Strategy to optimize the independent suspension system of an off-highway, agricultural tractor

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This article provides a more detailed discussion of the case study on the design optimization of the independent suspension axle of an off-highway vehicle (OHV) that was published in the summer edition of EnginSoft's *Newsletter* last year.

The purpose of the case study was to implement a design methodology that used multi-disciplinary simulation and an automated process to analyse thousands of product configurations and highlight vehicle performance distributions in terms of handling, comfort, and cost. This approach ensures that the best solution is always selected.

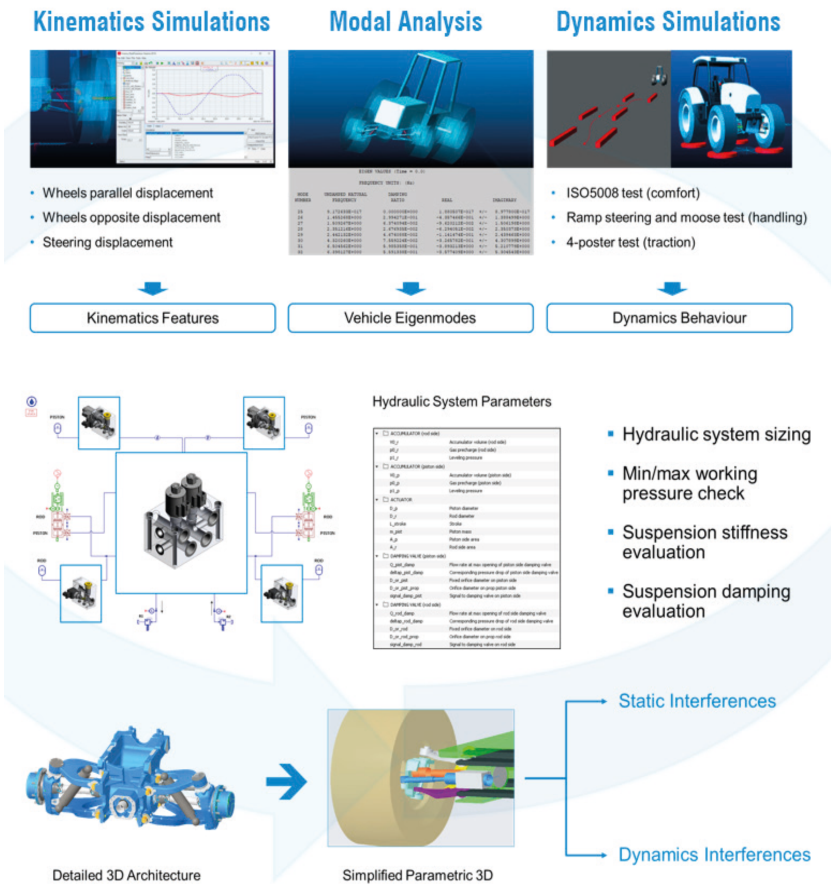

Fig. 1. Multiphysics representation.

Implementation of the methodology in modeFRONTIER

The methodology is suitable for any system integration project. In this case the kinematic configuration of the independent front axle and its hydraulic system, which ensures optimal stiffness

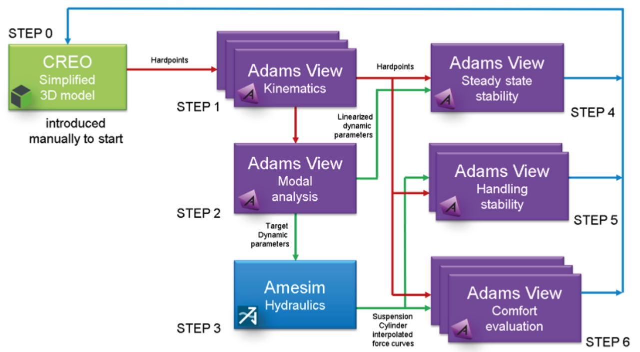

Fig. 2. Initial optimization workflow.

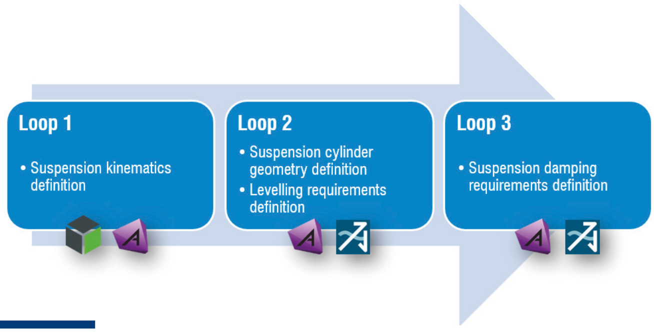

Fig. 3. Workflow split into three loops.

and damping of the axle, are integrated into the vehicle taking into account its specific geometry, mass, weight distribution, moments of inertia, and the characteristics of its tyres. In off-highway scenarios, the vehicle weight and weight distribution may vary according to the use of different agricultural equipment at the front, rear, or both of the vehicle, and the configurations analysed must consider all possible weight distributions. modeFRONTIER enables the entire system to be managed in a unique multi-environmental model using a workflow that includes a sequence of analyses from different software: Creo for geometry, Adams for the kinematics and dynamics, and Amesim for hydraulics. For each analysis, the workflow also contains: input variables (e.g. hardpoint coordinates, suspension stiffness and damping); objective functions (e.g. the vehicle's natural frequencies, comfort index, cost); and constraints (e.g. static and dynamic geometric interferences). Once all instructions are defined in the workflow, modeFRONTIER automatically performs the analysis and maps the objective functions for the configurations analysed, providing the Pareto frontier.

This methodology shortens development time and improves design efficiency and quality, allowing the best solution to be selected every time.

In this case study, the starting point was a 3D model of a specific design which was inserted into Creo manually. Adams was then used to check the kinematic characteristics of the model, evaluating parallel wheel displacement, opposite wheel displacement, and steering displacement. This was followed by a modal analysis of the entire vehicle using Adams to evaluate the vehicle's natural frequencies, which were entered into Amesim to size the hydraulic cylinders and accumulators. Once the kinematic and hydraulic parameters were defined, Adams calculated the vehicle's performance, assessing handling, comfort, and traction capability. This analysis was repeated for thousands of different configurations, yielding a distribution of the vehicle KPIs over the analysed configurations, and highlighting the Pareto frontier.

Due to the complexity of the model and the large number of input variables and objectives, many configurations were analysed, resulting in a long and inefficient process that was rather inaccurate. To solve these problems, the workflow was divided into three cycles or loops, each of which had fewer input variables, fewer objectives, and therefore fewer designs to evaluate than the initial workflow. As shown in Fig. 3, each loop represented the optimization of a certain aspect of the overall system.

This article will provide a detailed explanation of the strategy used to select the algorithms in loops 1 and 2, which make a significant difference to the results. But first we provide some background on loops 1 and 2.

Loop 1

Loop 1 begins by defining the hardpoints of the suspension kinematics and calculates their influence on the main kinematic parameters. Initially, the first hardpoints are entered manually.

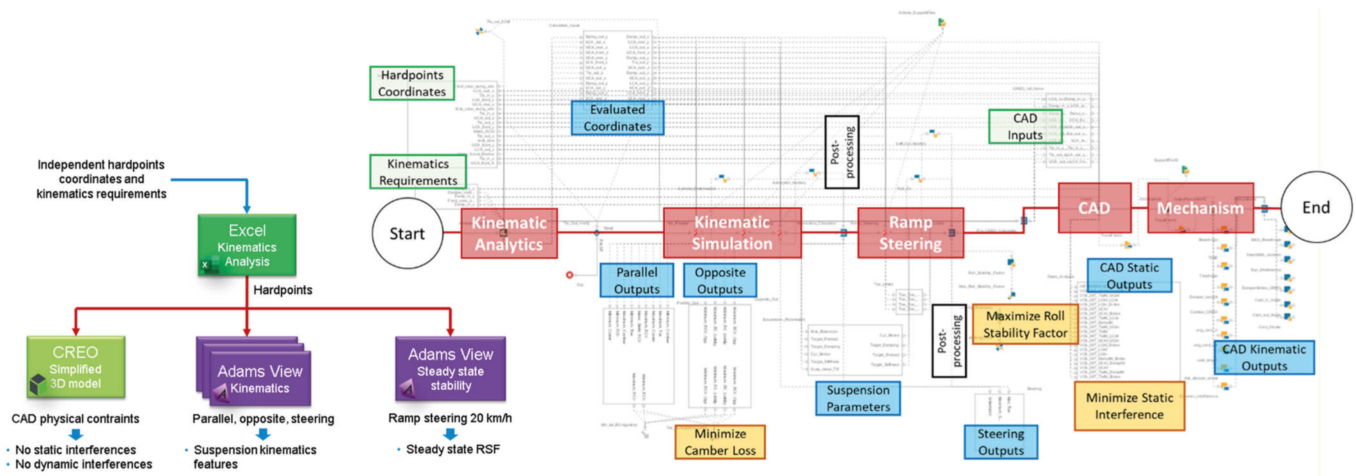

Fig. 4. Loop 1 workflow.

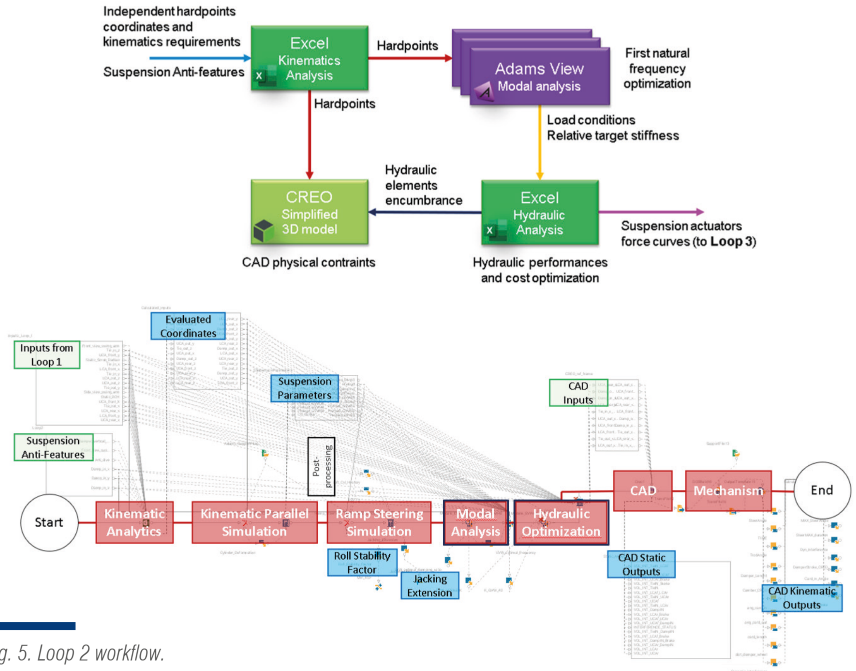

Fig. 5. Loop 2 workflow.

Adams received the 23 hardpoint coordinates as input variables and evaluated the kinematic performance of the axle.

The wheel displacements with parallel, opposed, and steered travel were evaluated and the minimum values of these kinematic characteristics together with the absence of static and dynamic interference formed the constraints. After a sensitivity analysis, camber loss minimization and roll stability maximization were selected as the objective functions.

The loop was repeated for thousands of configurations to obtain a distribution of the objective functions. The workflow concept for Loop 1 is illustrated in Fig. 4.

Loop 2

Using the optimized configuration of Loop 1 and considering stiffness and damping as input parameters, a modal analysis was performed to evaluate the geometry of the suspension cylinder and the stiffness value, as well as some hardpoint coordinates to minimize the natural frequency of the vehicle for each weight distribution. The natural frequencies determine the comfort of the vehicle. The results of Loop 2 are the design distributions with respect to the natural frequencies. The corresponding stiffness values are used to size the hydraulic circuit.

Strategy for Loop 1

First a design of experiments (DOE), DOE1, was calculated with the uniform Latin square (ULS) algorithm, which is based on the Monte Carlo method and it is used to generate a uniform distribution of designs for further optimization.

A statistical analysis was conducted with DOE1 to verify:

1. The correlation between input and output, within the input parameters, and within the output parameters (using the modeFRONTIER correlation matrix tool)
2. The influence between the constraints and the output (using modeFRONTIER's broken constraints tool).

This statistical analysis was used to reduce the number of constraints and relax the ones that most influenced and limited the output. We evaluated a new "DOE1 UPDATED" with fewer, relaxed constraints, but adding some objective functions to optimize certain kinematic parameters to obtain design solutions closer to the target. As a consequence, calculation time was reduced, and the number of feasible solutions was increased.

DOE1 UPDATED was then used for the optimization process, using the multi-objective algorithm MOGA which finds optimal solutions when there are multiple objectives.

The MOGA algorithm treats variables as discrete and considers constraints as penalty functions, favouring designs that least violate the defined constraints.

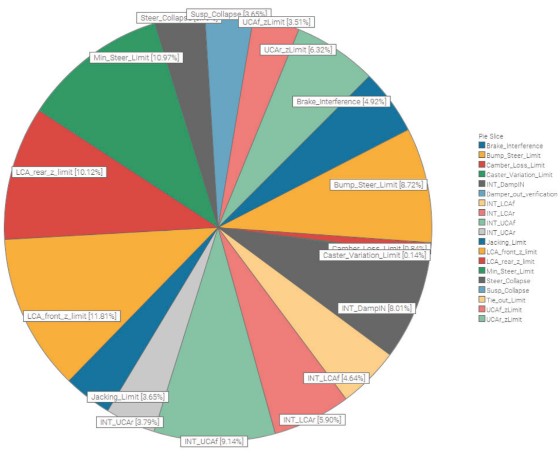

Fig. 6. Loop 1: influence of constraints on output.

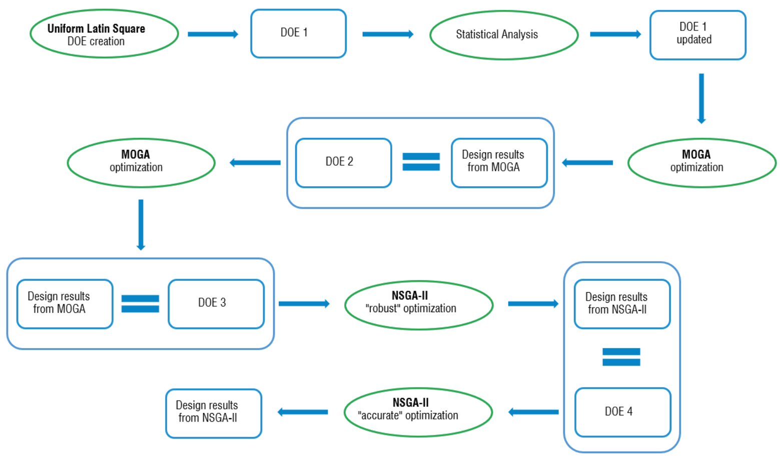

Fig. 7. Loop 1: optimization process diagram.

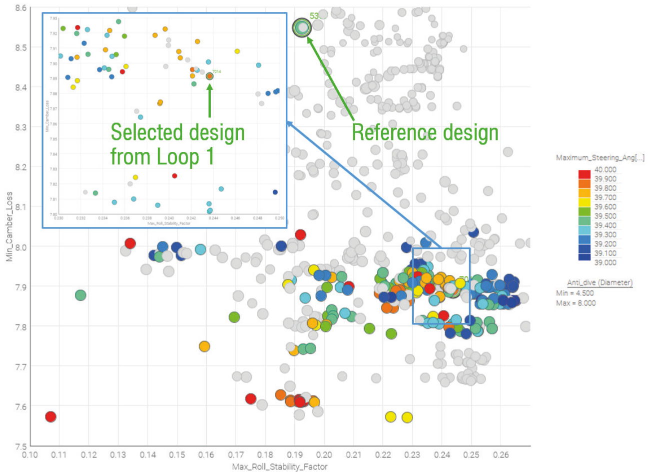

Fig. 8. Loop 1: design distribution output of the chosen and reference designs.

The design distribution of the first optimization process performed with MOGA was named "DOE2". This design distribution was used as the basis for further optimizations: starting from DOE2, however, the relaxed constraints were reset to their original values and the previously set objective functions were removed. A second optimization process was executed with MOGA that resulted in the definition of "DOE3".

The designs from DOE3 were good, but an additional step was taken to find even better results. Starting with DOE3, two further optimization processes were performed with the NSGA-II algorithm, which considers the variables constant and handles the constraints as objectives to be optimized. From DOE3, the first optimization with NSGA-II was executed using the robust setting to isolate designs with the global maximum of relevant objective functions, which were grouped into "DOE4". Then a second optimization was performed with NSGA-II but using the accurate setting to find the best designs within DOE4. At this point the results were considered satisfactory and the optimization process for Loop 2 was discontinued. An additional effort could have been made using gradient algorithms but the additional calculation time was not justified by the slightly improved output. Fig. 8 shows the results from Loop 1. It shows the design distributions with respect to camber loss and roll stability factor, including the steering angle (colour map) and anti-dive characteristics (circle diameter).

Strategy for Loop 2

The optimization process in Loop 2 was simpler: starting from the optimal design of Loop 1, the FAST algorithm was used at the main level, saving computational time. This algorithm defines the response surface by modifying the hardpoint coordinates and attempts to optimize the natural frequencies using a nested modal analysis that modifies stiffness and damping. The nested optimization process was performed using SIMPLEX, a heuristic algorithm that considers

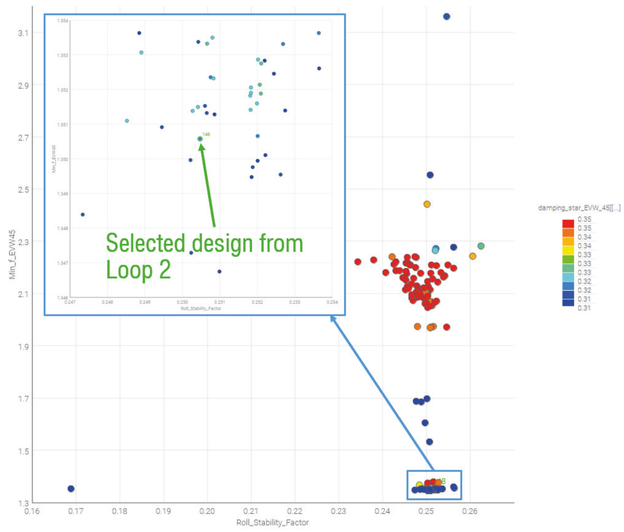

Fig. 9. Loop 2: design distribution output and chosen design.

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variables as discrete and guarantees robustness and accuracy. The aim of this optimization was to minimize the first natural frequency that had to be above a certain limit.

Fig. 9 plots the design distribution against the roll stability factor and the first natural frequency of the vehicle, while the colour represents the damping percentage. The design chosen, with the best compromise between the natural frequency of the vehicle, roll stability factor and damping percentage, is also highlighted.

Comparison with the reference design

The design configuration obtained with this approach can be compared with the reference design, which was defined previously using modeFRONTIER. Nevertheless, while the kinematic hardpoints of the suspension of the reference design were defined manually based on experience, the stiffness and damping were optimized using modeFRONTIER to improve vehicle performance by only changing the hydraulic sizing. The comparison is summarized in Table 1.

	Delta
Vehicle natural frequency	0.8%
Damping percentage	-6.7%
Roll stability factor	7.7%
Bump steering	-29.4%
Camber loss	-4.7%

Table 1. Optimized design vs. reference design.

While the first natural frequency is slightly higher, there is a major improvement in the other outputs: the damping ratio percentage is now optimal, roll stability increased by 7.7%, bump steer improved by 29.4%, and lastly camber loss improved by 4.7%.

Conclusions

From this article it can be concluded that it is very important to define the correct optimization strategy in modeFRONTIER in terms of types of algorithms and their sequence, as well as a good statistical analysis to understand the correlations between input/output variables. In fact, with a good strategy it is possible to significantly reduce calculation time and increase the design space, evaluating a larger number of potentially feasible options, which is the best starting point for further optimization processes. For example, moving from a robust to an accurate algorithm allowed us to first define a large number of designs using the robust setting to capture multiple global maxima, after which the accurate setting makes it possible to converge on the best ones.

In addition, moving from an algorithm that considers variables as discrete firstly and then as constant allows fine tuning to find the optimal solution. On the other hand, statistical analysis permits a better understanding of the physics of the problem through correlation between variables, important for reducing and relaxing certain constraints, with benefits for calculation time and number of designs. The result is very encouraging because through this process it was possible to find a design solution that was significantly better than the reference design (defined earlier with modeFRONTIER) in a reasonable calculation time.

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