



MOGA & MOGT OPTIMISATION STRATEGIES AND SOM RESULTS REPRESENTATION

Luigi Bregant¹, Giuseppe Miccoli^{*2}, Valentino Pediroda¹ and Marco Seppi²

¹Department of Mechanical Engineering, University of Trieste
Via A. Valerio, 10 34127 Trieste, Italy

²IMAMOTER, Institute for Agricultural and Earthmoving Machines
Via Canal Bianco, 28 44044 Cassana (FE), Italy
g.miccoli@imamoter.cnr.it

Abstract

Multi-disciplinary and multi-objective design optimisation tools are used more and more in order to help CAE designers and managers in their quest for higher product quality and returns. The present paper illustrates the comparison between the results achieved by means of the MOGT (Multi-Objective Game Theory) and the MOGA (Multi-Objective Genetic Algorithm) optimisation strategies. The aim of the application consists in a construction machinery cab vibro-acoustic performance optimisation. The less tested and more innovating MOGT strategy shows itself to be a robust and fast multi-objective optimisation tool too when combined with Evolutionary Algorithms. The recently developed results representation by means of SOM (Self-Organizing Maps) represents a powerful analysis tool. It allows a clear and fast qualitative comprehension of the relations between optimisation process design variables and objectives.

INTRODUCTION

Simulation tools are widely used for noise reduction and vibro-acoustic comfort achievement, aiming to reduce the interior sound pressure level in the industrial vehicles, in particular at the operator position. The inner vibro-acoustic field can be successfully evaluated as a design parameter by means of a linked computation between structural and acoustic solvers [1]. A 3D cavity representing the real cab has been modelled by means of a (Ansys) FE structural mesh. Starting from the cab vibration load experimental acquisition, a (Sysnoise) BEM coupled analysis has been carried out in order to evaluate the cab inner vibro-acoustic field as a function of the physical properties of each structural element. The numerical optimisation is included to find out the best solutions that fulfil the objectives. The multi-objective design

optimisation code (modeFRONTIER) drives the analysis process flow taking into account the cab parameter structural modifications and carrying out the vibro-acoustic field optimisation.

The present paper illustrates the results achieved by means of the MOGT (Multi-Objective Game Theory) optimisation strategy and the comparison with those obtained in a previous work [1] by means of the MOGA (Multi-Objective Genetic Algorithm) optimisation strategy. The above numerical tools are both implemented in the modeFRONTIER code. An exploration of the different methods, concerning the specific test case of an earth-moving machine cab, provides interesting results. Moreover, results representation by SOM is also illustrated. This methodology can be applied in parallel to the optimisation strategies, to investigate the numerical trends of the different parameters.

VIBRO-ACOUSTIC ANALYSIS AND OPTIMISATION

The test case earth-moving machine consists of a W130 Fiat-Hitachi. The cab FE model and the MOGA optimisation results obtained by the simulation are represented in Figure 1.

FEM/BEM solution

The FE model has been developed in order to represent correctly the vibro-acoustic structure-borne noise field and provide the parameters (design variables) to be changed in the optimisation phase (thicknesses, dimensions) [1]. The forces acting on the cab (loads) have been computed (forces identification) from the accelerations spectra measured at several points of the cab base and applied to the 4 cab mount positions. A Sysnoise indirect BEM coupled analysis has been carried out using as input the structural modal basis, obtained by an Ansys FEM calculation. A consistent agreement between measured and computed SPLs (sound pressure levels) at the operator ear position has been obtained by an appropriate definition of the admittance boundary conditions.

First MOGA optimisation

A first optimisation procedure has been carried out with the main aim of minimizing the spectral SPL amplitudes. Four optimisation objectives have been identified: three frequency bands and the peak value at 40 Hz. The sum of the sound pressure levels has been referred to each frequency band. Six constraints were also defined, i.e. four to be linked to the values of the objective variables and two to the peak frequency values at 160 Hz and 315 Hz.

At first five design variables have been identified: the glass ($s1$) and steel ($s2$) panels thickness, the stiffening tubes thickness ($s3$), the global dimensions by introducing a scale factor (dim), the location of an additional absorbing panel ($admb$). Subsequently, a second run has been carried out without taking into account the negligible importance of the stiffening tubes thickness and adding a constraint on the

cab total mass. Only three design variables have been considered, the location of an extra absorbing panel (*admb*) and two cab steel panel thicknesses.

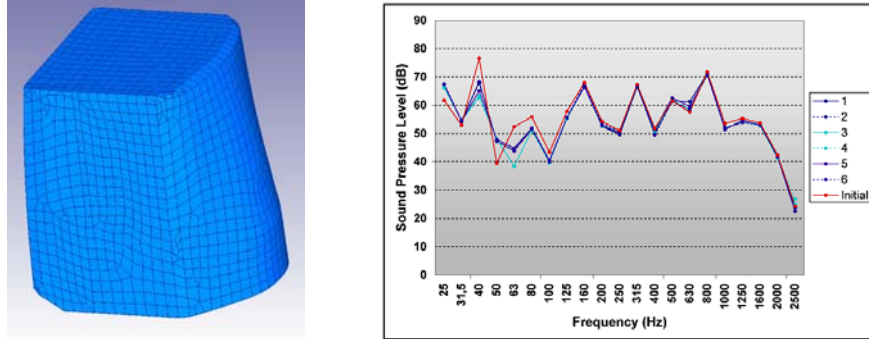


Figure 1: Cab FE simulation model and first MOGA optimisation results

OPTIMISATION METHODS

Some brief theoretical outlines are mentioned below, before discussing the application of the methodologies adopted.

MOGT

In a competitive game, the two players act following different objectives; in particular, player A has to choose his strategies in order to minimize the function f_A , while player B has to minimize the function f_B .

Of course, as generally both the functions depend on the two domains, the strategies of one player influences the choices of the other one. The two players act simultaneously until an equilibrium is found (Nash equilibrium point): in this case, each player has minimized his own function with a common pair of strategies.

In mathematical terms, $(x^*, y^*) \in X \times Y$ is a Nash equilibrium if and only if:

$$\begin{cases} f_A(x^*, y^*) = \inf f_A(x, y^*) & x \in X \\ f_B(x^*, y^*) = \inf f_B(x^*, y) & y \in Y \end{cases} \quad (1)$$

The procedure is complex in order to implement a competitive game since we need to define an algorithm that decomposes the variable space, assigns to each part of the decomposed space (that becomes a player own domain) the correspondent objective and provides a mono-objective optimisation algorithm to each player. From different tests considered [2], it seems that the most efficient algorithm to be run by each player is the Nelder and Mead Downhill Simplex [4]: for this reason from now it is used to referring to any competitive game algorithm as to Nash-Simplex algorithm.

SOM

Self Organizing Maps (SOM) [3] are an efficient way of visualization for multi-dimensional and highly complex datasets.

By means of a non linear ordered regression, SOM provides a topology preserving mapping from the high dimensional space of data to map units, which usually forms a two-dimensional lattice. This mapping typology guarantees that nearby points in the space of data are mapped to nearby points in the map and thus SOM can serve as a cluster analyzing tool.

The basic idea for SOM consists in performing a vectorial regression on data samples by a set of weight vectors, each one assigned to a map unit, its components being iteratively changed in such a way that they resemble the original data records as best as possible, leading to an ordered map. Regarding the visualization, if an inspection of variable correlation is required, the best choice consists in reporting n map displays, where n is the number of data variables, each one representing the value of a weight vector component. The (non linear) local correlations can be detected by comparing the colour code in the same map regions on different displays.

APPLICATION OF MOGT

MOGA and MOGT strategies have been compared considering a similar design number for both procedures. A DOE of 36 elements (one of them being the original design) is used in the MOGA test run. 9 generations are calculated, resulting in a total number of 324 designs (repeated designs included). DOE is not required referring to MOGT based on Simplex calculation. Hence, a value of 9 is used for the maximum number of players steps. The MOGT procedure requires some rules to be respected:

- The number of parameters must be equal to or greater than the number of objectives.
- The number of subdivisions for each input variable (base), i.e. the possible values that can be selected during the optimisation process, must be great enough. Fixed limits are not available, but a rule of thumb states that if the base is too small for a certain input variable, this parameter can not be considered in the “game” adequately.

Due to the first issue, only the initial test run has been repeated using the MOGT procedure, the second one having 3 parameters and 4 objectives. Due to the second issue, the base of each parameter has been increased proportionally: every subdivision has been divided again in 10 new intervals. In this case the engineering interpretation is inadequate, since a thickness of few millimeters can not vary in a range of more than 5 or 6 values. Nevertheless, the physical meaning is more evident during the optimisation phase and the approximation can be done at the end of the numerical process: the value to be chosen is not strictly the calculated one but the closest that can be achieved in a real engineering product.

Table 1: Number of subdivisions for each input variable (base), for different test runs

	MOGA - 1	MOGT - 1	MOGA - 2	MOGT - 2
<i>admb</i>	6	6	6	59
<i>dim</i> and <i>s1</i>	5	41	41	41
<i>s2</i> and <i>s3</i>	6	51	51	51

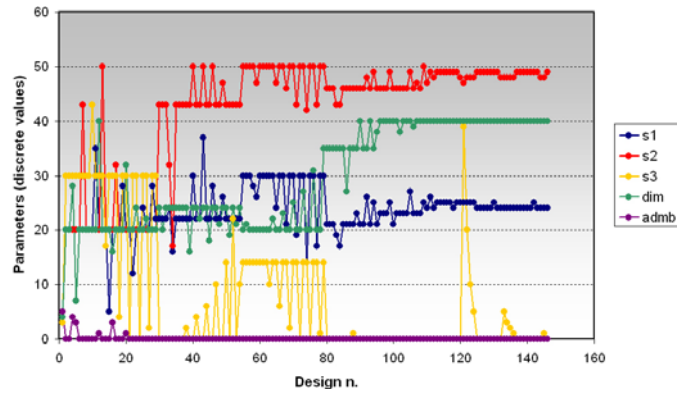


Figure 2: MOGT strategy parameters trends. The parameters are represented by discrete numbers inside the range

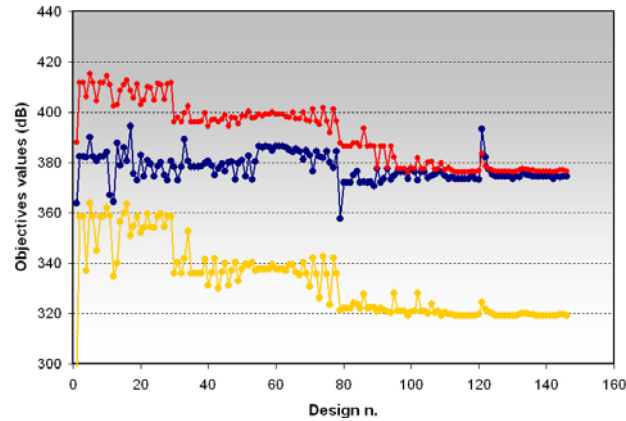


Figure 3: MOGT strategy objectives trends

MOGT vs. MOGA

MOGT and MOGA calculations are compared, the parameters bases having been extended as for MOGT (Table 1: MOGT-1 and MOGA-2 have the same characteristics). MOGT provides satisfactory results: the Nash equilibrium is achieved and the computation is fast: 144 designs are calculated, instead of 324 (Figures 2 and 3). The objectives are minimized and the trend observed for each design variable is correct: thicknesses and dimensions need to be increased, except for the stiffening tubes thickness, whose role is not significative. Only the parameter *admb* is not well represented. As expected, the base for *admb* (a discrete variable) is

too small in order to obtain good results and its values are not explored correctly.

MOGA calculates the 324 designs (9 entire generations) as defined from the beginning, but the results are more complete. The Pareto frontiers show a better behaviour when compared with the MOGT ones (Figure 4). It should be observed however that MOGT computation neglects a parameter (*admb*) almost completely, hence its performance is hardly comparable.

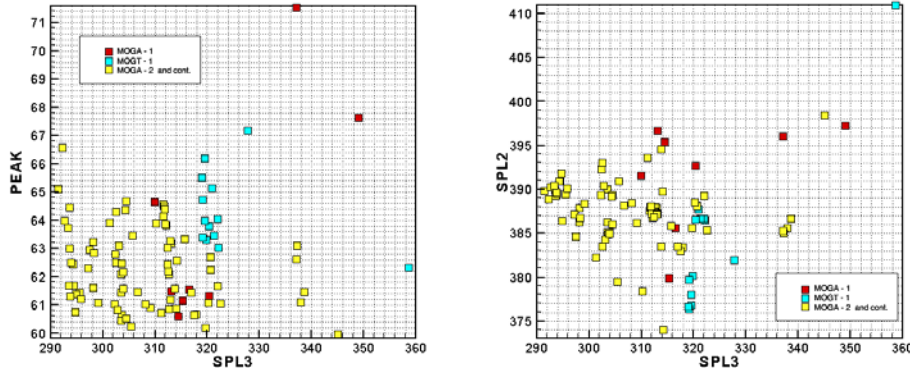


Figure 4: Comparison of MOGA-MOGT Pareto Frontiers. MOGT finds quickly good Pareto Frontiers (Nash equilibrium is reached), but one parameter (*admb*) is not well considered. MOGA Pareto Frontiers are better explored, even better when resuming the optimisation run

MOGT second run

An expedient has been used to try to solve the *admb* base definition problem. A large base (59 configurations) has been considered for this variable. An internal code procedure provides the approximation of the values to the closest integer (0-9 to 0, 10-19 to 1, etc.). Also this solution showed itself to be inefficient: the solver has been unable to choose values different from 0 for the *admb* parameter. In this case, it can be stated that a 6 element base turns out to be too small for a Simplex-based MOGT calculation. Hence, the *admb* variable can not be represented suitably.

APPLICATION OF SOM

A SOM analysis of the parameters role has been carried out, based on both the design databases created by the MOGA and MOGT procedures. The results are represented in the form of areas, in which different colours correspond to different values of the variable (Figures 5 and 6). The areas of all the parameters and objectives have to be compared each other, to find out the relations between the variables and hence the physical trend of the system.

The best designs correspond to points of the maps where the values of the four objectives are low. Since they are reduced at the same time (right side of the areas), the optimisation process has worked successfully. This behaviour can be observed for both the MOGA and MOGT case. Considering the different coloured areas

extensions, *SPL1* turns out to be the most difficult objective to be minimized, if compared with the others. *s3* turns out to be a non-significative parameter, because the area distribution is different if compared with that of the objectives. Other similar considerations can be found out by this method easily.

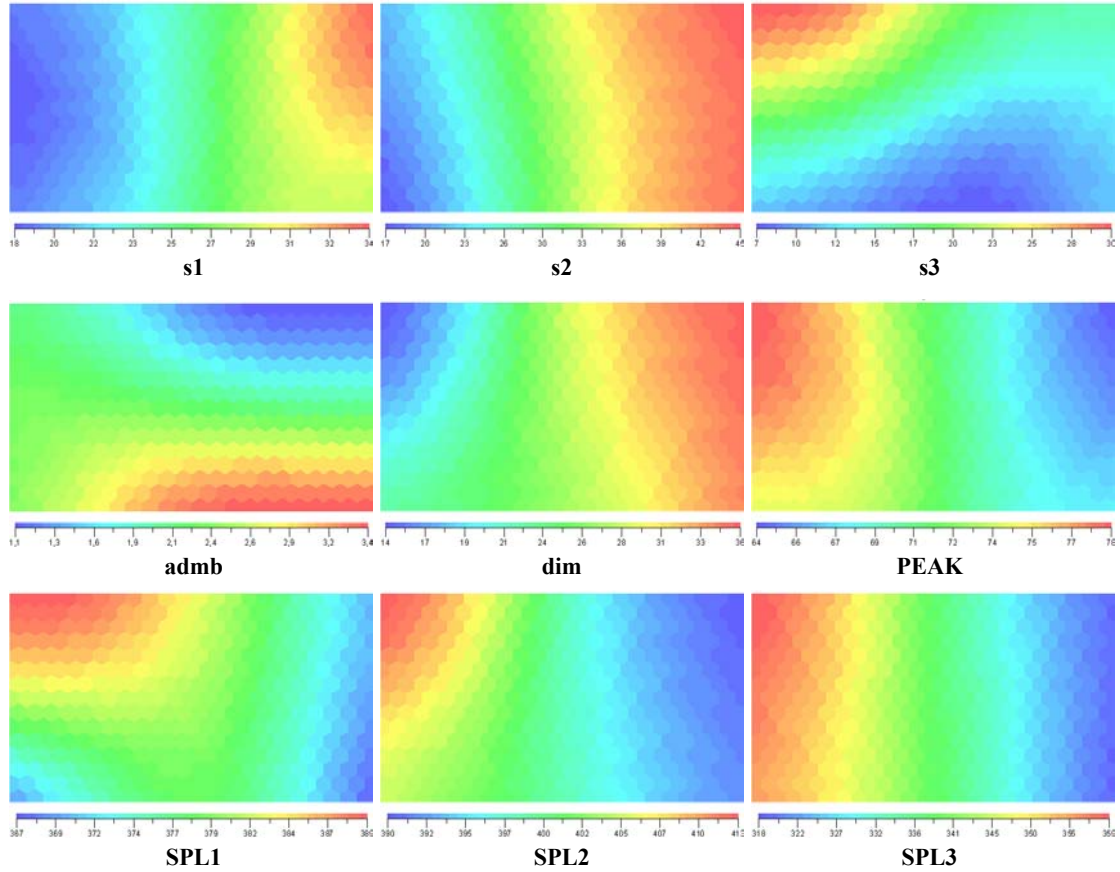


Figure 5: SOM obtained with the MOGA optimisation strategy (objectives in capital letters)

admb is not considered during the MOGT optimisation procedure. Hence it does not appear in the SOM results significantly, while it has an important role referring to the MOGA optimisation strategy. Different *admb* values are obtained, always different from 0 for the optimal designs. An expansion indeed of the area covered by sound absorbing material ensures a reduction of the global SPLs. Yet the location of this area, among the ones considered, is not extremely important.

The SOM are basically similar calculated by means of MOGA and MOGT strategies. Apart from the problem to be referred to the *admb* variable, another difference can be observed as far as the parameter *s3* is concerned: in the case of MOGA, the low significance of this variable is evident, while its behaviour is less clear in the case of MOGT. For all the other parameters, the results are comparable, as it can be seen from Figures 5 and 6, where some of the maps are represented as an example. The results obtained with the SOM representation are analogous to those obtained with other methods (Student parameter, relation between parameters and

objectives in the Pareto frontier designs and optimisation data comparison). Nevertheless, the qualitative comprehension of the relations between parameters and objectives turns out to be clear and faster by means of this kind of representation.

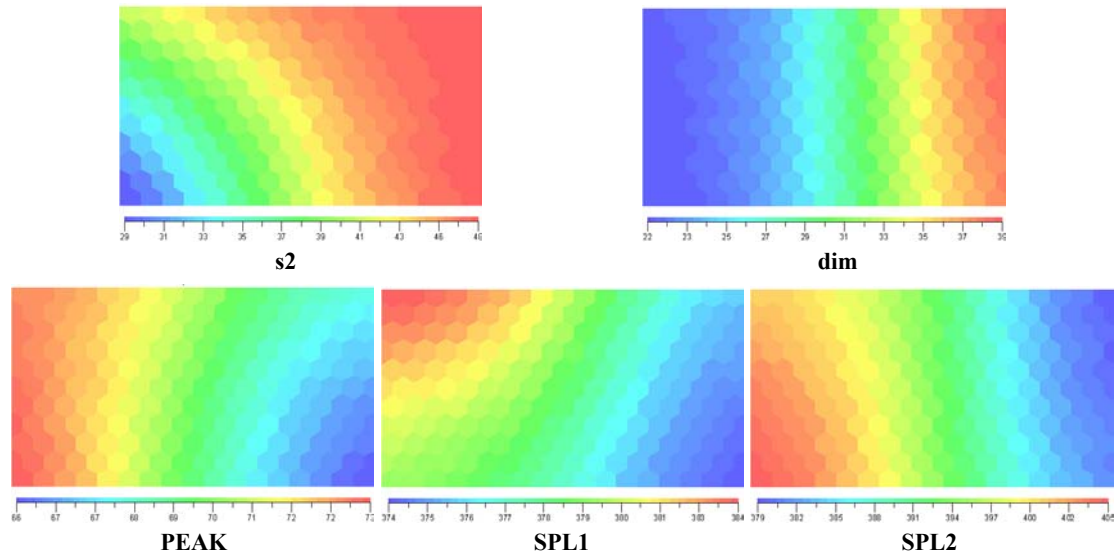


Figure 6: SOM obtained with the MOGT optimisation strategy (objectives in capital letters)

SUMMARY

The paper provided a comparison between MOGA and MOGT optimisation strategies as far as the performance of a construction machinery cab vibro-acoustic inner field is concerned. Both strategies show themselves to be robust and powerful and the optimisation run variables/objectives SOM representation turns out to be a useful analysis tool.

As future MOGT strategy developments and checks, the computation can be foreseen of a new test configuration obtained for example by reducing the number of objectives and/or by joining the SPL spectrum frequencies differently aimed at a new objective definition. Moreover, another useful comparison between MOGA and MOGT strategies can be achieved by fixing the *admb* value.

REFERENCES

- [1] Bregant L., Miccoli G., Seppi M., “Construction machinery cab vibro-acoustic analysis and optimisation”, Proceedings of the Nafems World Congress (Malta, 2005).
- [2] Clarich A., Pediroda V., Poloni C., Periaux J., “Comparison between different Game Theory Methodologies in Robust Design Optimization”, Int. Conf. on Computational Methods for Coupled Problems, *Science and Engineering Coupled Problems* (CIMNE, Barcelona, 2005)
- [3] Kohonen T., *Self Organizing Maps*. (Springer, Berlin, Heidelberg, New York, 2001, 3rd edition)
- [4] Rao S.S., *Engineering optimization, Theory and Practice*. (Wiley&Sons, 1996)