Exhaust System Manifold Development Enhancement Through Multi-Attribute System Design Optimization

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Recently, in the automotive industry, the pressure to improve profitability has been increasing sharply. We argue that, long-term profitable growth requires going beyond a simple cost cutting operation to holistically redesign man-centric processes and tools that eliminate waste and increase operational efficiency for the maximization of the value added to products. Product Development Computerization (PDC), i.e. the design activity carried out semi-automatically by CAx software, is believed to bring significant (about 50%) development cost and time savings and to enable unprecedented levels of business agility. In the present work, PDC has been applied to an exhaust manifold including a catalytic converter. The approach features a multi-disciplinary optimization executed in a highly integrated concurrent engineering software framework. Results are remarkably promising: projected development cost and time savings are higher than 70%, with important side effects of increased flexibility and product innovation. Technical challenges include the integration of disparate analysis codes as well as overcoming geometrical infeasibility of parametrized system designs. It was found that the Hooke-Jeeves algorithm was best equipped to explore the channels of feasibility in this problem.

Nomenclature

Variables

μ_{torque}	=	average of torque values
σ_{torque}	=	standard deviation of torque values
x_i^0	=	*i* design variable of baseline design
x_i^N	=	*i* design variable of N^{th} design

Abbreviations

CFD	=	Computational Fluid Dynamics
EDF	=	Enhanced Development Framework
FE	=	Finite Element
FEM	=	Finite Element Model
ICE	=	Integrated Concurrent Engineering
MDO	=	Multi-disciplinary Design Optimization
PD	=	Product DEvelopment
rpm	=	Revolutions Per Minute

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I. Introduction and Motivation for the work

THE Automotive industry is facing a tough period. Production overcapacity and high fixed costs constrain companies' profits and challenge the very existence of some corporations[1]. Strangulated by reduced profit margins and petrified by the organizational and products' complexity, companies find themselves more and more challenged with the fast pace and the rate of change of consumers and regulators demands.

To boost profits, nearly every company is pursuing aggressive cost cutting. However, aggressive cost cutting as the sole approach to increasing margins results invariably in a reduction of operational capabilities, which is likely to result in a decline in sales volume that leads to further cost reductions in a continuous death spiral[2].

Long-term profitable growth requires, instead, a continuous flow of innovative products and best-in-class processes. The focus should be, therefore, shifted from cost reduction to increased throughput[3]. Automotive companies need to change their business model, morphing into new organizational entities based on systems thinking and change, which are agile and can swiftly adapt to the new business environment. The advancement of technology and the relentless increase in computing power will provide the necessary means for this radical transformation.

For this transformation to happen, the Product Development Process (PDP) has to break the iron triangle of cost, schedule and product performance that constrains it[4]. Any new approach should be applied to the early design phases, where the leverage is higher, and should be targeted to dramatic reduction of the time taken to perform design iterations, which, by taking 50-70% of the total development time, are a burden on today's practice[5]. Multi-disciplinary Design Analysis and Optimization, enabled by an Integrated Concurrent Engineering virtual product development framework has the required characteristics and the potential to be at the core of the "Product Development Computerization" transformation, which will respond to today's and tomorrow's challenges.

The vision is to have the product or system not defined by a rigid, explicit CAD model which is then manipulated by product team engineers, but by a parametric flexible architecture handled by optimization and analysis software, with limited, but value-added, user interaction. In this environment, design engineers govern computer programs, which automatically select appropriately combinations of geometry parameters and drive seamlessly the analyses software programs (structural, fluid dynamic, costing, etc) to compute all the system's performance attributes. Optimization algorithms explore the design space, identifying the Pareto optimal set of designs that satisfy the multiple simultaneous objectives they are given and at the same time satisfying the problem's constraints. Human interaction is primarily required in setting up the framework, parameterizing the system, providing good initial starting points, selecting and tuning optimization algorithms, applying preference weights and selecting among the Pareto set of non-dominated designs.

In the present work, a prototype of an Enhanced Development Framework (EDF) has been set up for a particular automotive subsystem: a maniverter (a combination of exhaust manifold and catalytic converter) for internal combustion engines capable of handling up to five different performance attributes at the same time (Figure 1).

The platform, adequately simplified to cope with the research constraints, features a flexible bus architecture where the different analyses modules can be excluded and included with minor effort. Commercially available software is used, with some customization for the particular use. In contrast to many MDO applications in the automotive[6,7,8,9,10,11,12], particular emphasis is placed on the breadth of the engineering disciplines considered – which include fluid dynamics, pressure waves propagation, thermal management, vibrational behavior and mass properties – and on the inclusion of business elements, in the form of a parametric cost model.

The EDF with its high performance ICE platform is projected to enable a very fast execution of design iterations in the early phases of PD. Consequently, many solutions can be investigated at a relatively low cost. In addition, the MDO approach leads to evaluating each solution from all the relevant performance attributes standpoints. The combinations of the two factors, i.e. comprehensive design exploration and holistic perspective, is expected to reduce dramatically the cost of rework, thereby leading to the product's value maximization[13].

II. The Case Study: an Exhaust System Maniverter

In the present work, the EDF is built around a specific application. As a particular system an exhaust system manifold or, more precisely a maniverter (manifold+converter) for passengers cars, is chosen. The choice of this system is driven by multiple reasons. First and foremost, an exhaust maniverter is intrinsically a highly multi-disciplinary system: in fact, its design is governed by fluid dynamics requirements (pressure losses, engine tuning), heat management issues (gas temperature drop, radiated heat) as well as structural constraints (resonance frequencies, thermal stresses, vibration induced stresses), not to mention, packaging, manufacturability and cost. Second, the system is of a favorable medium-size complexity and therefore amenable to be managed with limited resources and yet it is not too simple to make the development trivial. Last, but not least, this is the type of systems which the writer, working for ArvinMeritor – one of the market leaders in exhaust system design – has first hand experience and can have direct access to related information. Specifically, we selected the four-cylinder Fiat Fire 1.4L 16V engine as a baseline for the case study (Figure 1). However, results are generalizable to any 4-cylinder engine.

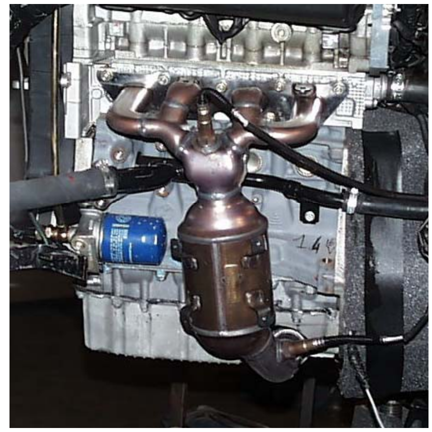

Figure 1. Example of a maniverter system

The exhaust system carries exhaust gases from the engine's combustion chamber to the atmosphere. Exhaust gases leave the engine in a pipework, travelling through an after-treatment sub-system, which often consists of a catalytic converter, and then through a silencing sub-system (muffler) before exiting through the tailpipe. Chemical reactions inside the catalytic converter change most of the hazardous hydrocarbons and carbon monoxide produced by the engine into water vapor and carbon dioxide, while the muffler attenuates the noise produced by the engine.

The exhaust manifold, in particular, is the first stage of the exhaust system. It conducts the exhaust gases from the combustion chambers to the exhaust pipe. In this work, we assumed that the manifold is made from stainless steel. Sometimes, a catalytic converter is placed just after the point where pipes coming out of the engine ports join. This particular position is selected in order to achieve a reduction in the converter warm up time after the engine is cranked-up and consequently to speed-up the start of pollutants conversion. In this case, quite often the term "maniverter" (manifold+converter) is used[14].

The design of an exhaust system maniverter is the result of a complex trade-off among different and equally important requirements:

- Exhaust gases should be kept at a high temperature in the exhaust pipework, especially at low rpm conditions
- For a non-sporty application, the engine torque curve should be as even as possible
- The engine should have the highest possible torque level and, consequently, the highest power for a given rpm.
- Particularly for sporty applications, the manifold should be designed in order for the sound emitted at the tailpipe to have a characteristic "color".
- Manifold system natural frequencies should not lie in the excitation frequency range of engine vibrations.
- In any case, the manifold structure should maintain a sufficient stiffness to avoid localized resonances and, consequently, unacceptable radiated noise.
- Thermal stresses arising from the thermal expansion that occurs when the manifold heats-up should be kept lower than the yield stress of the material.
- Similarly, stresses generated from the vibrations induced by the engine should be below the fatigue limit of the material at the temperature working conditions.
- The exhaust system manifold should fit the available space in the engine compartment and sufficient clearance for assembly tooling access in the production plant should be ensured.
- The manifold surface temperature and distance from the surrounding components should be such that the latter are not exposed to a temperature that exceeds the maximum working limit allowed by material properties.
- The manifold mass should be as low as possible.
- Manifold pipework should be designed to allow the gas stream to impinge on the surface of the converter with a flow velocity distribution as even as possible and with levels that do not exceed a given threshold.
- The manifold geometry (pipework, catalyst inlet and outlet cones, etc) has to satisfy the requirements of manufacturability and assembly with the available equipment of both the OEM and of the supply chain firms.
- Last but not least, manifold cost should allow the exhaust system manufacturer having a competitive price in the marketplace, while preserving or enhancing its product margins.

Each of those requirements put particular strain on the design and may drive different design solutions. The interaction between the effects on the performance attributes of the different design choices is not, generally speaking, evident and experience is usually the only valid guide for a cost-effective successful design.

We carefully scoped the activity described in this paper in order to create a framework which is adequately representative of the real environment but whose complexity is not so high as to impede any progress. For that purpose, we excluded aspects that were either of minor importance, or for which explicit knowledge did not exist within ArvinMeritor or that would require the use of excessively intensive calculations incompatible with the selected hardware platform. In addition, a deliberate decision was made to use commercially available software.

Details of the design aspect included and excluded in the prototype EDF are presented in Table 1.

Design aspect	**Included**	**Motivation for exclusion (if excluded) or software used (if included)**
Catalyst Inlet temperature	✓	1-D CFD. code (AVL BOOST)
Torque evenness	✓	1-D CFD code (AVL BOOST)
Max torque	✓	1-D CFD code (AVL BOOST)
Min Backpressure	✓	1-D CFD code (AVL BOOST)
Tuning	✓	1-D CFD (AVL BOOST)
First natural frequency	✓	FEA Code (MSC.Nastran)
Fit in the available space	✓	CAD package (Unigraphics NX2)
Thermal induced-stresses	×	Computationally too expensive
Vibration induced-stresses	×	Computationally too expensive
Temperature of surrounding components	×	Secondary aspect
Mass	✓	CAD package (Unigraphics NX2)
Flow distribution on the converter surface	×	Computationally too expensive
Max flow velocity in the converter	×	Computationally too expensive
Manufacturability and assembly	×	Usually based on experience. No software model available.
Sound quality	×	Secondary aspect
Radiated noise	×	Secondary aspect
Cost	✓	Spreadsheet (Microsoft Excel)

Table 1. Design Aspects Included and Excluded in the Prototype EDF

III. Building the Enhanced Development Framework

Having identified the individual design domains, the next step was selecting a robust and yet flexible architecture that was to link them in a consistent framework. The trade-off was between integral and modular.

Integral would have meant a deep interaction between the different software packages. In this sense, there are several attempts by different software vendors. The usual situation that is encountered is that CAD or CAE vendors, specialized in one domain with a flagship product, are trying to widen their area of action around that product offering an extension of their basic capabilities. No single CAE platform, however, exists that is able to incorporate seamlessly different codes of different vendors. This was one of the main motivations for the choice of the modular architecture. In this bus architecture a standardized and minimum set of data is exchanged among applications and the transfer occurs primarily between the bus and the individual module. The same software that handles the data transfer also handles the optimization process. A modular architecture has other advantages: 1) one CAE module can be replaced by another one, provided that the interfaces with the bus are the same; 2) if, at any time, an additional or enhanced CAE module becomes available, it can be easily integrated and only the interfaces with the bus (and not with all other packages) need to be defined.

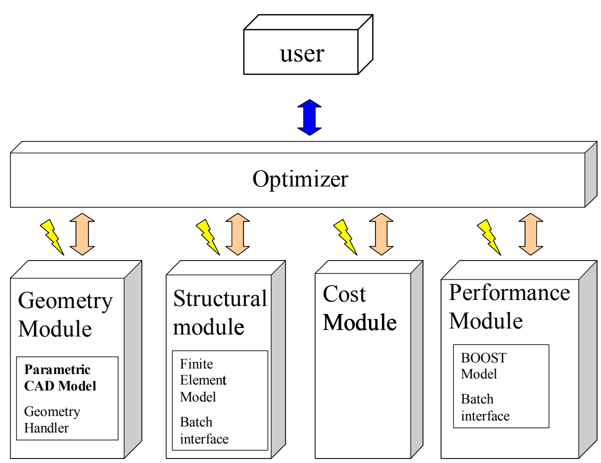

Figure 2. Overview of the ICE platform Architecture: ⇳ data flow, ⚡ client-server relationship

This approach works well in the case of a maniverter because the main interaction between disciplines is via the system's geometry only.

iSIGHT, from Engineous[15], was selected for the optimization / data transfer job. Through iSIGHT, a process flow of the different development steps is made, somewhat replicating the process in a normal product development environment: for example a CAD model is generated first and the structural analysis is performed afterwards.

The user specifies the application (i.e. engine type and overall constraints) and the goals for the system performance attributes (max, min, selected value). The product development definition starts with a selection of a set of baseline parameters with which the geometrical configuration is defined and through the execution of the different modules, the CAD model is generated and the required performance attributes are calculated. At the end of the design loop, the calculated attributes are compared with the target. If the goal of the optimization is reached, the process ends, otherwise a new product definition is generated in the form of a new parameters set, which of has the potential of having performances closer to the specified goals.

The loop features no iterations between the different modules because all Performance Modules depend on the Geometry Module.

In what follows, a description of the individual modules is made first and then a detailed illustration of their integration is given.

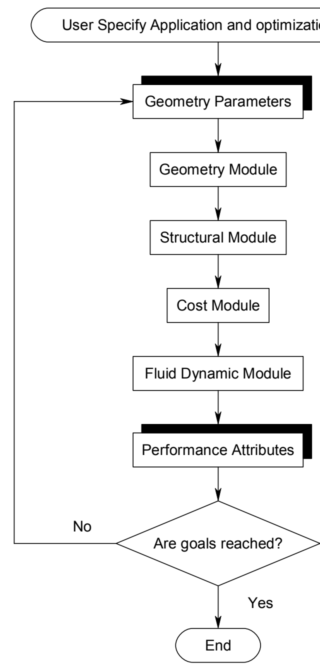

Figure 3. Flowchart of the design loop execution.

A. Geometry Module[13]

With appropriate simplifying assumptions, made to downsize design complexity to a manageable level, a maniverter parametric model is built which is able to represent a variety of configurations with a handful of parameters, the design variables. Unigraphics NX2 from UGS PLM Solutions was used as the CAD package[16].

The choice is made to focus on a manifold product for a four cylinder engine, out of a single skin tubular technology with a 4>1 topology (i.e. four pipes joining into a single junction) and embedding a ceramic catalyst.

The four pipes with a round cross section are connected to the inlet flange (which is imagined bolted on the cylinder head) and join in a plenum where all the gas streams mix. Then an inlet cone leads the exhaust gases to the catalytic converter and, when they exit from it, they are guided to the outlet pipe through an outlet cone. A bracket connected to the engine block supports the maniverter. It is implicitly assumed that the maniverter is followed downstream by an exhaust system where the silencers are placed.

All components are modeled with solid elements.

The resulting CAD model, is shown in Figure 4.

Here are some model figures. The total number of parameters is 196, of which:

- 118 are dependent
- 78 are independent. Of these: 32 are fixed with the application and 46 can be varied with the application, i.e. during the optimization process

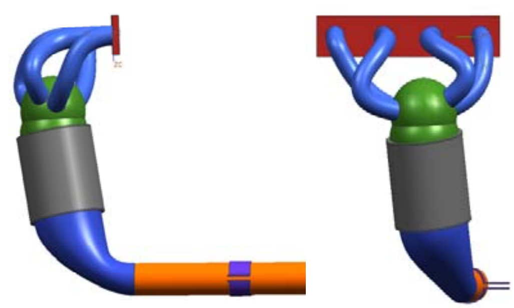

Figure 4. The Maniverter Parametric CAD Model

In addition, special software was developed to handle the geometry regeneration in batch given a set of parameters and to extract some required data from the model.

The routine, named KEFAOptimizer, has been developed in C language and has the following capabilities:

- It allows the geometry model to be changed w/o user intervention, given a set of parameter values.
- It extracts from the model some relevant physical and geometrical properties, such as dimensions and masses.

- It exports the native UG model (.prt) in a format (Parasolid) that can be read by FE codes.

The inputs to KEFAOptimizer are:

- The UG model to be changed.
- The list of parameters / expressions that KEFAOPtimizer will use to modify the geometry.
- The list of data to be extracted from the updated model.

The outputs that KEFAOptimizer provides are:

- The modified UG model.
- The data extracted from the updated CAD model.
- A Parasolid model.

B. Structural Analysis Module[13]

The only structural analysis is the calculation of the first resonance frequency. Design criteria state that this frequency should be as high as possible and not below 250 Hz.

For the analysis, a Finite Element model is built using the software programs MSC.Patran and MSC.Nastran by MSC.Software Corporation. The FEM is based on the Parasolid file created by the Geometry Module.

The system is considered in hot conditions, fixed at the inlet flange (which is connected to the cylinder head) and at the bracket (which is connected to the oil sump).

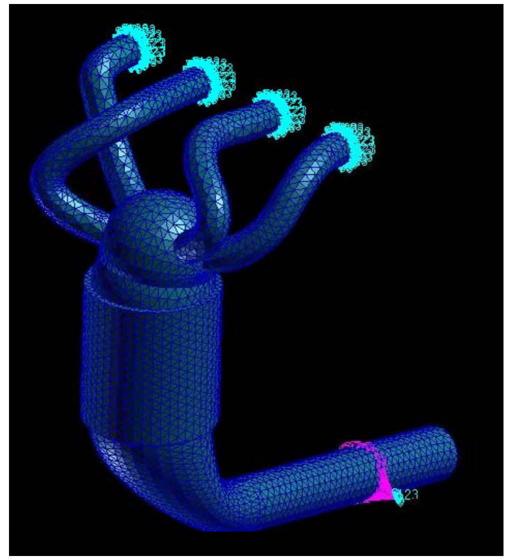

Figure 5. The Maniverter Finite Element Model

As type of element, we chose to work with tetrahedra because they can fit irregular boundaries and allow a change in elements size without excessive distortion. In addition, fully-automatic methods for generating triangular/tetrahedral meshes are well robust. The final choice fell on Tet-4 8 mm elements because the solution time is vastly shorter than with the others options.

In our application, for simplicity reasons, we considered that all metallic components of the maniverter are made of the same stainless steel material, which is known with the ANSI code AISI 304. In the working temperature range (at about 800°C) we also assume that the materials is isotropic, i.e. which has the same mechanical properties in all directions, and that it's linearly elastic.

C. Fluid Dynamic Module[13]

Two are the aspects that, with a fluid dynamic simulation, the EDF takes into account: 1) the engine performance that a maniverter design contributes to; 2) the warm-up time of the catalytic converter and therefore the engine pollutants conversion capabilities of the maniverter system.

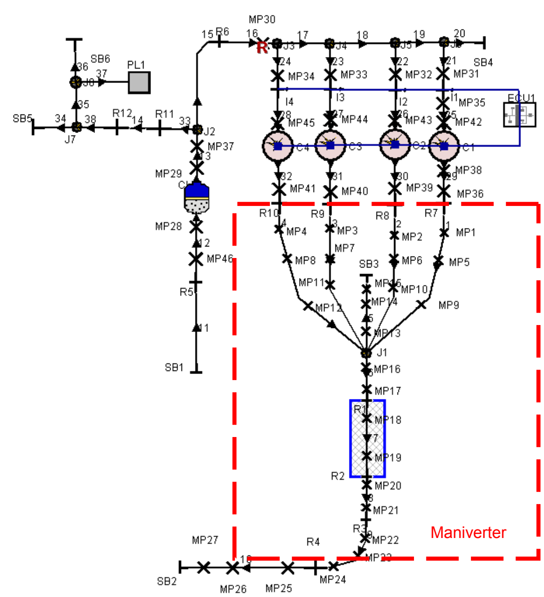

Figure 6. The Maniverter BOOST Model

A full 3D transient CFD calculation has been excluded because its computational cost is not balanced by an adequate added value, in terms of design information, for the specific application. A 1-D transient simulation has been preferred instead. This has been used to predict the effects of the different maniverter geometries on the engine power and torque curve as well as the catalyst conversion capabilities. The commercial code used is AVL BOOST 4.0.4[17]. The outcome of the calculation is the engine torque and the catalytic converter inlet temperature over the rpm working range.

Similarly to the geometry module, the fluid dynamic module is actually made by two parts: the model itself and the routine that manages the execution of the calculations in batch.

A BOOST model is built of the entire intake, Fire 1.4 16V engine and exhaust system (featuring the maniverter), since the performance characteristics of the engine are known to be influenced by all elements that are enclosed in the boundary that goes from the intake inlet to the tailpipe. (Figure 6).

Since the engine torque over the rpm range cannot be easily handled as a performance attribute during the optimization process, a single value that can work as a Performance index was elaborated. After extensive discussion with Fiat-GM Powertrain experts, the ratio of the mean and the standard deviation of the torque was identified:

$$Performance\ Index = \left(\frac{\mu_{torque}}{\sigma_{torque}} \right)^2 \qquad (1)$$

For a conventional low to mid-size car (i.e. not a sporty one), which is the vehicle a Fire 1.4 16V engine is likely to equip, two are the important features that a maniverter has to contribute to: 1) The highest torque, for best acceleration characteristics, 2). The most regular torque behaviour for good driveability. The mean value of the torque across the rpm range was selected as a metric of the first factor and the standard deviation (around the mean) as a metric for the second. The ratio is raised to the second power to create an indicator, which is more sensitive to variations.

Similarly, the temperature at the catalyst inlet curve was transformed into a single value that could represent the attribute expressing the converter warm-up characteristics. A weighted average temperature is selected where weights are higher for the low rpm values.

D. Cost module

It is rare in industry today that the cost of producing and maintaining a product is considered early in the design process. While much of the emphasis in Modelling & Simulation for design is on technology issues, integration of business issues is imperative to make a design that not only performs adequately, but also is cost-effective and guarantees adequate levels of profitability. For this reason, a cost model is included in the ICE platform. The approach that we embrace and we applied in our MDO framework is what is called "Parametric Cost Estimating" (PCE). In PCE costs are modelled based on past costs and "Cost Driver Parameters" are statistically/empirically fit. The assumption underlying PCE is that a clear linkage exists between cost and a product's cost drivers. PCE, therefore, search for product's / system's cost drivers and, based on past costs, tries to establish relationships between them.

	Value	Units
Material Cost	12.86	[€]
Raw material	11.69	[€]
Inlet flange	2.57	[€]
Pipe A (AISI 304)	0.38	[€]
Pipe B (AISI 304)	0.42	[€]
Pipe C (AISI 304)	0.35	[€]
Pipe D (AISI 304)	0.41	[€]
Inlet cone	1.32	[€]
Converter can (AISI 304)	1.01	[€]
Mat	1.69	[€]
Outlet cone	1.57	[€]
Outlet pipe	1.38	[€]
Bracket	0.60	[€]
Freight	0.24	[€]
Dependent on Part Size		[€]
Dependent on Part Weight	0.24	[€]
Material Overhead	0.94	[€]
	Value	**Units**
Production Cost	11.18	[€]
Labor cost	6.20	[€]
Labor cost per unit time	28.39	[€/h]
Machine Cost	4.98	[€]
Actual machine cost	4.52	[€]
Bending Cost	2.37	[€]
Cost per bending machine hours	35.00	[€/h]
No. Of hours of bending operations	0.07	[h]
Average time per bend		[s]
Welding Cost	1.66	[€]
Welding Robot Cost	11.00	[€/h]
Total Welding Robot Time	0.15	[h]
No. Of Welds	14.00	-
Operations Time per weld	4.00	[s]
Welding length	974.16	[mm]
Welding time	487.08	[s]
Sawing, Deburring, Calibrating, Leak Testing Costs	0.50	[€]
Machine Overhead	0.45	[€]
Manufacturing Cost	24.04	[€]
Material Cost	12.86	[€]
Production Cost	11.18	[€]
Total Cost	**28.49**	[€]
Manufacturing Cost	24.04	[€]
Scrap	0.24	[€]
Overhead	2.24	[€]
Alloy cost	1.97	[€]

Table 2. The Maniverter Cost Structure

The maniverter cost is made up by two components: material cost and production cost. Each of them and is then affected by an overhead which is usually a fixed factor of the cost component it is applied to.

Maniverter components, as far as material cost is concerned, are classified in the following categories: tubes, metal sheets, stamped components, support mat. For each of those categories, the main cost drivers were identified and, based on the extensive ArvinMeritor database, a statistical relationship worked out. Weight proved to be a prominent cost driver.

Production Cost consists of two components: the cost of machine operations and labour cost[13].

The resulting cost model is an Excel spreadsheet. As input it receives, from the Geometry Module, maniverter components masses and dimensions data (again KEFAOptimizer extracts those on purpose from the CAD model), and using the relationships between those data and the different cost components, gives back the maniverter cost. Since cost data are sensitive and proprietary to ArvinMeritor, a disguising factor was applied to the individual and overall values.

E. Working Mode of the EDF

All the modules are then integrated in an ICE platform (Figure 7), which enables to run seamlessly design loops. Deaign iterations are articulated in the following sequential steps.

1. The user specifies which of the five performance attributes (mass, frequency, performance index, catalyst average inlet temperature, cost) to be considered in the optimization process and, for each of those, the optimization goal (min, max or target value)
2. The design loop starts with a baseline geometrical configuration defined by its parameters values
3. The Geometry handler module creates the CAD model correspondent to the parameters values and calculates the geometrical and physical dimensions that will be used in the following steps. In addition, it creates the Parasolid file needed by the subsequent structural analysis.
4. The Frequency Calculator module, reads the Parasolid file and feeds back to iSIGHT the first natural frequency
5. The Cost Calculator module receives in input the necessary geometrical and physical data and feeds back the maniverter cost and its breakdown of material and production cost
6. The Fluid Dynamic Module receives in input the geometrical data of the maniverter and feeds back the torque values and the catalyst inlet temperature over the 1000-6000 rpm range
7. The Perfomance Calculator receives the torque values and the catalyst inlet temperature over the 1000-6000 rpm range and feeds back the Performance Index and the Weighted Average Catalyst Inlet Temperature
8. The Optimizer receives from the different modules the five maniverter performance attributes, i.e. mass, the first natural frequency, cost, performance index and catalyst inlet weighted average temperature and, if the target of the performance attribute(s) is achieved or the maximum number of iteration, the design process stops. Otherwise, depending on the optimization strategy, feeds back a new set of parameters values and a new loop starts (from point 3.)

The execution time of a complete simulation loop is about 20 min on a Pentium IV 1.8 GHz laptop with 1GB RAM. The breakdown is the following:

- 0.8 min for geometry creation
- 3 min for structural analysis
- 15 min for fluid dynamic analysis
- 0.7 min for Excel execution and optimization algorithms

We highlight once again that a loose coupling exists between the different applications. Interchanges occur only in the format of ASCII files (with the exception of the Parasolid file) through a data bus provided by the iSIGHT architecture.

While this approach has some limitations, it gives two fundamental advantages: 1) interoperability is guaranteed because the communication media are ASCII files, 2) a module can be eliminated or upgraded or a new module can be added with a minor effort because the interfaces are limited and simple. The latter feature, in its turn, has the powerful consequence of fostering scalability, both horizontally and vertically:

- Horizontal scalability: new performance attributes can be evaluated when the related prediction models become available;
- Vertical scalability: a module can be generated to be rather simple in the beginning but it could be refined both in its capabilities and in its accuracy

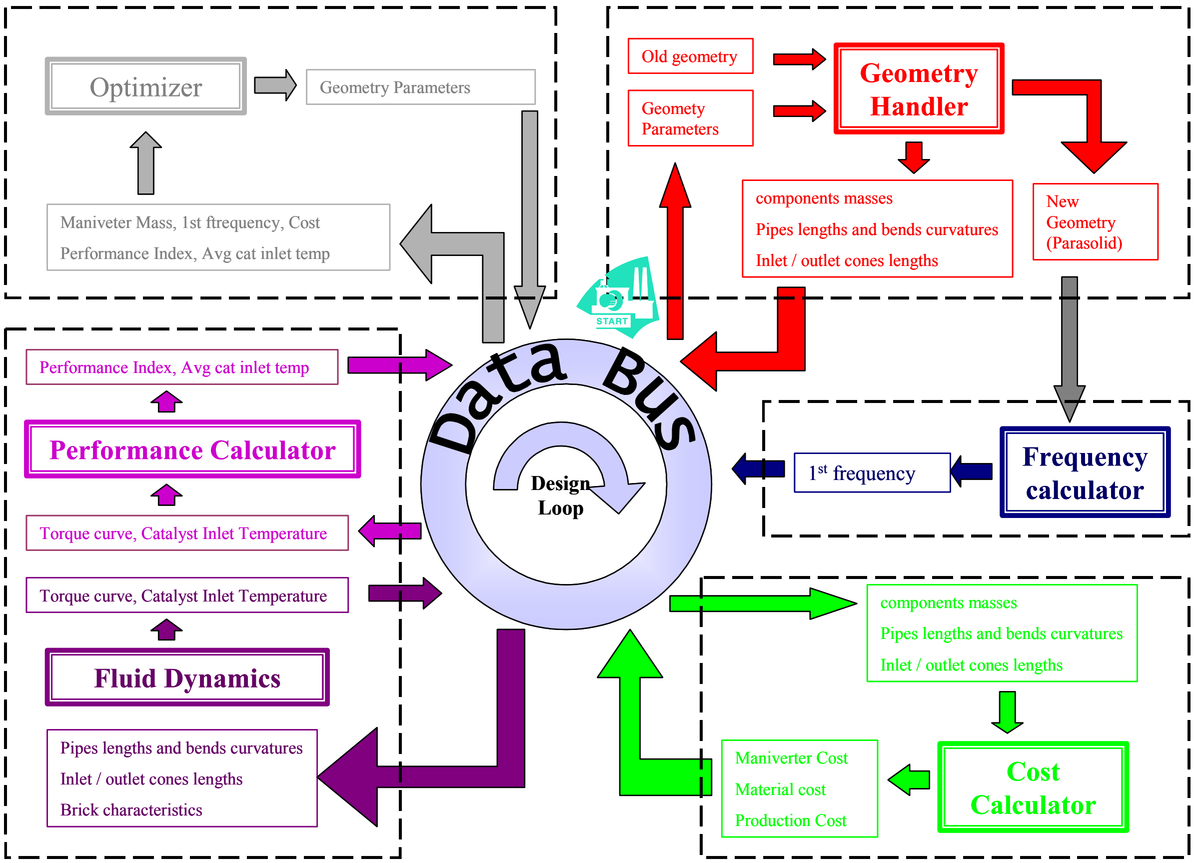

Figure 7: ICE Platform Data Flow

The EDF enables both the optimization of the design for a single performance attribute, or for multiple performance attributes at the same time. In the latter case, the Pareto set of non-dominated solution replaces the single optimized design as outcome. All solutions lying on the efficient frontier are potentially preferred by the decision makers and in order to ascertain which is actually preferred it is necessary to take into account the decision makers preferences. Since engineering decisions involve the resolution of design trade-offs, our approach is to identify the Pareto data first and to present them to the user to apply final preference weights and select the "best" solution.

F. Data Visualization[13]
Design exploration and Multi-disciplinary Design Optimization processes generate a huge amount of data, which, depending on the multi-dimensionality, can easily surpass the human cognitive capabilities. Hundreds or thousands design alternatives can be analyzed in a MDO process and each design can be characterized along several dimensions. To enable effective engineering decisions, an appropriate method to harness this complexity and to transform data to information and to knowledge is required.[19]

Raw data coming out of any MDO analysis can essentially be though of as filling an *m* x *n* matrix where each of the *m* lines refers to a particular design and each of the *n* columns is a specific response. Non-dominated (or Pareto) solutions are extracted from the complete data pool. For each of the performance attributes, the best and the worst are identified; then each value is ranked from 0 to 1 according to the proximity to the "best" point: 0 identifies the worst and 1 identifies the best. To each of the values, a color is attributed. A typical resulting plot, generated with Poptools, is shown in Figure 8: each row corresponds to a design configuration and each column refers to a specific performance attribute.

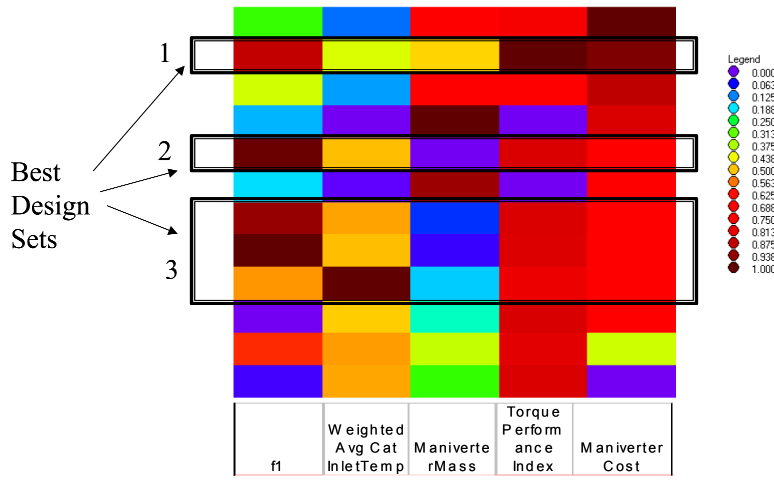

Figure 8. Pareto Data Qualitative Rainbow Plot

IV. Using the Tool: Developing Products Efficiently

Making use of the developed EDF we simulated the design task of developing a maniverter for the Fire 1.4 engine.

Given the high number of design variables (48 in total), the search for the most efficient frontier (which, in this case, is actually an hyper-surface) is done in two phases:

- In Phase I, a sort of testing phase, only the centerline of the maniverter piperuns are allowed to change during the development process, while their diameters, thickness and the rest of the converter are fixed. This gives a total of 24 design variables.
- In Phase II: all available design variables (48) are considered actually variable.

In Phase II, the identified solutions are compared, in terms of performance and piece cost with a baseline, which was tuned to reproduce an actual design that ArvinMeritor developed in 2002 for the same application with the purpose to get an indication of the design improvement that the novel approach is capable of delivering.

At the same time, development time is recorded and compared with a standard ArvinMeritor leadtime for this type of application to estimate the reduction in development costs and in time to market and the increased design flexibility enabled by the use of the EDF.

G. Phase I: Testing the EDF on the maniverter

Whenever a new problem is tackled, for which very little is known about the design space and the behavior of the system, good practice suggests exploring it in a systematic manner. Typical techniques used for this design exploration activity are DoE or Monte Carlo analysis[20]. In DoE, sample points are selected in the design space (several methods exist for point selection) and performance attributes computed. In Monte Carlo analysis, design variables are varied around baseline points according to a probability distribution. Design Space exploration can be an effective technique to locate the zones where optima are; in addition the sensitivity of performance attributes to the different design variables can often be easily established.

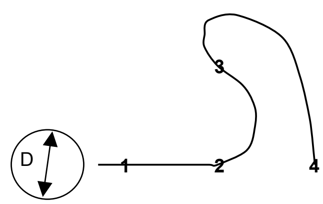

Figure 9. An example of unfeasible geometry

However, both DoE and Monte Carlo analysis cannot be run in our EDF, since they are impaired by a major roadblock: geometry regeneration failures. Let's illustrate the issue with a simple example.

Let's consider a pipe whose centerline is defined by 4 control points which are allowed complete freedom in the design space. Since there is no restriction in the choice of parameters values, a combination of control points which gives the path shown in Figure 9. If the pipe has the diameter *D* shown, we intuitively understand that the pipe cannot be geometrically generated: the curve between point 3 and point 4 is, in fact, too tight. We, therefore, intuitively grasp that a loose coupling exists between the selected variables, even though the relationship cannot be straightforwardly determined.

Generalizing, we can represent the design space as defined by “feasibility channels” where certain combinations of design variables give feasible solutions, delimited by ridges beyond which no solutions exist. To partly uncover the nature of this channel-like design space, a pseudo-Monte Carlo analysis is run. The strategy is the following. Starting from a baseline feasible design configuration, a “local” Monte Carlo analysis is performed where design variables are allowed to change by +/- 20% with respect to the baseline. This guarantees that a sufficient percentage of the runs are feasible. Then, the farthest point in the design space is selected, i.e. the design vector N, which features the highest design variables distance $\sqrt{\sum_n (x_i^N - x_i^0)^2}$, from the baseline and a new Monte Carlo analysis is run. A fixed number of advancement steps (100) and “local Monte Carlo analysis” (10) are set, for a total of 1000 runs.

Figure 10 collects a sample of 4 of the 276 pairwise scatter plots of the 24 design variables.

The points where the geometry generation failed are indicated by circles, the feasible points by full dots. The direction of the stochastic path is given by the arrows.

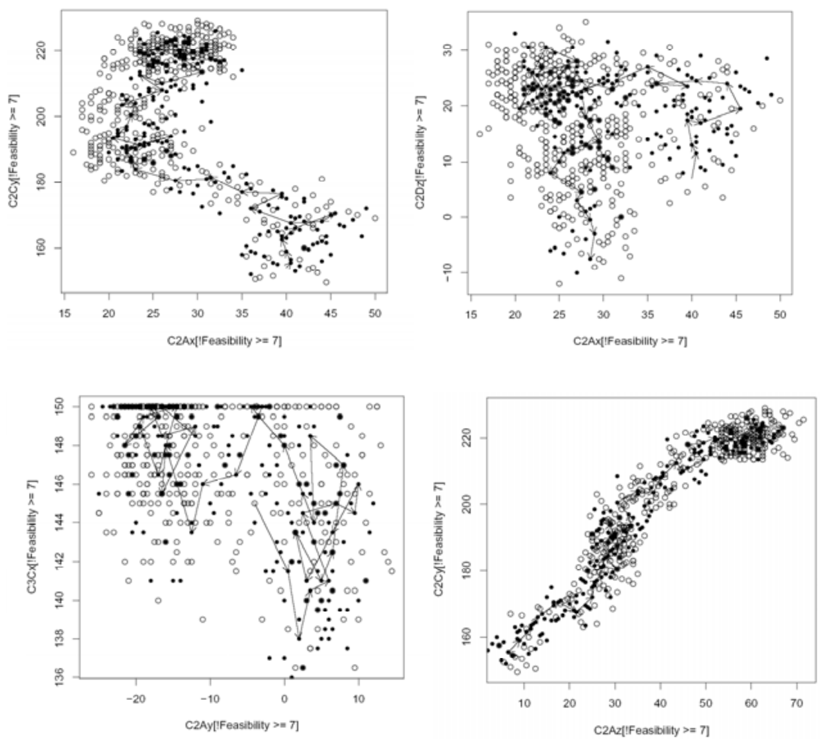

Figure 10. Design Space Feasibility Channels

Feasibility channels clearly emerge. Many different patterns appear: some of the variables are poorly or non-correlated at all, some of them are loosely correlated and some others are highly correlated.

The situation is further complicated by the fact that channels shape and dimensions change with the other design variables that were fixed in this testing phase, i.e. the pipe diameters and thicknesses.

When running a DoE or a Monte Carlo analysis, values of the design variables are selected randomly in the whole design space. The morphology of the design space made by unpredictable narrow feasibility channels causes the majority of random combinations to generate unfeasible geometries. Out of a Monte Carlo trial we did with uniform probability distribution, we estimate that the feasible runs are about 1-3% of the total number of runs. Even though geometry regeneration time is remarkably low (<1 min), to have any given number of feasible geometry sets, a number of runs about 100 times larger would have to be executed (without imposing additional constraints). Constraints are not typically imposed apriori for DOE or Monte Carlo simulation.

If, given the peculiar shape of the design space for this application, traditional design space exploration techniques are not affordable, on the other hand, gradient-based techniques proved to be effective. A particular effective method in “riding” the channels proved to be Hooke-Jeeves[24]. The Hooke-Jeeves search, in fact, is made especially for ridge-following. Its strength is that it is able to find the ridges itself and can recover if a ridge comes to an end. With H-J feasible runs are about 70% of the total.

Using the H-J algorithm, the following single-objective runs were performed and the following results obtained:

- Min mass. The total mass was reduced by 479g (from 5946g to 5467g), i.e. by 8%; however, if we take into account that all maniverter's design variables were fixed, except for the piperuns, whose mass is 1224g, we get a more sensible figure of 39% mass reduction
- Max Performance. The performance index was increased by 7%, from 130 to 139. A closer look at the components of the performance index, i.e. the mean value of the torque and its standard deviation, reveals that the improvement arises from the reduction in the standard deviation, more than from the increase in the mean value. The optimization process led to an evening of pipe lengths which is consistent with manifold design best practices that recognize the benefit of having even pipe lengths on the regularity of the torque.
- Min Cost. Even if with disguised cost figures, we note that the cost reduction has been remarkably high, from €36.8 to €24.6, i.e. nearly 35%. Maniverter cost was reduced essentially by leveraging production cost, while material cost remained essentially the same. Production cost is reduced by reducing the number of bends and the bend angle of the four pipes. The cost model for pipe bending appears to be highly sensitive to curvature.

Single-objective runs allowed getting first results from the framework. The results are sensible since they match common design experience and offer intriguing insights from a business perspective.

After the single-objective preparation runs, we turned to the main goal, which is multi-objective optimization.

For multiobjective optimization, Genetic Algorithms (GAs) are very effective. One of the most recent (2002), the Neighborhood Cultivation Genetic Algorithm (NCGA), was used for the maniverter multi-objective analysis.

NCGA is selected for maniverter development because, in addition of being a powerful GA for Pareto set extraction, its iSIGHT's implementation gives the possibility to give a start population that the algorithm evolves. This is the mechanism that we exploited, together with the results of the previous single-objective runs, to overcome the feasibility issue. In fact, if we tried to run any GA without a special initialization, since the starting population is generated through a random selection of design variables combination, we would face the same feasibility problem with many generated solutions being infeasible. What we interestingly found, on the other hand, in our particular application is that "feasibility" appears to be a characteristic of the "DNA" of any feasible solution. This has, as a consequence, that if the GA starts with a population of feasible solutions, it proceeds without encountering any major obstacle because, crossing over two "feasible" members results, in general, in feasible offspring. This is not always true in other problems, where destructive mating between two feasible solutions can occur if they are far from each other in x-space, as measured by the Euclidian distance metric mentioned above. Therefore we successfully followed the steps of generating feasible solutions with a pattern search algorithm such as H-J and then composing the population to be given as the initial set to the NCGA.

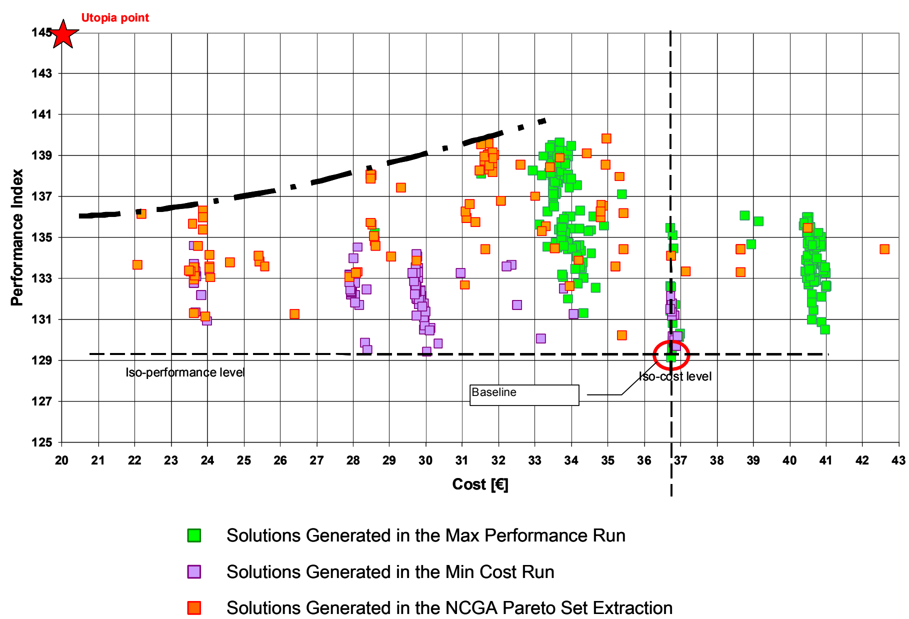

Figure 11. Phase I: Testing Phase – Performance-Cost Trade-Space

In Phase I the multi-objective analysis was limited to two out of the five different performance objectives only. The two populations generated in the previous cost minimization and performance maximization runs are considered. Ten members are selected from both populations to form the starting set, which is then carried forward for 10 generations, for a total of 100 runs. About 90% of the runs were feasible.

In Figure 11 results are reported in the Performance-Cost trade-space, see Eq. 1 for performance index, see Table 2 for cost calculation. Green squares identify the results of the previous max performance runs, purple squares are the results of the previous min cost run, orange squares are the solutions generated by the NCGA process.

We note that a good coverage of the performance attributes space is achieved thanks to the diversity of the initial set and that some very interesting solutions were found which have higher performance than the baseline at a much lower cost.

H. Phase II: Running the EDF with full capabilities

In this last phase of the research, we released all the variables that are allowed by the parametric model. This allows the optimization algorithm to consider the following elements: piperun centerlines, pipe diameters, position and inclination of the converter, thicknesses of pipes and inlet / outlet cones. For each of the design variables adequate lower and upper boundaries were set.

Following the methodology identified in Phase I, the development run, has been articulated in two consecutive phases:

- "Anchor points" identification with single optimization runs: min mass, max frequency, max performance index, max catalyst inlet temperature, min cost. Approximately 100 runs of a single objective optimization for each of the five selected performance attributes have been done. The algorithm used was Hooke-Jeves. The five single objective runs totalled 7 days of computing time.
- Pareto hyper-surface extraction. Four design configurations per each of the five performance attributes among the best of those identified in the exploratory runs have been selected for a total of twenty designs. These were used to compose the initial population used in the Pareto set extraction run. The initial population of feasible designs was instrumental to keep feasibility as high as 80%. The NCGA algorithm was used for this purpose. The population was advanced for 25 generations for a total of 500 runs. As for the 500 preliminary runs, 7 days of computing time were required.

f1	Weighted Avg Cat InletTemp	Maniverter Mass	Torque Performance Index	Maniverter Cost	f1	WeightedAvg Cat InletTemp	Maniverter Mass	Torque Performance Index	Maniverter Cost
4.93	1188.86	5238.26	136.01	15.83	28.48%	11.28%	70.42%	79.41%	100.00%
415.26	**1204.38**	**5556.17**	**152.96**	**18.56**	**86.92%**	**41.48%**	**48.65%**	**100.00%**	**96.44%**
319.92	1190.33	5150.39	133.48	25.28	40.61%	14.14%	76.44%	76.34%	87.69%
268.17	1183.06	4806.43	70.79	28.49	15.47%	0.00%	100.00%	0.20%	83.52%
440.06	**1208.96**	**6266.49**	**139.27**	**35.09**	**98.97%**	**50.39%**	**0.00%**	**83.38%**	**74.92%**
3.48	1183.89	4918.21	70.62	35.27	18.06%	1.61%	92.34%	0.00%	74.69%
91	**1210.14**	**6146.74**	**139.31**	**35.47**	**93.07%**	**52.68%**	**8.20%**	**83.42%**	**74.43%**
442.18	**1209.00**	**6208.10**	**139.20**	**39.16**	**100.00%**	**50.47%**	**4.00%**	**83.28%**	**69.63%**
346.86	**1234.46**	**6019.93**	**137.27**	**40.64**	**53.70%**	**100.00%**	**16.89%**	**80.94%**	**67.70%**
236.31	1208.38	5947.09	139.67	42.43	0.00%	49.26%	21.88%	83.85%	65.36%
361.97	1210.38	5689.49	138.36	61.50	61.04%	53.15%	39.52%	82.26%	40.53%
243.15	1210.02	5853.49	139.45	92.64	3.32%	52.45%	28.29%	83.59%	0.00%

Table 3. Final Run – Pareto Data Quantitative Rainbow Plot

The Pareto set was generated automatically by iSIGHT's NCGA's algorithm and included 12 designs solutions. Pareto data were transformed into a rainbow plot[13]. The quantitative version is represented in Table 4. The dark red cells identify "good" performances, the light red or white cells, "bad" performance levels. The yellow header block on the left contains actual numerical values, while the white header on the right shows the percentage ranking (100% being best).

The rainbow plot conveys pictorially and intuitively several qualitative important information:

- Maniverter mass and Catalyst Inlet temperature are negatively correlated, i.e. good values (i.e. low) of the former correspond to bad (i.e. low) values of the latter. This is evident by observing that strong red colors in mass column are, in general, associated to light colors in temperature column.
- Mass is positively correlated with Cost, i.e. lower mass corresponds to lower cost. This is testified by the fact that designs are associated similar colors in the cost column and in the mass column.
- The inverse happens with Mass and Performance: high levels of performance attributes are generally associated with poor (i.e. high) values of mass. This is consistent with design experience which states that high performance is achieved with long piperuns.
- Torque performance does not exhibit huge variability and it is particularly insensitive to the variation of the other performance attributes. This is the highlighted by the fact that its related column features a red-side color for most of the designs.

- High levels of all performance attributes at the same time are difficult to achieve. This is witnessed by the fact that no rows with red color marked in all columns exists.

Since there is no design which shows good values in all the five performance dimensions, we isolated designs with, at least, four distinctively good performance attributes (highlighted in bold).

We then applied a preference set, which estimates as too high a mass of 6200g. The choice, then, fell on the solution with 5556 g (boxed in blue, Table 3).

Performance Attribute	Optimization Target	Baseline	Selected Solution	Difference
Torque Performance Index	⇧	129.70	152.96	17.94%
Cost [€]	⇩	36.83	€ 18.56	-€ 18.27
1st Natural Frequency [Hz]	⇧	340.71	415.26	74.55
Catalyst Inlet Temperature [°C]	⇧	1178.68	1204.38	25.70
Mass [g]	⇩	5945.63	5556.17	-389.46

Table 4. Performance Attributes Comparison: Optimized vs. Baseline Solution

In Table 4, the identified "Pareto-optimal" solution is compared with the baseline design that was the starting point in our optimization work and which, as mentioned, constitutes a solution that took ArvinMeritor about 9 weeks to develop and to optimize for the particular application in 2002. Even though the results are as good as the underlying models, the new solution appears far better in all dimensions: it has better torque performance (+20%), better vibration characteristics (+75 Hz), better pollutant conversion characteristics by ensuring faster warm-up of the catalytic converter (+25 °C) and lower mass (-389g). Last but not least, it has a remarkable 50% lower cost, mainly driven by the pipe bending radii.

The new design looks odd to the eye of an "experienced" designer because of the different pipe diameters and different thicknesses and in no way this would be the result of a typical manual development effort (Figure 12). We note that similar situations, i.e. high performance solutions that do not correspond to well-established design patterns, are likely when performing automatic optimization. Optimization algorithms, in fact, are not forced to ride the old paths of experience but are only governed solely by the goals they are given. In addition, contrary to current practice, fast execution of design iterations enables many designs to be checked and the "sweet spots" to be identified.

The designer must be therefore be willing to replace the natural scepticism with an authentic open mindset and be ready to accept the solution proposed by the optimization process. Sanity checks are anyway required to avoid making a mistake due to modelling errors, or forgetting important constraints, but when they will give confirmation of the performance of the optimised solution, the design engineer should take the time to reflect on the reasons why the performances of the identified solution are so good. That phase is a fruitful moment of knowledge creation.

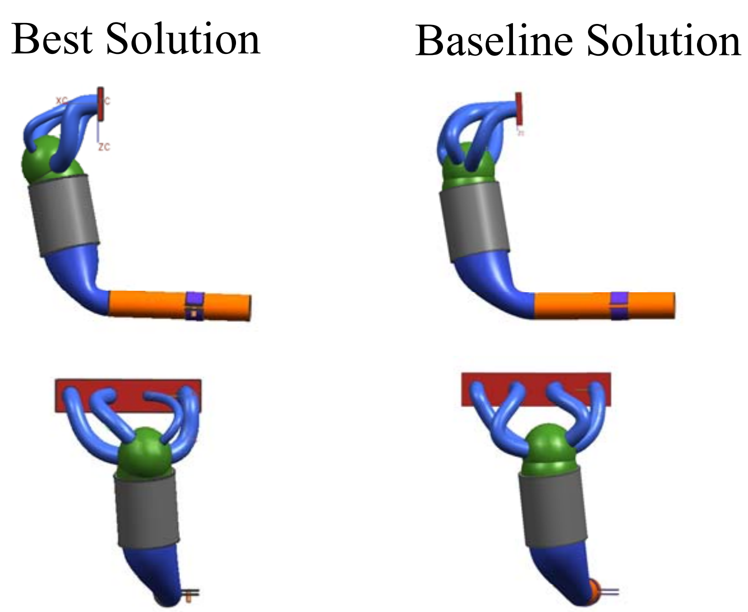

Figure 12. Baseline (right) and Optimized (left) Maniverter Geometry

As a possible physical explanation of some of the good performances of the optimized solution, after an accurate analysis of its design features, we mention:

- The two external pipes, with their higher diameters, contribute to raising the first natural frequency, which corresponds to a lateral movement.

- The higher total pipe cross sectional area, in addition, contributes to lowering the backpressure.
- The maniverter mass is lower, thus raising the frequency and lowering the cost
- The number of bends is lower and bends with smaller values of diameter/bending radius ratios, lower bending cost.
- The pipework mass is lower, thus raising the average catalyst inlet temperature
- Pipe diameters are different to compensate for different lengths and bends: 1) smoothness of piperun is a factor for backpressure reduction and can be balanced against a smaller radius; 2) the same tuning frequency can be achieved with a longer pipe with small radius or with a shorter pipe of a big radius.

In a nutshell, we postulate therefore that semi-automatic multi-disciplinary design optimization, compared with the traditional design process, has several benefits:

- Lower development time (14 days of computation against 60+ of normal practice)
- Lower development costs (related to development time and resource allocation)
- Better product performance, given the better design exploration (1000 maniverter designs checked)
- Innovation, ease and speed with which new variants can be designed
- Knowledge Increase

V. The value of the tool: summary of insights

Besides the good results exposed in the previous section, throughout the whole research project, in the setup, building, testing and utilization phases, we came across several findings that, even if strictly limited to the specific application, are believed to have the potential to constitute general insights. We deemed useful to group all of them together in a list of lessons learned. Hereafter they are listed from general design related items to more specific MDO implementation related issues.

I. Design:

- Design solutions exist with similar performance along one dimensions but much different along at least one other.
- Design solutions with extremely good performance attribute levels in many dimensions represent a tiny subset of the design space.
- The majority of the current product designs are characterized by inefficient performance if compared with what those systems have the potential to deliver because normal design practice, limited by time and budget constraints, results in poor design space exploration. Even if product experience may guide to explore good design areas, in general only 50-60% of the value that could be obtained by a system is extracted. Therefore a huge opportunity exists for both product cost reduction or product performance enhancement.
- Relationships between performance attributes are not intuitively obvious for complex systems and not even for simple ones. Intuition, engineering knowledge and experience usually drive the design: design engineers use them to correlate performance attributes to design characteristics. However, for complex systems, the interrelations between physical phenomena is so intertwined that human limited cognitive capabilities may fail to find the right relationships, even in the case of relatively simple systems. A false intuition pushes the designer in wrong directions.
- Effective designs can be found by exploiting the characteristics of the Pareto frontiers. Inter-dependence of performance attributes is, in general, not linear. Regions of the design space can exist where, by worsening slightly the performance attribute A, a huge benefit can be obtained in attributes B and/or C, etc. Moving from one area of the design space to the other, the relationship may invert, i.e. attributes B and/or C, etc. may be insensitive even to a huge variation of the attribute A. The inflexion point can represent a zone where to search for the "best design".
- Semi-automatic Optimization widens design knowledge paths but requires an open mindset. We've seen that optimization algorithms in some cases confirmed current maniverter design practices. However, they are not constrained by "common sense" and "past experience", but they chase only numerical minima or maxima. In doing that, they are not restrained from riding new design avenues and, by doing that, they become a

means for innovation. Design engineers must be open-minded, take the solution proposed by the EDF tool and find the necessary confirmation. In some cases loopholes are exploited because of missing constraints, in other cases truly new designs are discovered within the bounds set by the problem parameterization. If performances are confirmed, the innovation is real and the examination of the root causes leads to extended current product knowledge.

- Multi-disciplinary analysis shifts the engineering focus from design to performance evaluation and decision-making. Quite often, in a design review, the question is asked, by management or customers, "what if I wanted more of this attribute?" or "what if I needed less of that attribute, can I get something in exchange?" The request invariably starts a design iteration, which consequently results in lengthening the development time. With enhanced development tools such as the one object of the current study, all the design solutions are evaluated in advance and trade-offs explored at the outset. Data are presented to the design engineer / manager for him/her to take the ultimate decision.

J. MDO implementation:

- Geometry generation importance cannot be overemphasized. If a CAD tool is used, its flexibility in representing with completeness the design family and its robustness with respect to parameters variation are key to the successful execution of the design search process and to the significance of the obtained outcomes.
- Knowledge-based design can be used proficiently to generate an adequate geometry for optimization. Embedding design rules in the geometry generation is an efficient way of establishing the dependence relationships between the parameters. This greatly helps in making the design space more continuous and consequently in having a simpler and faster design exploration.
- If the design space is discontinuous and characterized by channel–like feasibility zones, the Hooke-Jeeves algorithm shows good performances in single-objective optimization: it locates ridges of a channel and follows them efficiently up to the optimum. However, it shows its weaknesses when a channel is forking: the algorithm, in fact, follows the branch of the channel, which looks more promising, completely neglecting the other(s). Future research might resolve this issue.
- Design of Experiments, Monte Carlo Design Space Exploration, and Genetic Algorithms have difficulty exploring design spaces made up primarily of feasibility channels. Only a few percent of the randomly generated solutions fall into the feasibility channels, the rest cause those algorithms to be so highly inefficient as to be useless. However, Genetic algorithms with explicit Pareto optimality management, suitable for Pareto hyper-surface extraction, if properly fed with an initial population of feasible solutions, may generate feasible offspring and be able to locate the Pareto front efficiently.
- Software interoperability and interface management are key in the success of any MDO approach. Clear and comprehensive analysis of requirements of each analysis module must be done at the outset to ensure efficient execution.
- In designing any engineering tool for analysis of complex systems, information processing capabilities of human users must be taken into account. Failure to recognize the essential role of the tool/human interface may lead to develop tools that, despite their power, are perceived as too complicated and ultimately rejected by the engineering users community. That's why it's particularly important to develop adequate methods of presenting the huge amount of data coming out of the design space exploration in a way that captures the attention of decision-makers and allows using the powerful capabilities of intuition and synthesis of the human brain.
- The semi-automated MDO process has the potential to identify solutions with performance attributes levels much higher than with traditional manual processes at vastly lower cost and time, provided the initial cost in setting up the MDO environment can be amortized over time. Key in time savings are: 1) the resolution of the interfaces issues once for all the design iterations; 2) efficient jobs scheduling allowed by computerized queuing; 3) 24/7 activity possible only with machine operations (downtime excluded).
- Modular architecture for the ICE platform is to be preferred. MDO requires different analyses to be performed at the same time. For an effective implementation, it's important that incremental development is possible: whenever a new analysis module becomes available, it must be inserted seamlessly in the platform; similarly, whenever an existing module needs to be removed or upgraded, the operation needs to be transparent for the platform. Only a modular architecture and particularly a bus architecture (see Figure 2) gives the required flexibility.

VI. Conclusions and Future Outlook

Automakers and Tier1 suppliers search ways to increase their speed, agility, situational awareness and ability to innovate and, in consequence, improve their competitive position. Following our industry and PDP analysis[13], MDO in an ICE framework is viewed and proposed as a mindset and a methodology to cope with the challenging demands that the market is imposing on automotive manufacturing firms, helping the transition in the product-development and engineering processes from a "test, analyze, and fix" paradigm toward an industry-ideal "design-right-the-first-time" for value maximization. In a case study of an automotive system such as an exhaust system maniverter, the improvements in the design process have been impressive: from 60 days of the current design practice to 20 min for one single design iteration loop, with the consequent reduction in design costs. The fast design iteration allowed 1000 different configurations to be analysed in 14 days, with the consequent increase in performance characteristics of the final design.

Our vision for the future of engineering design, and for automotive systems design in particular, is that of a environment where it is possible to perform the Multidisciplinary Design Optimization of complex engineering systems using computational tools. These tools, taking advantage of the interoperability of the different systems, will automate much of the design configuration process, putting product engineering at the heart of the design process. This automation will not be "black-box" engineering, but rather the efficient execution of known engineering steps to evaluate design alternatives, providing engineers with information to make better decisions and to rapidly respond to defined and projected needs at manageable cost.

The ability to re-engineer products rapidly and the emphasis on design assessment, comparison and improvement will almost inevitably lead to better engineering solutions to product design problems and to solutions configured instantaneously to meet fast changing customer needs.

The optimization algorithms, not constrained within the well-known ridges of common sense and practice could venture safely in new areas of the design space leading to innovative, high performance designs.

The freeing of experts from team supervision, teaching and routine engineering work will further enhance their ability to discover engineering improvements and allow them to devote to research and innovation, triggering a virtuous growth spiral.

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