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Multiobjective optimization framework for designing a vehicle suspension system. A comparison of optimization algorithms

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A R T I C L E I N F O

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A B S T R A C T

Recent advances in robotics and digital technologies in the automotive industry, allow the integration of vehicle systems with their virtual twins, thus facilitating their modelling and optimization. As a result, the systems design time and manufacturing costs are substantially reduced, while their performance, safety and fatigue life are expanded.

This work presents a multiobjective optimization framework for developing an optimal design of a front double wishbone vehicle suspension system based on a four-bar mechanism. This is carried out by coupling several computer-aided design tools (CAD) and computer-aided engineering (CAE) software. The 3D CAD model of the lower control arm of the suspension system is made using SolidWorks®, the Finite Element Analysis (FEA) of the suspension assembly is modelled using ANSYS® Workbench, while the multibody kinetic and dynamic of the designed suspension system is analysed using MSC ADAMS®. They are embedded in a multidisciplinary optimization design framework (modeFrontier®) with the aim of determining the optimal hardpoint locations of a lower control arm by minimizing the chassis pitch accelerations to improve the passengers' comfort, reducing the volume and mass of the suspension system to increase the vehicle stability and manoeuvrability, while decreasing the maximum stresses to extend the system fatigue life and enhancing safety.

The methodology has been successfully applied to several driving scenarios entailing different vehicle dynamics manoeuvres with the aim to find the Pareto optimal front, and to analyse the suspension assembly performance together with the vehicle dynamic behaviour. Results show that the use of such approach may significantly improve the design of the suspension system. Furthermore, a comparison of different optimization strategies and algorithms is performed.

1. Introduction

The automotive industry is experiencing an unprecedented period because of the adaptation to the digital transformation, green economy, sustainable development, and compliance with climate change targets and policies [1–6]. Furthermore, manufacturers are carrying out this transformation in the context of a highly competitive and changing marketplace, where vehicles are growing in complexity and rapidly changing. In this sense, the smart manufacturing era faces the challenge of combining maximum vehicle performance, comfort, environmentally friendly, quality and safety with minimum weight, cost, and design and production time [7–9].

The suspension system connects the vehicle body to the ground, so there is a transmission of forces and moments between them. Therefore, it directly influences the vehicle dynamic behaviour under the different operating conditions. Likewise, suspension systems play a key role in the vehicle performance since they are directly related to the comfort of passengers, safety, stability, manoeuvrability, amongst others. These can be conflicting goals, in which the achievement of one objective is impaired by the other, and the improvement and worsening of the vehicle performance must be counterbalanced [10,11].

The suspension system usually encompasses three main mechanical components. First, a structure that bears the vehicle weight and establishes the suspension geometry. Second, a spring that transforms kinematic into potential energy, and third a shock absorber, which is designed to dissipate kinetic energy [12]. The main function of the suspension is the vibration control of vehicle, which depends on the road surface. Vibration control reduces transfer oscillating movements of the

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vehicle axles to the frame. This protects the crew and the cargo transported from adverse shocks (passenger comfort) and maintains continuous contact tires with road (controllability and driving stability of vehicle). The suspension system connects the wheels to the vehicle body, allowing their vertical movement relative to the body, with the aim to reduce the noncyclic vibrations and transmit force and torque between them. They encompass vertical forces due to vehicle loads, longitudinal forces because of traction and braking forces, lateral forces as a result of centrifugal forces, and moments of longitudinal forces, which considers driving and braking moments [13].

Suspensions can be active or passive, although the latter are most widely used due to their simplicity, lower costs, and high reliability. Passive suspension systems in vehicles work with a series of springs and shock absorbers whose purpose is to reduce disturbances derived from the irregularities of the road. Therefore, they depend on the damping and stiffness coefficients. Active suspensions share the same purpose but using an onboard computer system that applies pressure to each wheel independently, rather than reacting like passive ones.

An exhaustive review of the theoretical foundations regarding vehicle suspension systems can be found in the literature [12], while vehicle dynamics problems regarding handling, stability and ride comfort is explained in [14–17]. The design of suspension systems and the optimization of parameters affecting the behaviour of the vehicle dynamics has also been tackled in the literature through different approaches [18,19]. For instance, using analytical equations and different optimization approaches such as evolutionary or genetic algorithms (e.g., [20–24]), or coupling different well-known packages such as vehicle dynamic packages and optimization framework (e.g., [25–27]).

Therefore, accurate numerical models of vehicle dynamics behaviour are needed to meet the expected quality standards for the manufacturing of the suspension system components. In this sense, this paper goes a step further in the current literature by presenting an efficient design of a suspension system by posing a multiobjective optimization problem with a wide range of explanatory and response variables while considering full vehicle kinematics and dynamics behaviour and several driving scenarios entailing different vehicle dynamics manoeuvres.

The rest of the paper is organized as follows. First, a brief description of suspension systems is presented, together with the key parameters affecting the vehicle dynamics and a literature review about how the design of a suspension system has been modelled is provided. Then, the methodology and the optimization framework are explained. Subsequently, the methodology has been successfully applied to different case studies, in which the optimization procedure finds a suitable compromise amongst the design variables, thus allowing to reduce development time and costs. Finally, a discussion of the results and conclusions are presented.

2. Materials and methods

2.1. Methodology

The design process of a complex suspension system requires extensive use of optimization-simulation tools, which allows to emulate real driving conditions in a virtual environment during the development phase. The results can be used to estimate the key parameters of the suspension system and their influence on the dynamic behaviour of the vehicle. In this sense, the developed methodology is intended to design a suspension system and determine the suspension parameters affecting the passenger's comfort, and vehicle handling and security.

The developed methodology considers the desired features that an efficient design of a suspension system should comprise:

- Independency: the movement of a wheel on one side of the axle is advisable to be independent from the other.
- Reliable camber control: it is the wheel angle about its longitudinal axle. A negative camber is advisable because it leads to an improvement in vehicle handling. Nevertheless, the convex shape of roads tends toward a positive angle to reduce tire wear. Because of surface irregularities and vehicle body roll, the angle will ultimately change. A well-designed suspension system can help to control this angle.
- Reliable body roll control: the hypostatical line that connects the rear and front suspension roll centers is named roll axis, on which the vehicle rolls during cornering maneuvers. Since the geometry of a suspension system influences the vehicle body roll motion and its lateral behaviour, an optimization of the location of the roll axes is advisable.
- Great structural efficiency: the suspension system should properly handle the vehicle weight and the applied moments and forces. For that, an efficient transfer of mechanical loads from the suspension system to the vehicle body is desirable.
- Satisfactory isolation: the suspension system is intended to improve the ride quality and isolating surface road irregularities.
- Low weight: the suspension system mass should be minimized by means of optimal designs and/or lightweight materials to reduce the transmitted shocks to the vehicle body, and hence, improve the ride quality. This is because the kinetic energy of a suspension system is proportional to its mass.
- Long fatigue life of all components: a durable suspension system design should resist all sorts of damages, wear, and pressure.
- Low cost: an appropriate balance regarding the suspension systems costs between the more high-performance and the affordable systems should be determined for each vehicle range, which depends on the quality of the materials, number of bushings, etc.
- Other considerations: suspension system features should also take into account anti-dive (where the front of the vehicle dips and the tail rises) and anti-squat (opposite action) phenomena, which take place during the breaking and acceleration processes, respectively. Although these phenomena are slight, the human body is highly sensitive to pitch motion, so that the mitigation of this rotational movement is recommendable to increase the passengers' comfort.

To tackle all these considerations the methodology poses a multiobjective optimization framework for determining the optimal parameters of a vehicle suspension system. It involves the geometry characteristics and material properties of a suspension system, the full vehicle kinematics and dynamics behaviour, the structural analysis of main components of the suspension system, and a vibration analysis for an efficient design of a front double wishbone vehicle suspension system based on a four-bar mechanism.

The flowchart diagram of the optimization framework is shown in Fig. 1. It displays how the different computer-aided design tools (CAD) and computer-aided engineering (CAE) software are coupled, and depicts the flow of information and connections about them. The methodology comprises a 3D CAD model of the lower control arm of the suspension system, which is made using SolidWorks®; a Finite Element Analysis (FEA) of the suspension assembly modelled using ANSYS® Workbench; and a multibody kinematic and dynamic analysis of the designed suspension system is performed using MSC ADAMS/Car®. SolidWorks allows to design the geometry of the suspension system and determine its mass and volume. ADAMS/Car creates a virtual vehicle prototype and allows to model the kinematic and dynamics characteristics of all their subsystems and assemblies. This software package relies on default or users' built templates that can be further modified to change the parametric data and to create suspension or full-vehicle assemblies, which are combination of coupled subsystems. For a suspension system the template depends on the topology of hardpoints, and spring, bushing stiffness, and damping properties. In the present methodology, ADAMS/Car is used to determine the chassis pitch acceleration and mechanical loads (forces and momentums) that are applied to the lower control arm of the suspension system. Subsequently, these loads are transferred to ANSYS to estimate the maximum von-Mises

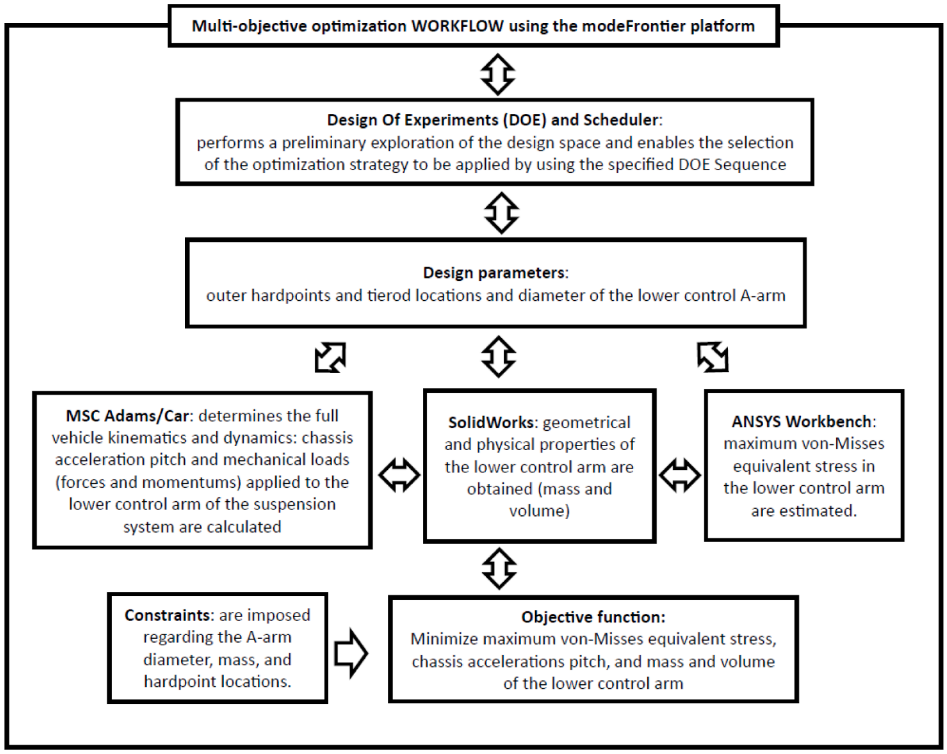

Fig. 1. Flowchart diagram of the optimization framework.

equivalent stresses (SEQ).

Eventually, these tools are embedded in a multidisciplinary optimization design framework (modeFrontier®) with the aim of determining the optimal hardpoint locations of a lower control arm of a suspension system based on a four-bar mechanism by minimizing: a) chassis pitch acceleration to improve the passengers' comfort, b) volume and mass of the lower control arm of the suspension system to increase the vehicle stability and manoeuvrability; c) maximum von-Mises equivalent stresses to extend the system fatigue life and enhancing safety. The layout of the optimization framework implemented in modeFrontier is shown in Fig. 1.

Hardpoints are locations at which suspension components are attached to the vehicle body and play a major role in the vehicle kinematic and dynamics characteristics. This is because they determine certain parameters such as angles associated with wheel alignments (i.e., camber, caster, toe), scrub radius, king-pin inclination, etc. The optimization of the hardpoint locations of the suspension system is justified with the aim of improving the vehicle handling, which is more than stability. The vehicle should smoothly respond to the driver's commands (i.e., steering, braking, and accelerating) in a predictable way. Suspension systems can influence vehicle handling in different ways, e.g., by minimizing the vehicle pitch and roll motion, controlling wheels angles, and decreasing lateral load transfer while cornering.

An objective of the optimization problem is to minimize chassis pitch acceleration, since lower acceleration correspond to higher ride comfort. Significant parameters affecting the suspension system are the spring and shock absorber coefficients and the sprung mass. The minimization of the chassis pitch acceleration is justified in order to increase the ride comfort (RC), which seeks to minimize the shocks experienced by passengers and that are due to road surface irregularities, aerodynamic forces, and lateral or longitudinal load transfer due to dynamic processes of the vehicle, for instance, during braking. There are also inner vibration sources because of the vehicle engine and transmission. Therefore, the minimum is the sprung mass acceleration, the maximum is the ride comfort. RC is defined by the ISO 2631–1–1997, which prevents passengers from many harmful effects on body due to vehicle vibrations. They cover disorders of the back like back pain, hyperventilation, osteoarthritis, slipping of disc, etc. [11]. According to this standard RC depends on root mean square (RMS) values of the sprung mass acceleration and the frequency of vibrations acting on body. These frequencies can be classified within a health and comfortable range (0.5–80 Hz) and harsh or motion sickness (0.1–0.5 Hz). On the other hand, the vehicle tire ability to stay in contact with the road terrain is known as road holding (RH).

2.2. Optimization approaches comparison

Optimization approaches can be sorted as either local (generally gradient based) or global (generally non gradient based or evolutionary) algorithms. This paper also compares results amongst several optimization procedures, which comprise heuristics optimizers, evolutionary algorithms, multistrategy optimizers, and gradient-based algorithms. Nevertheless, it should be taken into account the serious challenges when comparing the performance of such optimization approaches. Hence, the comparison has been carried out following the recommendations of in the specialized literature [28].

For the sake of conscience, subsequently is presented a brief description of the optimization techniques, even though an exhaustive explanation is available, for example, in [29].

Evolutionary algorithm (EA) is a general term that comprises population-based stochastic direct search approaches, which make use of mechanisms inspired by biological evolution, including reproduction, recombination, mutation, and selection. As an advantage, these techniques do not need any gradient information and generally make use of a set of design points (i.e., a population) to find the optimum set of values. Contrary, the disadvantages cover inadequate constraint-handling capabilities, high computational cost, ad hoc parameter tuning for each problem, limited problem size, and may lead to a hasty convergence to a local optimum. These approaches start by randomly generating an initial population of individuals. In the optimization problem candidate solutions imitate the role of individuals in a population. Next, for each individual an evaluation of the fitness in that population is carried out (for instance, in terms of time limitation, sufficient fitness attained, etc.). Then, various regenerational steps are replicated until termination, which include the selection of the best-fit individuals for reproduction (i.e., parents), the breed of new individuals through crossover and mutation operations leading to offspring, the appraisal of the individual fitness of such individuals, and the replacement of the least-fit population with additional ones. EAs are suitable for all kinds of problems as it allows for any assumptions about the underlying tuning landscape. This allow EA approaches to be applied to complicated optimization problems, encompassing those with high dimensionality, strong nonlinearity, multimodality, and no differentiability, or with the existence of noise and time dependant functions.

Several EA algorithms are applied in this paper, which cover the nondominated sorting genetic algorithm (NSGA-II), the multiobjective genetic algorithm (MOGA-II), evolution strategies (ES) and the adaptive range multiobjective genetic algorithm (ARMOGA).

Heuristic methods are intended to solve optimization problems more quickly than classic methods, which fail to find an exact solution or are excessively slow. In this regard, these algorithms trade accuracy, optimality, precision, or completeness for speed. Optimality implies the ability to attain the best solution, while completeness stands for the capability to determine all feasible solutions for a given problem. These techniques establish a heuristic function, which ranks the different alternatives in the search algorithms at each branching step depending on the available information to figure out which branch to follow. Heuristic methods find a similar problem already solved and determine both the technique used for its resolution as well as the solution obtained.

As a result, these techniques lead to an approximate solution in a reasonable time that is adequate to solve the problem at hand, even though the best solution may not be reached. Hence, these methods present the disadvantage in deciding whether the obtained solution is good enough, since their theoretical underlying is not very sophisticated. These optimizers are suitable in problems with imperfect, incomplete information, or limited computing capacity. Additionally, they are also suitable when used in conjunction with other techniques to improve their efficiency, for example, to generate appropriated seed values. amongst the different types of heuristics methos, we have used the multiobjective particle swarm optimization (MOPSO), which is based on the social behaviour of bird flocking, and multiobjective simulated annealing (MOSA).

Multistrategy algorithms combine the strengths of several approaches to enhance their performance. This study applies some of these optimizers. Firstly, the multiobjective efficient global optimization (MEGO) algorithm, which is an optimization surrogate-assisted technique based on Gaussian procedures. These algorithms find the global optimum by means of the achievement of an infill criterion for choosing search designs. MEGO is a steady-state algorithm, and hence, it usually saturates the available threads. They use It uses a restraint management technique based on the probability that the design is feasible.

Secondly, the FAST algorithms use response surface models (RSM) (i.e., meta-models) to speed up the optimization process. Thirdly, the HYBRID algorithms combine the global exploration capabilities of genetic algorithms with the accurate local exploration assured by sequential quadratic programming (SQP) procedures.

Fourthly, the pilOPT approaches represent a multistrategy self-adapting techniques that integrate the advantages of global and local search algorithms. The optimal Pareto front is constructed by adjusting the ratio between real and RSM-based (i.e., virtual runs based on Response Surface Methodology) design evaluations on account of their performance. They provide a suitable performance in spite of handling complex output functions and restrained problems. It is usually recommended for multiobjective problems, but it can also handle single-objective problems. It is advisable to deal with both continuous and discrete variables. Instead, it is no able to manage categorical variables. Another advantage is that only one parameter is needed, which refers to the number of design evaluations. In this way, the algorithm stops when this number is reached.

Gradient-based optimization algorithms are iterative techniques in which search directions are established by means of the gradient information of the objective function in the successive iterations. They provide insight regarding the behaviour of a function (i.e., the shape of the surface), such as extremes in the parameter space and steepness. This may lead to a drastic reduction of the convergence of the search algorithm. However, this information is generally not available. This work relies on the Mixed Integer Programming Sequential Quadratic Programming (MIPSQP), which makes use of sequential quadratic programming (SQP) and allows to solve mixed integer optimization problems. SQP is an iterative technique for restrained nonlinear optimization problems, in which the objective function and the restrains are twice continuously differentiable. Additionally, the Levenberg–Marquardt algorithm is used, which is highly recommended to minimize the sum of squares of nonlinear functions. Table 1 provides a comparison of these optimization approaches with regard to their main features, advantages, and disadvantages. The comparison of these approaches is carried out using the modeFrontier platform, which allows an easy integration of the different CAD/CAE tools within the framework of optimization environment.

3. Application of the methodology to case studies

The methodology has been successfully applied to two case studies consisting of different vehicle driving scenarios, in which the optimization procedure finds a suitable compromise between the design variables, thus allowing to reduce development time and costs, while improving ride comfort and vehicle performance. The case studies are based on the front double wishbone suspension system of a full vehicle assembly of the MSC Adams Car software package, which is a multibody modelling and simulation environment. The first virtual test analysis entails a driving scenario carried out during a straight-line braking event (S1), while the second driving scenario implies a braking in turn event (S2). In both scenarios a chassis acceleration pith occurs. Table 2 shows the parameters used during such events.

The analysis focuses on the hardpoints locations (x, y, z coordinates) of the outer left lower control arm and the corresponding tierod, since they are the most influential parameters in the vehicle dynamics behaviour and in order to avoid overparameterization problems, which may lead to convergence difficulties and high correlations of the

Table 1
Comparison of optimization approaches.

Approach	Features	Advantages	Disadvantages
Evolutionary algorithms	Mechanisms inspired by biological evolution	Global search, robustness, flexibility and adaptability, applicable to complex problems	Computationally demanding, needs a specific setting of parameters, premature convergence to a local minimum
Heuristics methods	Partial search procedure that leads to acceptable solutions	Fast, appreciate in cases of incomplete or imperfect information	Low accuracy and completeness
Multistrategy algorithms	Combine strengths of several approaches	Global optimum	Those of the approaches on which they are based
Gradient-based optimizers	Iterative techniques in which the search directions are obtained using the gradient information of the objective function	Reports information regarding the shape of the objective function surface	Computationally demanding, local minima

Table 2
Parameters used in the driving scenarios, which are based on a straight-line braking (S1) and a braking in turn (S2) event.

Parameters for Scenario S1	Values	Parameters for Scenario S2	Values
Event simulation time	5.0 s	Lateral acceleration	0.4 g
Number of steps	50	Turn radius	30 m
Initial velocity	100.0 km/h	Brake deceleration	0.1
Deceleration	0.5 m/s^2	Max brake duration	2 s
Gear position	5	Gear position	2
Brake ratio	0.55		
Front brake maximum torque	1.7E+06 N·mm		
Rear brake maximum torque	1.0E+06 N·mm		
Maximum roll angle	90.0 deg		
Steering ratio	27.6		
Rack ratio	174.5		

estimated parameters (Fig. 2).

The damping and spring physical properties of the suspension system are shown in Figs. 3 and 4, respectively.

Some constraints in the multiobjective optimization problem are imposed regarding the A-arm diameter, mass, and hardpoint locations. In fact, the optimization process allows to modify the initial guess of the parameter set, as presented in Table 3, within a range of 7% to maintain a good vehicle handling and stability and not to interfere with the frame and other vehicle systems. This has been implemented as restrictions in the optimization problem. It is worthwhile to mention that the optimization procedure of the suspension system has been carried out to withstand the maximum mechanical loads as calculated by ADAMS/Car. Additionally, the optimization problem gives equal weights to the three objectives.

Eventually, using the modeFrontier platform a Design Of Experiments (DOE) has been defined to perform a preliminary exploration of the design space and a selection of different optimization strategies are applied by using the specified DOE sequence. For each optimization strategy and driving scenario a total of 500 runs are obtained.

Fig. 5 shows a scatter plot of the parameter values used in the optimization process regarding the outer hardpoint locations of the left lower control arm and the tierod. Parameters present a large parameter dispersion, which allows to sweep the entire design space during the optimization process and reach the global optimum.

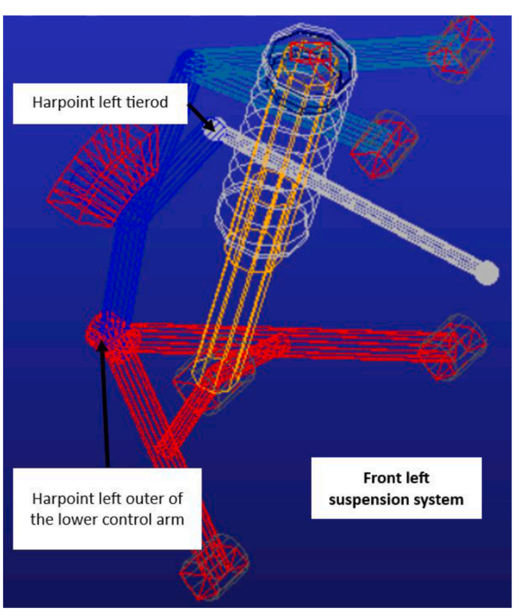

Fig. 2. Selected parameters for the optimal design of a front suspension system.

4. Results and discussion

A total of 500 simulation runs for each optimization method have been obtained for each driving scenario. In all cases, a large percentage of feasible simulations of around 98% was achieved, with only 2% of error runs.

The proposed methodology provides a Pareto-optimal front, which consists of a set of non-dominated solutions that optimize the three objectives in the posed multi-objective optimization problem, which encompass the chassis pitch acceleration, and mass and maximum equivalent stress in the lower control arm of the suspension system. Fig. 6 depicts for scenario S1 a scatter 3D plot with the globally Pareto-optimal front of the entire feasible search space of the objective function. The results are presented for the PilOpt algorithm due to the fact that it provides the better results as discussed below. Therefore, there is no solution that is better on all goals than those represented in the Pareto optimal front, i.e., it illustrates a set of non-dominated solutions with diverse trade-offs between the conflicting goals. Hence, a change in the vector of the design variables could not improve all goals simultaneously in comparison to the set provided by the Pareto optimal front, thus worsening at least one objective. In other words, the Pareto optimal front focus the attention to a set of efficient choices, and to assess the trade-offs within this set, rather than considering the full range of each parameter.

The results of the dynamic vehicle analyses between the optimized and non-optimized suspension systems have been compared. On the one hand, Table 3 presents the initial and optimized coordinates of the hardpoints locations of the outer left lower control arm (lca) and the corresponding tierod for the two driving scenarios. On the other hand, Fig. 7 illustrates for scenario S1 that the optimized objectives lead to a reduction with regard to the non-optimized designs of up to 22.46% for the control arm mass, 21.88% for the maximum equivalent stress, and 17.20% for the chassis pitch acceleration. In this sense, the developed multiobjective optimization framework has found the best compromise solution for an optimal design of a suspension system by considering several conflicting objectives and constraints related to its geometry, physical properties, and kinematics and dynamics characteristics. Furthermore, it allows to simultaneously optimize the vehicle handling, stability, and ride comfort design variables.

The simulation results also present an adequate degree of precision while the behaviour of the real vehicle has been adequately modelled. Note that the simulation of the vehicle kinematics and dynamics has been performed seeking a compromise between the level of detail of the model and the computational cost and quality of the results, thus avoiding overparameterization problems due to inadequate knowledge of parameters.

It is worthwhile measuring the linear relationship between the objectives. A moderate Pearson correlation of 0.455 is detected between the maximum equivalent stress and chassis pitch acceleration, while a low correlation is presented between the maximum equivalent stress and the lower control arm mass (0.076), and between the chassis pitch acceleration and the lower control arm mass (0.004). Note that there is a perfect correlation between the volume and the mass of the control arm due to its geometry and uniform density, which leads to a joint minimization of both design variables for the same set of parameters.

Response surface methodology (RSM) allows to examine the correlations between several explanatory variables and one or more response variables. Fig. 8 shows the application of a statistical approach named as the response surface methodology (RSM) for exploring the relationships between explanatory variables (hardpoints locations) and one of the objectives (maximum von-Mises equivalent stresses reached in the left lower control arm of the suspension system). RSM allows to deal with complex real-world systems while reducing the computational cost and the number of simulations needed to reach the global optimum. This is because RSM, instead of relying on real-physics models (which are unaffordable in terms of computational time), is based on dataset in order

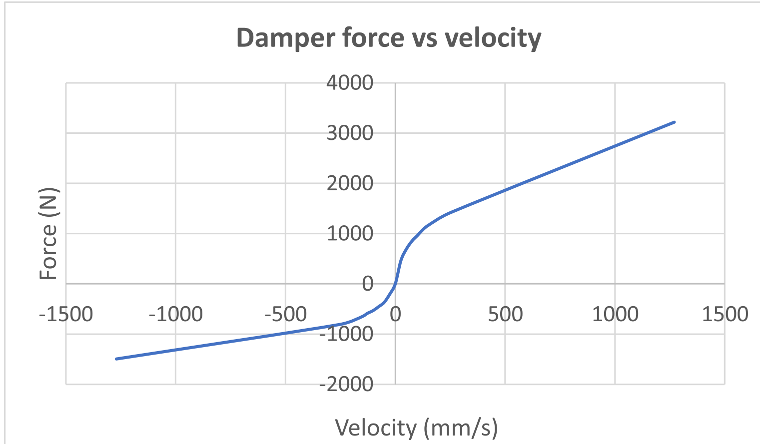

Fig. 3. Damper force vs velocity of the front suspension system.

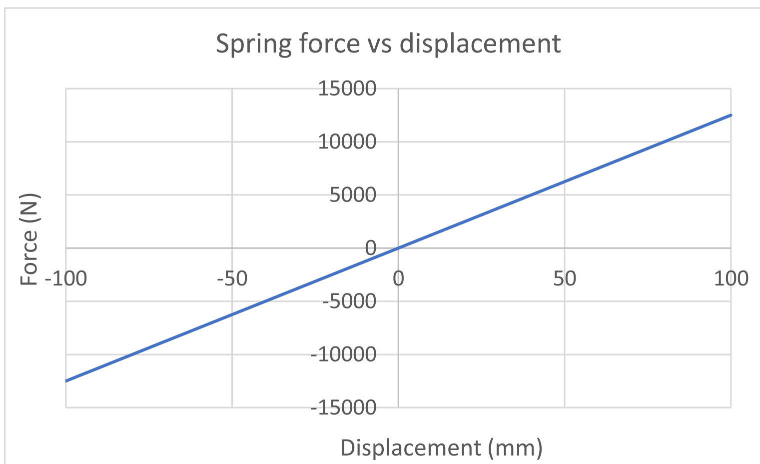

Fig. 4. Spring force vs velocity of the front suspension system.

Table 3
Initial and optimized hardpoints locations of the outer left lower control arm (lca) and the corresponding tierod for the two driving scenarios. The initial guess of the parameter set is allowed to change within a 7%, which has been implemented as restrictions in the optimization problem.

Parameter (coordinates)	Initial guess (mm)	Optimized hardpoint locations for scenario S1 (mm)	Optimized hardpoint locations for scenario S2 (mm)
X lca_outer	267	280.35	272.84
Y lca_outer	−750	−787.50	−787.50
Z lca_outer	130	129.15	136.50
X tierod_outer	417	437.85	396.15
Y tierod_outer	−750	−712.50	−713.08
Z tierod_outer	330	313.50	318.65

to predict system response to an unknown configuration and carry out a virtual optimization. This methodology through Machine Learning algorithms makes possible to develop a quick and effective meta-model based on dataset that allows to validate its accuracy and carry out a reliable RSM-based optimization. Therefore, using RSM as a surrogate model allows to explore the design space using appropriate Design Of Experiments (DOE) and perform the optimization process faster with a limited number of designs.

Additionally, a comparison of different optimization strategies and algorithms is performed. Moreover, it allows to obtain accurate results in finding the Pareto-optimal front of the problem in hand, while overcoming the possible drawbacks of each optimization procedure. The optimization approaches can be categorized as either local (generally gradient based) or global (generally non gradient based or evolutionary) algorithms. This work compares the results between several optimization methods, which encompass heuristics optimizers, evolutionary algorithms, multistrategy algorithms, and gradient-based optimizers. Nevertheless, it is worth to mention the challenges in comparing the performance of the different optimization algorithms [28,30]. Because of that this work follows the recommendation reported in the literature to carry out the comparison. The best results for the multiobjective optimization problem were achieved through the PilOpt algorithm as shown in Table 4. It provides minimum objective values, as well as short computing time, fast convergence, greatest number of feasible solutions and great diversity of solutions. This is because the pilOPT algorithm integrates the capabilities of local and global search algorithms. When searching for the Pareto-optimal front the algorithm adjusts the ratio between real and virtual RSM-based design evaluations on account of their performance. Additionally, it avoids complex parametrization since it relies only on one parameter. It should be noted that the values of Table 4 belong to the Pareto-optimal front, which depicts a trade-off between objectives. Moreover, some approaches lead to similar results to those obtained with the pilOPT algorithm, such as the MEGO strategy. Finally, it is worth mentioning that the computation time required to perform 500 simulations with a Core i5 processor with a clock speed of 2.90 GHz and 8 GB of RAM is around 12 h.

Table 5 compares the results of both driving scenarios for the pilOPT

Fig. 5. Scatter plot of the parameter values used in the optimization process regarding the outer hardpoint locations of the left lower control arm and the tierod, in which the dimensions are expressed in mm.

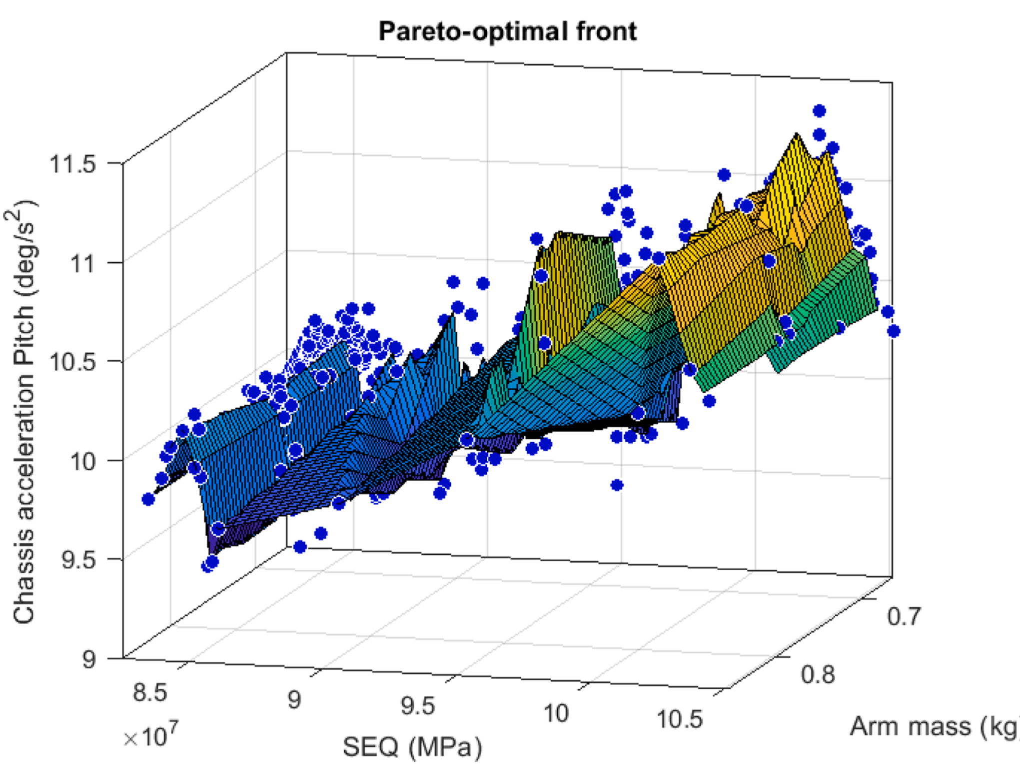

Fig. 6. Pareto-optimal front set for scenario S1 showing the feasible solutions for the three objectives, which encompass the chassis pitch acceleration (deg/s^2), mass (kg) and maximum equivalent stress (MPa) in the lower control arm of the suspension system.

algorithm. Similar conclusions can be derived from both vehicle maneuvers, but due to the different dynamic situations to which the vehicle is subjected in each driving scenario, disparate results are obtained regarding the hardpoint locations (Table 3) and objectives (Table 5). In this way, the optimal values for the hardpoints locations, arm mass and chassis pitch acceleration are quite similar. Contrary the optimal maximum von-Mises equivalent stress obtained for S2 is less than for S1, since the dynamics loads that appear for this vehicle manoeuvre are less demanding for the lower control arm. Eventually, a good compromise between the design variables for all possible vehicle maneuvers and dynamic behaviors should be selected.

5. Conclusions

A multi-objective optimization framework for an optimal design of a suspension system has been developed, which integrates well proven simulation tools and considers many design variables, objectives, and constraints. This approach simultaneously considers for the design of key suspension parameters, the vehicle stability, handling, and ride comfort, as established in standardized test procedures. In this sense, the

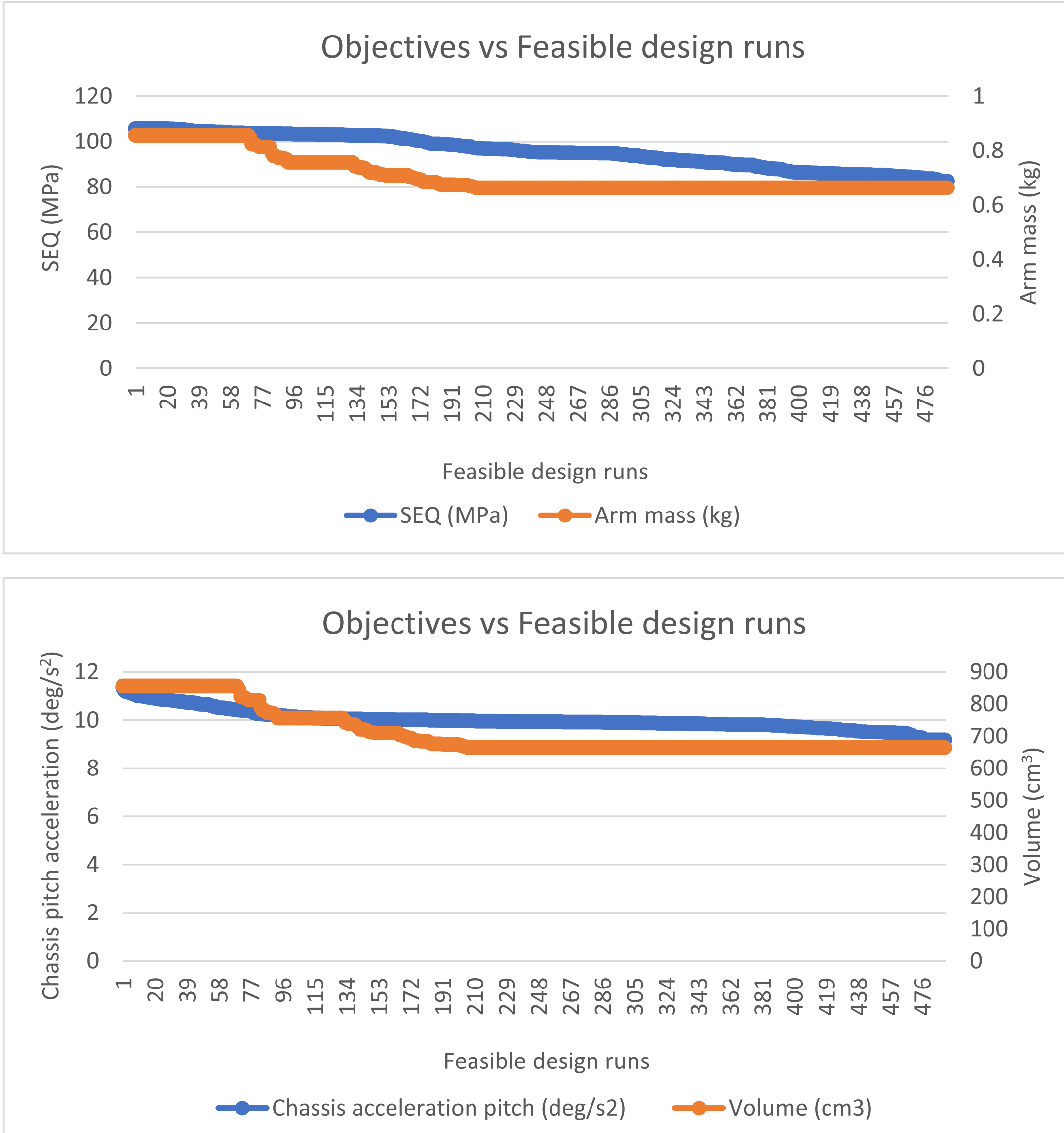

Fig. 7. Optimal values of the objectives achieved for the 500 design runs for scenario S1 (up: mass and maximum equivalent stress (SEQ) in the lower control arm of the suspension system; down: chassis pitch acceleration, and volume).

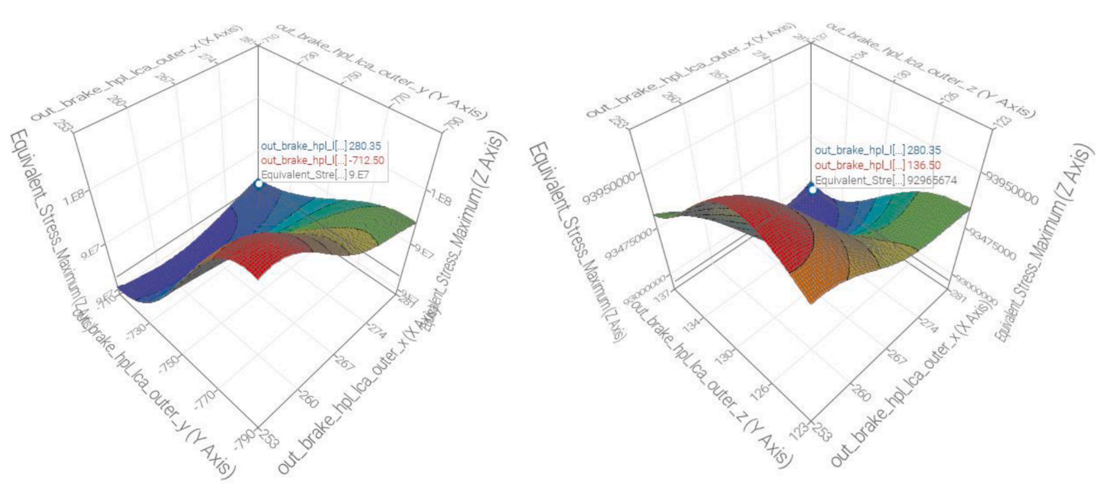

Fig. 8. Response surface methodology (RSM) for exploring the relationships between explanatory variables (hardpoints locations) and the objective related to the maximum von-Mises equivalent stresses reached in the left lower control arm of the suspension system.

Table 4
Comparison for scenario S1 of the different optimization approaches for the minimum values reached of the objectives.

Objectives / Algorithms	Arm mass (kg)	Maximum von-Mises equivalent stress (SEQ) (MPa)	Chassis pitch acceleration (deg/s^2)
Evolutionary algorithms			
NSGA-II	0.708	89.438	9.509
MOGA-II	0.711	85.736	9.350
ARMOGA	0.776	88.347	9.683
Evolution strategies	0.744	89.593	9.464
Heuristics optimizers			
MOSA	0.733	85.751	9.793
MOPSO	0.633	85.976	9.510
Multistrategy algorithms			
HYBRID	0.685	86.476	9.604
pilOPT	0.663	82.526	9.170
FAST	0.745	86.416	9.384
MEGO	0.663	82.527	9.420
Gradient-based optimizers			
NBI-AFSQP	0.702	87.226	10.170

Table 5
Optimal solution using the pilOPT algorithm for both driving scenarios.

Driving scenario / Objectives	Arm mass (kg)	Maximum von-Mises equivalent stress (SEQ) (MPa)	Chassis pitch acceleration (deg/s^2)
S1	0.663	82.526	9.170
S2	0.663	8.869	10.245

optimization environment considers a wide range of design variables, which comprise geometry characteristics and material properties of the suspension system, the full vehicle kinematics and dynamics behaviour, the structural analysis of main components of the suspension system, and a vibration analysis.

The methodology has been successfully applied to different driving scenarios to analyse the suspension assembly performance and the vehicle dynamics behaviour. Furthermore, different optimization strategies were compared with the aim of finding accurately the Pareto-optimal front of the multiobjective problem. Results have shown that the efficient optimization approach presents a suitable degree of accuracy and allows to reduce the suspension system design time and manufacturing costs, while their performance, safety and fatigue life are expanded. In addition, a great convergence, diversity of solutions, and percentage of feasible solutions are obtained for all optimization approaches, which allows to find the Pareto optimal front. This set of nondominated solutions allows to efficiently assess the suspension system performance and analyse the trade-offs amongst the design parameters. It shows how a different combination of such parameters may lead to highly contrasting results in terms of vehicle stability, handling, and ride comfort, which proves the worth of the methodology for significantly improving the design of a suspension system. Specially, if the developed optimization framework is compared with conventional simulation engineering approaches for vehicle development.

In this way, the proposed optimization methodology has proven to be an exceptional support tool to help designers in the determination of the set of parameters that best fit the suspension system to provide the desired dynamic behaviour. The optimal parameter set provides higher performance and a smooth and comfortable ride to the passengers by balancing several competing factors. Therefore, the proposed optimization framework is an effective tool for the optimal design of passive suspension system parameters. Furthermore, the proposed framework allows flexibility in the choice of the trade-offs between the design solutions.

As further research, other suspension system parameters could be considered, and a sensitivity analysis of their influence on the vehicle dynamics might be carried out. Moreover, other tests could be analysed to assess a specific dynamic behaviour of a vehicle, since each vehicle manoeuvre requires the evaluation of diverse dynamic characteristics. This will allow to select the better compromise between the design variables for all possible vehicle manoeuvres and dynamic behaviours. Finally, it is worth mentioning that the methodology presented can be easily extended to other vehicle systems, such as the transmission, steering or braking system. Furthermore, it can be extended to the design of any mechanical system. The only limitation lies in the difficulty of properly modelling with CAD/CAE tools its geometric and material properties, kinematics, and dynamics of the mechanism, together with the boundary conditions applicable to each specific problem.

Data availability statement

The data that support the findings of this study are available on request from the corresponding author.

CRediT authorship contribution statement

Carlos Llopis-Albert: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Visualization, Supervision. **Francisco Rubio:** Methodology, Validation, Investigation, Writing – original draft, Visualization. **Shouzhen Zeng:** Software, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Visualization.

Declaration of Competing Interest

The authors declare no conflict of interest.

Data availability

Data will be made available on request.

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