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MULTI-OBJECTIVE OPTIMIZATION MODEL IN THE VEHICLE SUSPENSION SYSTEM DEVELOPMENT PROCESS

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Original scientific paper
In order to improve conceptual phase of vehicle development, this research is focused on development of new multi-objective optimization model for determining the optimal parameters of the suspension system. In this research emphasis is on the development of suspension system from the viewpoint of full vehicle dynamics behaviour. The new optimization model consists of the integration of fast simulation tools with a suitable degree of accuracy for analysis of suspension system kinematics and analysis of vehicle dynamics into multi-objective optimization environment. The necessary steps that proceed to development of optimization model are identification of influence parameters, definition of criteria for the evaluation of vehicle dynamic characteristics in different test procedures and selection of multi-objective optimization algorithms, primarily contemporary evolutionary algorithms. In comparison of the algorithms, the best results in terms of convergence, number of solutions, short computing time and Pareto front approximation were achieved with the FMOGA-II algorithm.

Keywords: *evolutionary algorithms; multi-objective optimization; suspension system parameters; vehicle dynamics*

Višekriterijski optimizacijski model u razvoju ovjesa vozila

Izvorni znanstveni članak
U cilju unapređenja konceptualne faze razvoja vozila, ovo istraživanje je usmjereno na razvoj novog višekriterijskog optimizacijskog modela za određivanje optimalnih parametara ovjesa vozila. U ovom istraživanju naglasak je na razvoju ovjesa vozila promatrano kroz dinamičko ponašanje kompletnog vozila. Novi optimizacijski model temelji se na integraciji brzih simulacijskih alata s zadovoljavajućom razinom točnosti za analizu kinematike ovjesa i dinamiku vozila unutar okruženja za višekriterijsko optimiranje. Nužni koraci koji prethode razvoju optimizacijskog modela su identifikacija utjecajnih parametara, definiranje kriterija za ocjenu dinamičkih karakteristika vozila u različitim ispitnim procedurama i odabir višekriterijskih optimizacijskih algoritama, prvenstveno suvremenih evolucijskih algoritama. Usporedba optimizacijskih algoritama pokazala je da se najbolji rezultati u pogledu konvergencije, broja mogućih rješenja, trajanja računanja i približavanja Pareto fronti postižu s FMOGA-II algoritmom.

Ključne riječi: *dinamika vozila; evolucijski algoritmi; parametri ovjesa vozila; višekriterijsko optimiranje*

1 Introduction

Competition in the automotive industry imposes a constant improvement of vehicles and their subsystems as well as vehicle development process. Improvements can be achieved through innovations, optimization and by reducing development time and costs. In order to improve vehicle suspension system development process, this research is focused on the use of optimization methods in the conceptual phase of vehicle development.

Suspension system development process is usually a challenging multi-objective optimization task, due to the existence of many influential parameters, complex and often conflicting objectives. Even when considering only vehicle dynamics, vehicle and suspension system must meet various requirements related to stability, handling, ride comfort, etc. The task of the designer is to find a suitable compromise. Although design process is and probably always will be based on designer intuition, dynamic simulation and optimization tools can provide significant improvement in the process itself.

Design process of complex systems, such as a suspension system, requires extensive use of simulation-based design and analysis tools. Using dynamic simulation tools, real driving conditions can be simulated in a virtual environment, meaning that many issues can be predicted and resolved in the early development phase. Simulation models are used to determine the value of main parameters and to understand their influence on vehicle behaviour. The next logical step is the ability of optimization of parameters with the goal to improve the behaviour of vehicles still in a virtual environment.

Conceptual phase provides an opportunity to change the design, what is a huge potential for optimization (Fig. 1). Improvements in conceptual phase provide a shortening of overall development process time and reducing of development costs. In the view of progressive increase of design change costs versus development time it is essential for concept relevant issues to be solved in the earliest phase of development.

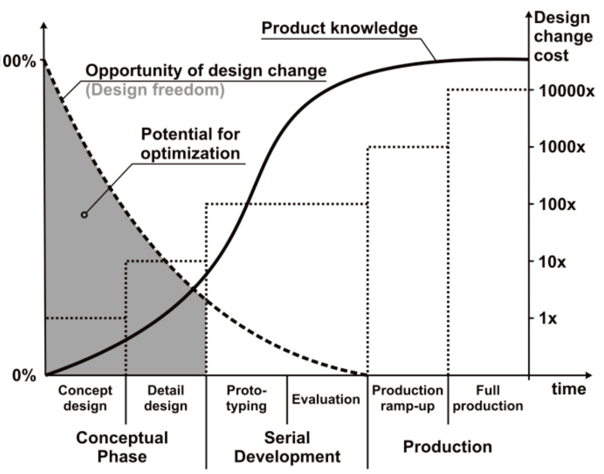

Figure 1 Illustration of huge potential for optimization in the conceptual phase of development

Due to frequent design changes at this stage of development it is required to analyse a large number of possible solutions in a limited time frame. In order to speed up the process, parallelism is necessary (Fig. 2). This parallelism can be achieved by using appropriate optimization algorithm. Multi-objective optimization algorithms can be divided into classical, gradient based algorithms and stochastic, heuristic algorithms. In this research emphasis is on usage of evolutionary algorithms, from group of heuristic algorithms, since these algorithms offer a kind of parallelism in terms of use of population of individuals (design solutions) in each optimization step of optimization process.

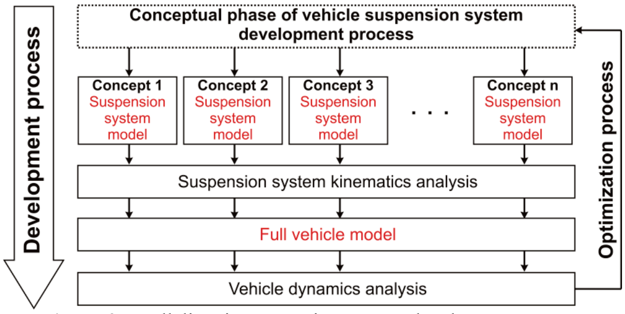

Figure 2 Parallelism in suspension system development process

2 Literature overview

Numerous papers deal with vehicle dynamics problems, especially with topics such as vehicle handling, stability and ride comfort. Similar situation is in the topic of evolutionary algorithms. However, the number of papers that deal with both topics simultaneously is relatively small. Usually, these papers deal with solving partial problems of vehicle dynamics.

Several important researches that deal with the analysis of influence of suspension system parameters on the behaviour of the vehicle and with optimization of those parameters for different types of suspension system, by using evolutionary algorithms, are described in [1, 2, 3, 4, 5]. Fujita et al. [1] showed optimization of multilink suspension parameters with the goal to improve vehicle handling and stability. In this research a simple genetic algorithm was used and a hierarchical categorization of design characteristics (parameters) and their influence on dynamic characteristics was presented. Examples of multi-objective optimization of the geometric parameters of double wishbone suspension using a genetic algorithm, with the goal to improve vehicle handling and stability, were shown by Hwang et al. [2]. Khajavi et al. [3] showed multi-objective optimization of suspension parameters to improve vehicle handling and ride comfort. In their research, NSGA-II (Non-dominated Sorting Genetic Algorithm) algorithm and 8 degrees of freedom vehicle model were used. Multi-objective optimization of vehicle parameters with the goal to improve vehicle handling was shown by Fadel et al. [4]. A vehicle passing through three test procedures related to handling was simulated in the research. Results obtained by using evolutionary algorithms were compared with the results obtained by the Monte Carlo method. Schuller et al. [5] showed multi-objective optimization of vehicle parameters in order to improve vehicle handling. It is important to mention that in all of those researches relatively simplified models of suspension systems or full vehicle were used.

Review and comparison of multi-objective optimization methods, including evolutionary algorithms and their application on vehicle development problems was given by Gobbi et al. [6]. According to this survey, neither method turned out to offer advantages concerning all criteria for all types of problems. Evolutionary algorithms have been evaluated as a robust algorithm that can manage a large number of objective functions, with appropriate adjustment of several key parameters (population size, mutation probability and crossover, etc.) to achieve the desired convergence.

In topic of usage of multi-objective optimization methods, especially evolutionary algorithms in vehicle dynamics problems, there is still a lot of room for improvement. Main goal of this research is to combine the capabilities of the modern simulation tools for suspension system analysis and vehicle dynamics analysis with multi-objective optimization methods based on evolutionary algorithms [7, 8]. With this approach which includes more complex simulation models and high efficiency advanced optimization algorithms, compared to previous research, the aim is to improve the concept phase of vehicle development.

3 Simulation models

The intensive use of computational engineering tools in recent years and the transition from an experiment to a simulation driven product development has become a key factor in achieving success in a highly competitive marketplace. Intention of research is to analyse suspension subsystem within framework of a complete vehicle. In this optimization process two simulation models are used, very detailed kinematics model of suspension system and less detailed full vehicle model.

Position of suspension system hard points completely determines the specific suspension system configuration and defines the kinematic characteristics, like camber, caster, toe, kingpin inclination, scrub radius, etc. The kinematic characteristics change due to wheel vertical travel, wheel steering and vehicle roll. The kinematic characteristics have a direct influence on dynamic (driving) characteristics of vehicle [9]. Also, characteristics of the spring and the shock absorber are influence parameters, and they are as well as coordinates of characteristic suspension system hard points, input variables in optimization model (Fig. 3). A solid overview of the theoretical foundations related to vehicle suspension can be found in the literature [9, 10, 11].

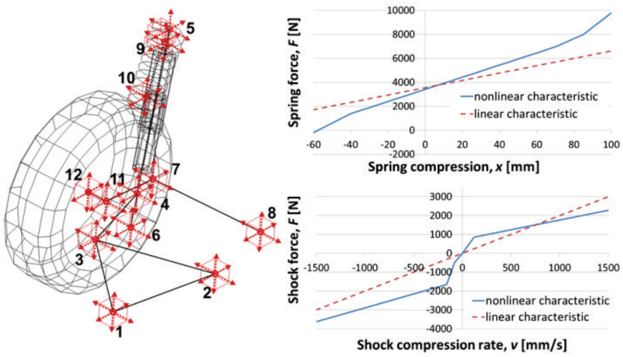

Figure 3 Input variables in optimization process

In conceptual phase of development simulation models of suspension system and vehicle must be sufficiently detailed. Simulation results must reach a suitable degree of accuracy and clearly demonstrate behaviour of real vehicle. On the other hand, level of detail should be limited because a detailed model will be an expensive development process, in terms of increasing development time and computing power. Another problem of very detailed model is the amount of parameters which are often not known sufficiently and effect the quality of the results although the full vehicle was modelled in great detail [12].

Simulation models of full vehicle are used to predict behaviour of vehicle in different ride conditions. Model of full vehicle was built in software package CarSIM (Fig. 5). The CarSIM mathematical model covers the entire vehicle system and inputs from the driver, ground and aerodynamics. Suspension system model in CarSIM is defined by kinematic characteristics (camber, caster, toe, etc.) in form of curves or data tables. This type of modelling approach is suitable for fast simulation, but does not provide insight into suspension system geometry and position of suspension system hard points. Because of this modelling limitation, suspension system model is extended. Lotus Suspension Analysis (Fig. 4), kinematics analysis software, is used to generate kinematic curves using suspension system hard points data. Its camber, caster, toe, and other kinematic curves are implemented in CarSIM full vehicle model.

Depending on the vehicle class there are various test procedures defined to give the comprehensive figure of the real driving performance. A vehicle whose suspension parameters should be optimized in optimization process passes through a series of test procedures. Test procedures or manoeuvres simulation results are the basis for the evaluation of dynamic characteristics of vehicles (output variables). Test procedures or manoeuvres are a sample of various scenarios to which a vehicle can be subjected in real driving. Most of the test procedures have been standardized by different authority bodies. There are different tests for the assessment of stability, handling and ride comfort of vehicles. The goal is to use several manoeuvres to assess a specific dynamic behaviour of a vehicle, and each manoeuvre requires the evaluation of different dynamic characteristics.

Table 1 Test procedures related to handling, stability and ride comfort of vehicle

	Handling	Stability	Ride comfort
Test procedures	Double lane changes (ISO 3888-1: 1999)	Sine with dwell – ESC test (FMVSS 126, ECE R13H)	Bounce sine sweep (ISO 2631: 2004)
		Braking in μ-split (ISO 14512:1999)	
	Obstacle avoidance (ISO 3888-2: 2011)	Crosswind/Lateral wind (ISO 12021:2010)	Driving over small sharp bump (ISO 2631: 2004)
		Braking in turn (ISO 7975:2006)	
	Steady-state circular driving (ISO 4138:2012)		
	Weave test/Sine wave steer input (ISO 13674-1:2010)		Driving on real road surface profile (ISO 2631: 2004)
	Fishhook test/J-turn test (ISO 7401:2011)		
	Lateral transient response test methods (ISO 7401:2011)		
	Steering-pulse/Steering-release (ISO 17288-1,2: 2011)		
Dynamic characteristics	offset from design path, yaw, roll, yaw rate, roll rate, lateral acceleration, transient roll gain, steering angle, etc.	yaw rate, roll rate, lateral acceleration, longitudinal acceleration, wheel slip angle, vehicle slip angle, understeer, oversteer, etc.	pitch, pitch rate, vertical acceleration, root mean square (RMS) value of the vertical acceleration, etc.

Objective functions or criteria for evaluation of vehicle handling, stability and ride comfort should be defined depending on the vehicle class. In [2, 3, 5, 13] can be found a solid overview of test procedures, as well as criteria for evaluation of vehicle handling, stability and ride comfort. In these cases, test procedures such as double lane change, J-turn, fishhook, crosswind, acceleration and braking on road surfaces with different coefficients of friction (μ-split) and criteria such as vertical, longitudinal and lateral acceleration, roll, pitch, yaw angle and rate, slip angle, forces at the tire contact surface are used. In our optimization model objective functions are defined on the basis of objective functions in mentioned researches as well as on recommendations from the literature that covers automotive chassis development [10, 11]. Typical handling, stability and ride comfort test procedures are shown in Tab. 1. Some procedures provide simultaneously insight into handling and stability behaviour of vehicle. At the bottom of the same table are also shown some dynamic characteristics that can be analysed as a result of simulation or real testing of specific test procedures. These characteristics, or their peak value, ratio of characteristics, phase delay, and other derived values can be the basis for the objective functions definition.

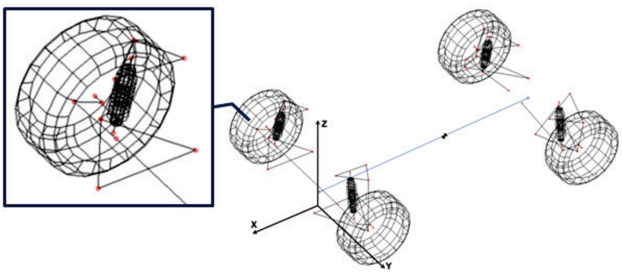

Figure 4 Suspension system simulation model

Accurate (validated) simulation models of suspension system and full vehicle are necessary for further use in optimization process. Simulation tools were evaluated by simulating a vehicle from series production, 2003 Ford Expedition, with the known test results [14, 15, 16]. Comparison of simulation results with real testing results was made for two test procedures related to stability and handling: Sine with dwell and Double lane change (Fig. 5). In both test procedures two dynamics characteristics were observed, lateral acceleration and yaw rate of vehicle. The comparison between the simulation and the test results demonstrated good consistency [17].

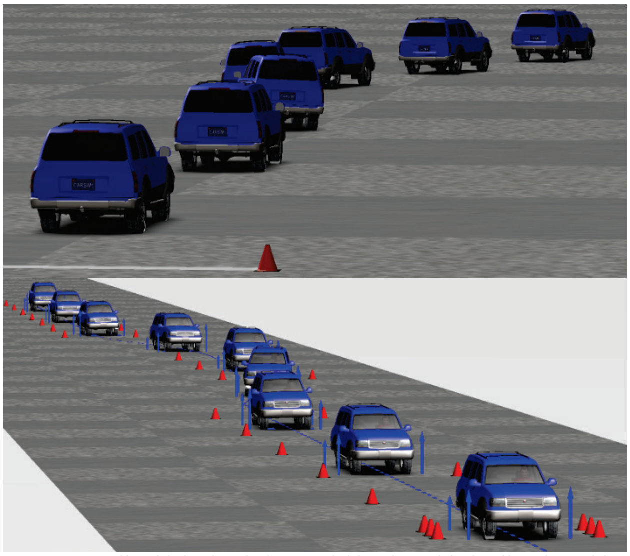

Figure 5 Full vehicle simulation model in Sine with dwell and Double lane change test procedure

4 Multi-objective optimization

Most of optimization problems in the vehicle development process are multi-objective and often include several conflicting objectives. Instead of one global optimal solution, usually there are numerous solutions for these problems located on the Pareto front. There are two goals in a multi-objective optimization, first, to find a set of solutions as close as possible to the Pareto-optimal front, and second, to find a set of solutions as diverse as possible [18].

In mathematical terms, the multi-objective problem can be written as [19]:

$$\min/\max\ \boldsymbol{y} = \boldsymbol{f}(\boldsymbol{x}) = [f_1(\boldsymbol{x}), f_2(\boldsymbol{x}), \dots, f_k(\boldsymbol{x})] \tag{1}$$
$$\boldsymbol{g}(\boldsymbol{x}) = [g_1(\boldsymbol{x}), g_2(\boldsymbol{x}), \dots, g_m(\boldsymbol{x})] \leq 0 \tag{2}$$
$$\boldsymbol{x} = [x_1, x_2, \dots, x_n] \in \boldsymbol{X} \tag{3}$$
$$\boldsymbol{y} = [y_1, y_2, \dots, y_k] \in \boldsymbol{Y} \tag{4}$$
$$x_i^L \leq x_i \leq x_i^U \quad i = 1, 2, \dots, n \tag{5}$$

where f_i is the i-th objective function, g_i is the inequality and equality constraints, $\boldsymbol{x}$ is the decision vector, $\boldsymbol{y}$ is the objective vector, $\boldsymbol{X}$ is denoted as the decision space, and $\boldsymbol{Y}$ is the objective space, k is the number of objective functions, m is the number of constraints. Constraints $\boldsymbol{g}(\boldsymbol{x})$ determine the set of feasible solutions.

Objective functions $\boldsymbol{f}(\boldsymbol{x})$ and constraints $\boldsymbol{g}(\boldsymbol{x})$ can be expressed with algebraic equations or computer simulations [20].

In optimization problem all objectives need to be minimized or maximized and all objectives are equally important. It can be assumed that a solution to this problem can be described in terms of a decision vector $(x_1, x_2, \dots, x_n)$ in the decision space $\boldsymbol{X}$.

A function f: $\boldsymbol{X} \rightarrow \boldsymbol{Y}$ evaluates the quality of a specific solution by assigning an objective vector $(y_1, y_2, \dots, y_k)$ in the objective space $\boldsymbol{Y}$. The feasible set $\boldsymbol{X_f}$ is defined as a set of decision vectors $\boldsymbol{x}$ that satisfy the constraints $\boldsymbol{g}(\boldsymbol{x})$:

$$\boldsymbol{X_f} = \{\boldsymbol{x} \in \boldsymbol{X} | \boldsymbol{g}(\boldsymbol{x}) \leq 0\} \tag{6}$$

The feasible set contains not only optimal solutions, but also solutions that are not optimal. Based on the concept of Pareto Dominance, the optimality criterion for multi-objective problem can be introduced.

It can be assumed that solution $\boldsymbol{a}$ exists, which is optimal in the sense that it cannot be improved in any objective without causing degradation in at least one other objective. A decision vector $\boldsymbol{a}$ is said to be nondominated by any other decision vector.

Pareto optimality: A decision vector $\boldsymbol{x} \in \boldsymbol{X_f}$ is said to be nondominated regarding a set $A \subseteq \boldsymbol{X_f}$ if

$$\nexists \boldsymbol{a} \in \boldsymbol{A}: \boldsymbol{a} \succ \boldsymbol{x} \tag{7}$$

Moreover, $\boldsymbol{x}$ is said to be Pareto optimal if $\boldsymbol{x}$ is nondominated regarding $\boldsymbol{X_f}$.

Pareto optimal set (nondominated set): Let $A \subseteq \boldsymbol{X_f}$. The function $p(\boldsymbol{A})$ gives the set of nondominated decision vectors in $\boldsymbol{A}$:

$$p(\boldsymbol{A}) = \{\boldsymbol{a} \in \boldsymbol{A} \mid \boldsymbol{a} \text{ is nondominated regarding } \boldsymbol{A}\} \tag{8}$$

The set $p(\boldsymbol{A})$ is the nondominated set regarding $\boldsymbol{A}$. The corresponding set of objective vectors $f(p(\boldsymbol{A}))$ is the nondominated front regarding $\boldsymbol{A}$. The set $\boldsymbol{X_p} = p(\boldsymbol{X_f})$ is called the Pareto optimal set.

Pareto front: The set $\boldsymbol{Y_p} = f(\boldsymbol{X_p})$ is denoted as the Pareto-optimal front.

For all solutions on Pareto front any further improvements in any of objectives cannot be made without causing degradation in at least one other objective.

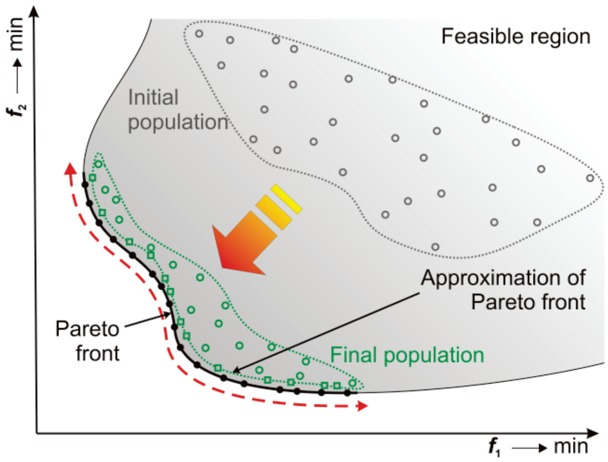

Figure 6 Pareto front

Uniformly filled Pareto front stretched between the edges of objective functions space (red dashed line) is shown in Fig. 6 for a problem with two objective functions.

5 Optimization model

As mentioned before, suspension system development process is a challenging multi-objective optimization task. Also, this is a multi-disciplinary task which presents a computational and modelling challenge. Fig. 7 shows the basic idea of optimization model for the case of integration of simulation tools into multi-objective optimization environment on the example of the multi-disciplinary approach to the analysis.

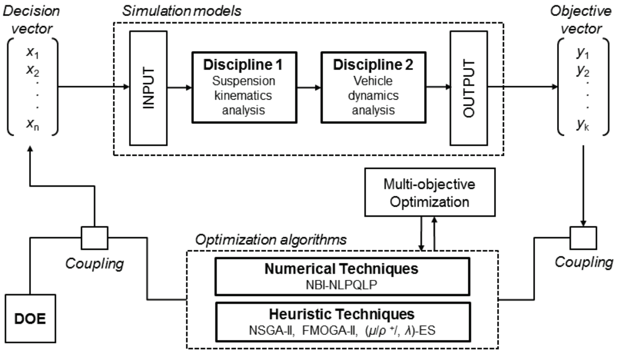

Figure 7 Basic idea of optimization model

Optimization model is built in software package mode Frontier. To create optimization model it was necessary to couple simulation tools Lotus Suspension Analysis and CarSIM with modeFrontier. Scripts (Matlab, VisualBasic) define transfer of data and files between different software packages and define the order of steps in simulation and optimization process [21, 22]. In optimization process, simulation tools run without usage of the graphical user interface what significantly speeds up the process. Fig. 8 shows data flow of some basic files in optimization process.

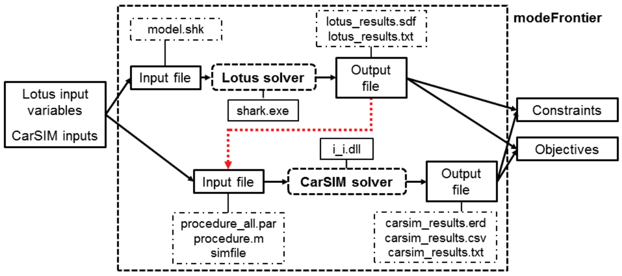

Figure 8 Interactions between simulation packages

Layout of optimization model in mode Frontier is shown in Fig. 9. Each icon on the layout represents some type of connection to the specific files of the simulation tool, which are usually in the form of ASCII files.

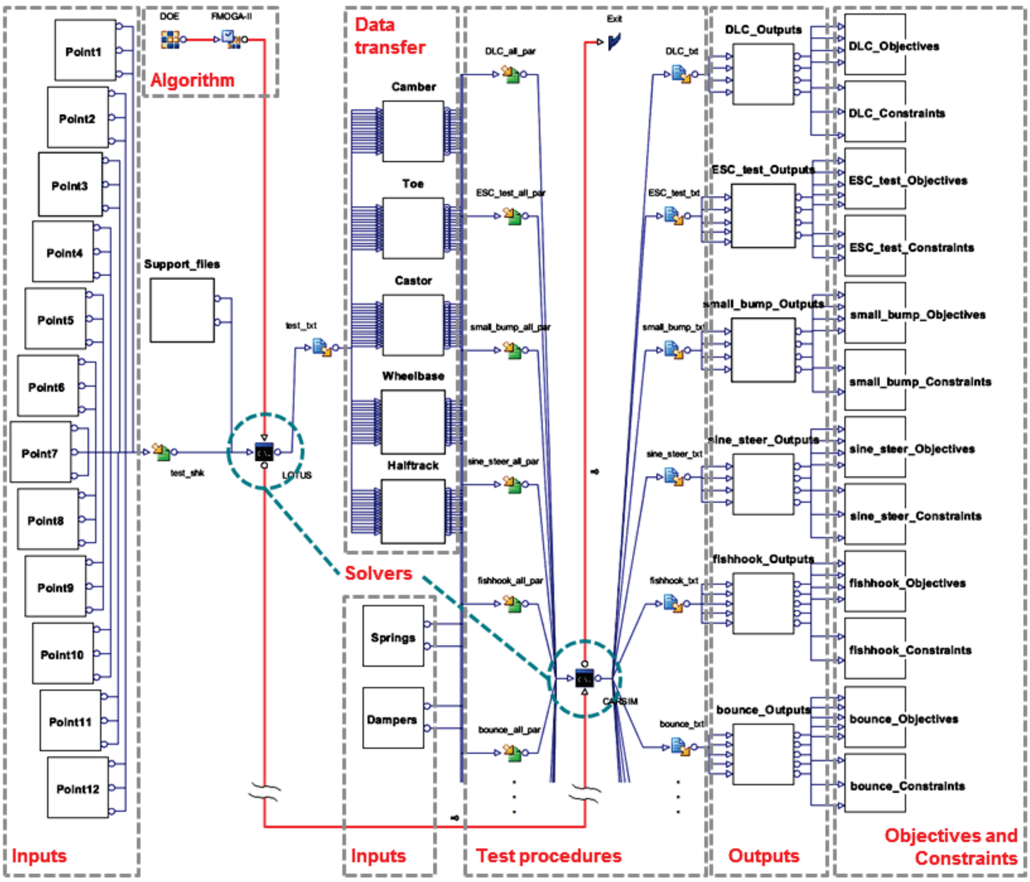

Figure 9 Optimization model (mode Frontier layout)

Inputs or input variables in optimization model are x, y and z coordinates of hard points of suspension system and spring and shock absorber characteristics. Suspension parameters are optimized on the basis of vehicle passing through a series of test procedures related to the stability, handling and ride comfort (see Tab. 1). Outputs or output variables are vehicle dynamic characteristics, and they are the basis for definition of objectives (see Tab. 1) and constraints. Also, in optimization model, optimization algorithm should be defined. In this optimization process evolutionary algorithms are used and each individual in population represents one design solution, which is a set of input variables that completely define suspension system, and vehicle. Individuals are improved from generation to generation according to requirements defined with the objective functions.

6 Results

In numerous papers evolutionary algorithms have been evaluated as a robust algorithm that can manage a large number of objective functions, can provide wide Pareto front and achieve the desired convergence. These algorithms are imposed as a good choice for this problem. Three different algorithms from class of evolutionary algorithm (NSGA-II, (μ/ρ +/, λ) evolutionary strategies and FMOGA-II) are tested and compared with the deterministic multi-objective algorithm. For this purpose, deterministic optimization algorithm NBI-NLPQLP is chosen. Genetic algorithms NSGA-II and (μ/ρ +/, λ) evolutionary strategies are well known and proven algorithms. Relatively new FMOGA-II algorithm (Fast Multi Objective Genetic Algorithm) [23] uses the concept of meta-model (Response Surfaces Methodology) implemented within MOGA-II algorithm [24] to increase the speed of convergence of optimization problems which demand high computational cost. NBI-NLPQLP is a multi-objective algorithm based on the Normal Boundary Intersection (NBI) method [25] coupled with the NLPQLP algorithm [26]. Table 2 shows several key parameters of optimization algorithms, required to define algorithms in optimization model. Parameter values are chosen on the basis of real optimization problems from literature, usually complex mechanical systems, with similar complexity as a problem in this research. The best results for a particular optimization algorithm are achieved with parameters marked in red and bold.

Table 2 Basic parameters of algorithms

Algorithm	Parameter	Value
NSGA-II	Number of Designs	15;**20**; 25
	Crossover Probability	0,7; 0,8;**0,9**
	Mutation Probability	0,05;**0,1**; 0,15
	Number of Generations	15;**30**; 50
FMOGA-II	Number of Designs	15;**20**; 30
	Number of Iterations	15;**30**; 50
	Exploration Fraction	0,45;**0,5**; 0,55
μ, λ-ES	Number of Generations	30; 40;**50**
	Number of Offsprings	**15**; 20
	Selection Type	**+**;,
NBI-NLPQLP	Number of Design Evaluations per Subproblem	30;**40**
	Number of Pareto Points (Subproblems)	**21**; 42
	Final Termination Accuracy	0,01;**0,1**; 1

In simulation test the vehicle model passes through 10 test procedures related to vehicle handling, stability and ride comfort (Tab. 1). The following test procedures were simulated: Double lane changes, Sine with dwell, Braking in μ-split, Crosswind, Steady-state circular driving, Sine wave steer input, Fishhook test, Bounce sine sweep, driving over small sharp bump and driving on real road surface profile. For these test procedures 42 objectives and 28 constraints were defined.

In the comparison of the algorithms, the best results in terms of short computing time, number of solutions, convergence and Pareto front approximation were achieved with the FMOGA-II algorithm.

Table 3 Efficiency of the algorithms

Algorithm	Number of iterations	Feasible solutions	Time
NSGA-II	600	444 (74 %)	36 h 16 min
FMOGA-II	600	470 (78 %)	36 h 47 min
(μ/ρ +/, λ)-ES	750	255 (34 %)	48 h 11 min
NBI-NLPQLP	820	246 (30 %)	52 h 55 min

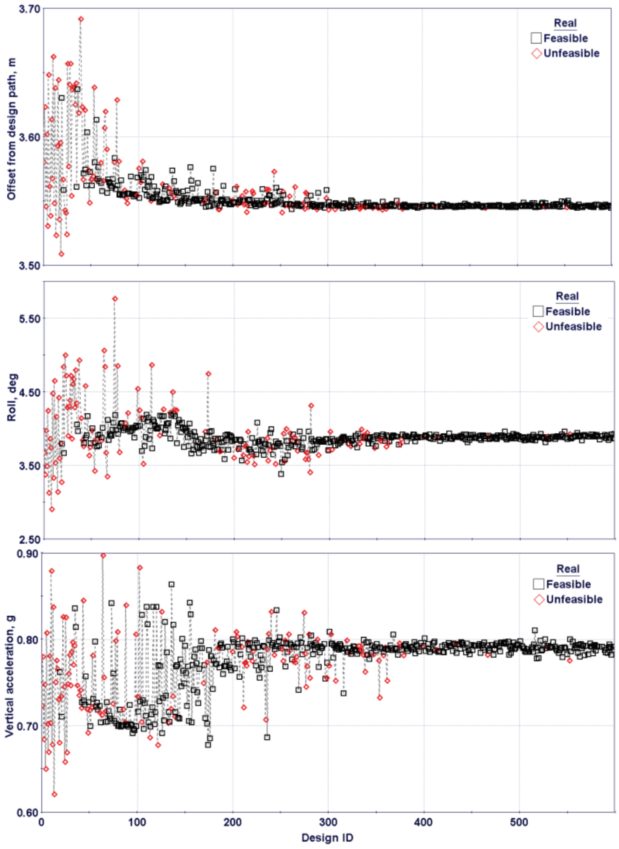

Figure 10 Convergence of three objective functions with FMOGA-II algorithm

FMOGA-II algorithm provided short computing time, similar to NSGA-II algorithm (Tab. 3). To compute 30 generations with 20 individuals with FMOGA-II algorithm took about 37 hours on standard desktop PC. FMOGA-II algorithm reached the convergence after 300 iterations. Fig. 10 shows convergence of three random selected objective functions: offset from design path in Double lane change, vehicle roll in Sine with dwell and vertical acceleration of sprung masses in Bounce sine sweep test procedure.

In approximating Pareto front results obtained by FMOGA-II algorithm (Fig. 11) show the best fit to the results of deterministic optimization method, NBI-NLPQLP algorithm (Fig. 12). Besides that, good fit to the results of deterministic optimization method in approximating Pareto front, between the proposed evolutionary algorithms, FMOGA-II algorithm also provides the greatest number of solutions that meet the requirements while maintaining great diversity of solutions. FMOGA-II algorithm provides uniformly filled

Pareto front stretched between the edges of objective functions space. If Figs. 11 and 12 are compared, near the Pareto front there are a large number of solutions that meet the requirements, while this is not the case with NBI-NLPQLP algorithm. Figs. 11 and 12 show solution space defined by objective functions: vehicle lateral acceleration in Double lane change, vehicle roll rate in Sine with dwell test procedure, and minimum was requested for both objective functions in optimization process. Blue point represents initial solution (initial configuration), a vehicle from series production used to validated suspension system and full vehicle simulation models (Figs. 4 and 5). In optimization process all parameters of the vehicle have original values as in the case of validated vehicles. Only suspension system is changed (suspension configuration, spring and shock absorber characteristics). Instead of original suspension system with double wishbone (Fig. 4), suspension system with McPherson strut was simulated and optimized (Fig. 3).

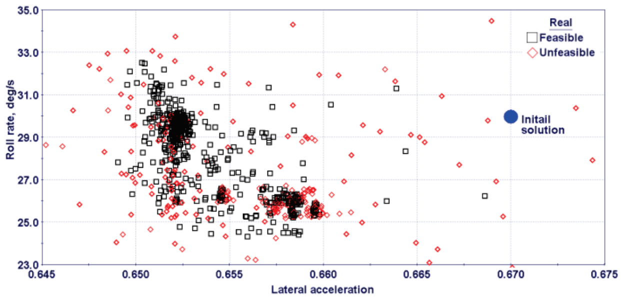

Figure 11 Solution space of two objective functions with FMOGA-II algorithm

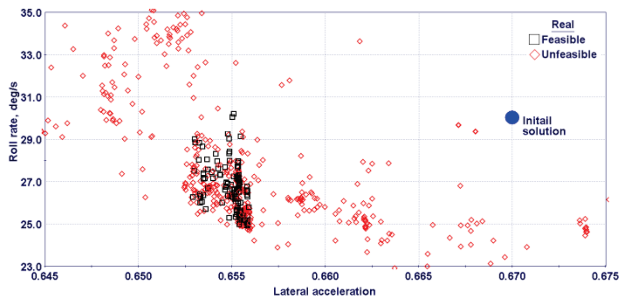

Figure12 Solution space of two objective functions with NBI-NLPQLP algorithm

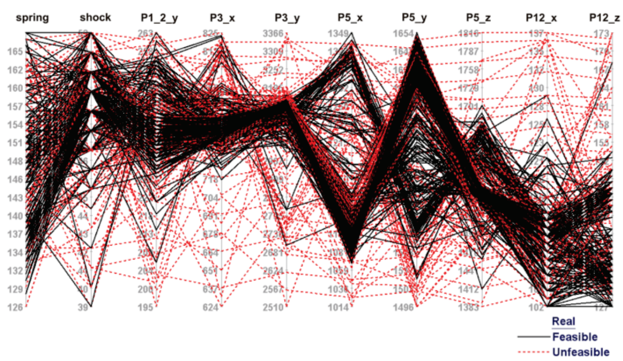

Figure 13 Input parameters values of solutions obtained with FMOGA-II algorithm

Every polyline in Figs. 13 and 14 represents one solution. On the vertical axis there are the values of certain input parameters (hard points coordinates, spring and shock absorber characteristics). Black solid polylines present feasible solutions, all solutions that meet the set of requirements, objective functions and constraints. Although optimization process with NBI-NLPQLP algorithm has higher number of iterations, total number of solutions that meet the set of requirements is smaller compared to FMOGA-II algorithm. Besides that, optimization process with FMOGA-II algorithm offers a greater diversity of solutions. A large number of solutions in process with NBI-NLPQLP algorithm have small variations in the values of certain input parameters, while this is not the case with FMOGA-II algorithm.

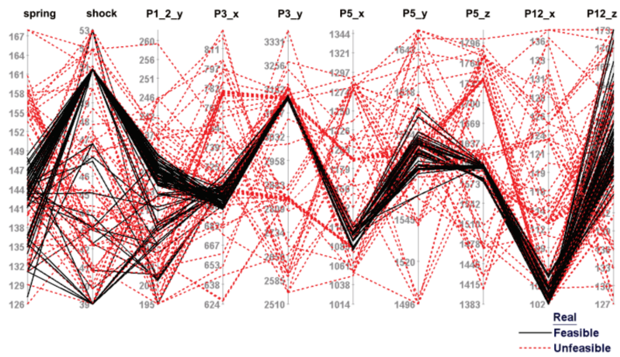

Figure 14 Input parameters values of solutions obtained with NBI-NLPQLP algorithm

Some preliminary results of new optimization model application in obtaining a set of optimal suspension system parameters of low-floor minibus are shown in [22]. Using new optimization model large number of numerically evaluated conceptual solutions, which meet all in the optimization process defined requirements, was obtained. A few solutions (vehicle with different suspension system configurations) close to the Pareto front were compared with the initial configuration (solution obtained by conventional engineering approach to vehicle development). In all dynamic characteristics in all test procedures simulated in the optimization process improvements were achieved.

7 Conclusion

Multi-objective optimization model for determining the optimal suspension system parameters has been developed through integration of simulation tools into multi-objective optimization environment. Fast and well proven simulation tools with a suitable degree of accuracy are used for the analysis of the suspension system kinematics and vehicle dynamics. This approach provides development of a suspension system from a full vehicle dynamics behaviour viewpoint and optimization of suspension system parameters simultaneously through stability, handling and ride comfort related standardized test procedures.

Optimization model was examined on the example of test vehicle and variation in terms of efficiency, obtained number of feasible solutions, convergence and Pareto front approximation between the used evolutionary algorithms was found. The best results were achieved in optimization process with the FMOGA-II algorithm. In approximating Pareto front, FMOGA-II algorithm showed the best fit to the results of deterministic optimization method. Additionally, FMOGA-II algorithm provided short computing time, fast convergence, greatest number of feasible solutions and great diversity of solutions.

Proposed methodology showed promising results in parameters determination process compared to the conventional intuitive engineering approach to vehicle development and it was found as suitable for optimization of a large number of the suspension system variables with a large number of objectives and constraints.

Result of the application of the optimization model is a set of optimal, numerically evaluated solutions, and after that, from mathematical point of view, the optimization problem can be considered solved. From the real engineering problem point of view, to finish the process, it is necessary to select a feasible solution that best meets the requirements of the decision maker by using some of the decision making methods.

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