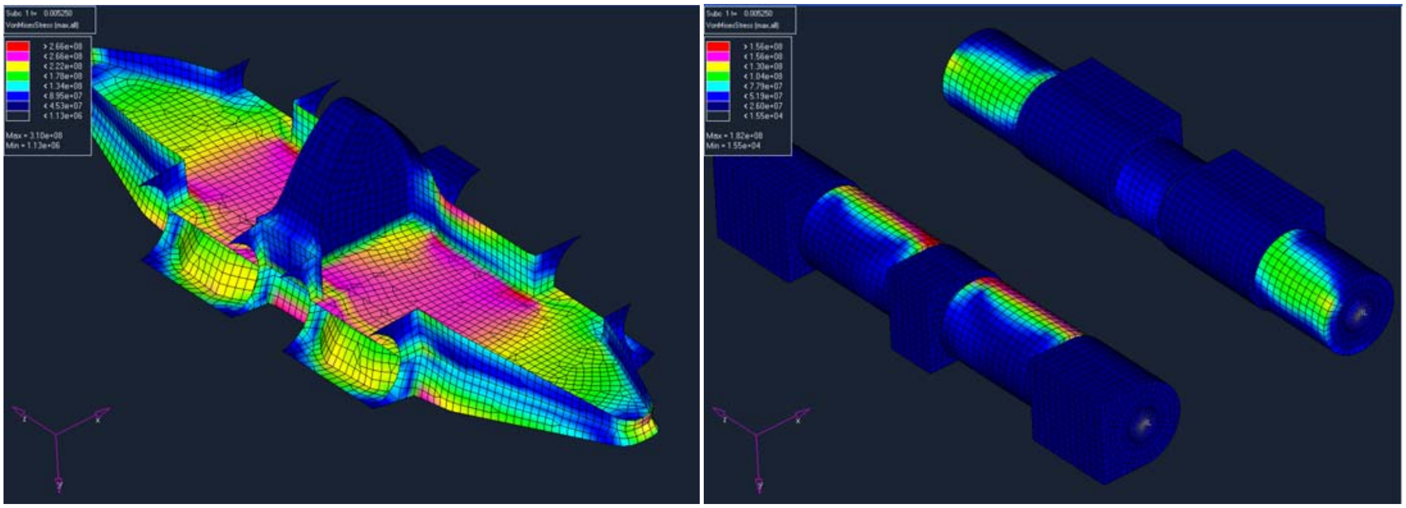

Figure 7. von Mises Stress due to Dynamic Loading

At the starting design for the optimization the mass of the track is 45.3 kg. The results for the design variables are presented in a non-dimensional form (i.e. the value for a design variable equal to 1 represents the starting point). Each design variable is allowed to vary between 50% and 150% of its original value.

As stated previously, the MLS algorithm optimizes each discipline individually and then compares and manages design variable values at the top level. In order to identify the balance achieved by the MLS algorithm, results from the two discipline optimizations conducted separately are discussed first. The results for the design variables from the blast pressure optimization are summarized in Table 1.

t1	**t2**	**t3**	**t4**	**t5**	**t6**
0.5	0.5	0.5	0.82831	0.78663	0.56856
Total Mass	29.19 kg				

Table 1. Summary of Optimal Values for Design Variables under Single Discipline Blast Optimization

The design variables of the middle section all reach their lower limit of one half of the original thickness. This limit was set as part of the optimization problem definition. The physics of the distributed load are responsible for this behavior. The distributed mass of the wheel against the horizontal section of the track limits the stress that it is exposed to. The pin assembly, due to the external force holding the track in place, experiences much higher stress. The results for the maximum stress encountered in the blast discipline optimum design if analyzed under blast loading and under dynamic loading are summarized in Table 2.

	Maximum Stress of Initial Design	**Maximum Stress Constraint**	**Maximum Stress of Optimal Design**
Dynamic Load Discipline	3.950E8	4.740E8	**9.420E8**
Blast Load Discipline	5.186E8	6.400E8	**5.850E8**

Table 2. Maximum Stresses Encountered in the Blast Discipline Optimal Design under Blast Loading and under Dynamic Loading

The results in Table 2 show that the optimal design for the blast discipline meets the stress constraints for the blast survivability, but it exceeds the maximum stress constraint of the cyclic dynamic loading discipline by almost a factor of 2.

In a similar manner, Table 3 summarizes the values of the design variables when the track is optimized under dynamic loading considerations. In this case the rod, the ring, and the pin related design variables are reduced to their minimum allowed values, while the center section is increased above the thickness of the initial track model. The center portion of the track is subject to much higher stresses than the pin assembly because it acts like a bridge over the 'hole' that is simulated in the problem definition. The results for the maximum stress encountered in the dynamic discipline optimum design if analyzed under blast loading and under dynamic loading are summarized in Table 4. The results in Table 4 show that the optimal design for the dynamic discipline meets the stress constraints for the cyclic dynamic loading discipline, but it exceeds the maximum stress constraint of the blast survivability.

t1	**t2**	**t3**	**t4**	**t5**	**t6**
1.1516	0.66023	0.85776	0.5	0.5	0.5
Total Mass	37.043				

Table 3. Summary of Optimal Values for Design Variables under Single Discipline Dynamic Loading Optimization

	Maximum Stress of Initial Design	**Maximum Stress Constraint**	**Maximum Stress of Optimal Design**
Dynamic Load Discipline	3.950E8	4.740E8	**4.738E8**
Blast Load Discipline	5.186E8	6.400E8	**7.920E8**

Table 4. Maximum Stresses Encountered in the Dynamic Loading Discipline Optimal Design under Blast Loading and under Dynamic Loading

The MLS algorithm performs simultaneous optimizations of each discipline. Once each discipline has converged to an optimum, the optimum design variables are passed back to the top level. The two sets of design variables are managed at the top level, where a new set of design variables is generated for optimization at each of the discipline levels. This new set is a weighted average of the two sets of optimum variables that are passed up to the top level by the discipline level optimizations. The top level weights the new initial values towards the discipline that is improving the most rapidly. Table 5 summarizes the values for the design variables of the system level optimum, and Table 6 summarizes the results for the maximum stress in the dynamic discipline and in the blast simulation discipline.

t1	**t2**	**t3**	**t4**	**t5**	**t6**
1.0565	0.77448	0.95195	0.77458	0.65477	0.62844
Total Mass	40.059				

Table 5. Summary of Optimal Values for Design Variables under System Optimum

	Maximum Stress of Initial Design	**Maximum Stress Constraint**	**Maximum Stress of Optimal Design**
Dynamic Load Discipline	3.950E8	4.740E8	**4.480E8**
Blast Load Discipline	5.186E8	6.400E8	**6.070E8**

Table 6. Maximum Stresses Encountered in the System Level Optimum Design under Blast Loading and under Dynamic Loading

This optimum design meets the stress constraints for both disciplines and reduces material by 11.6% relative to the initial design. The fact that the maximum stress of the optimal design is so close to the constraint for both disciplines is an indication that the optimal configuration is not overdesigned. The optimization analysis has removed as much material as possible while satisfying the constraints of each discipline. It has also balanced the conflicting directions that each discipline is directing the selection of the design variables.

SUMMARY/CONCLUSIONS

The work presented in this paper demonstrates the power of multi-disciplinary optimization in solving vehicle design problems with competing requirements. The total mass of a typical track section has been optimized both for the dynamic cyclic loading originating from the operating conditions of the vehicle, and under blast survivability concerns. The optimal design has reduced the mass by 11.6% relative to the initial design. The optimal design satisfies the stress constraints stemming from the cyclic and blast load cases. High fidelity analysis tools were used in this optimization, guaranteeing a realistic and feasible optimal design. A MLS optimization algorithm was utilized for consolidating the solutions offered from the discipline level optimizations into a single optimum configuration.

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