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OPTIMIZATION OF NOZZLE: CONVERGENCE USING ANSYS WITH RSM, MOGA

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ABSTRACT

In this paper, a multi objective optimization based on Genetic Algorithm, Response Surface Method and Design of Experiments are adopted in order to calculate the optimal CFD model parameters, retaining the convergence. Objective functions to be optimized simultaneously in such a real world complex multi-objective optimization problem. These objective functions are either obtained from experiments or computed CFD approaches, unless a simple but effective meta-model is constructed over the response surface from the numerical or experimental. So that modeling and optimization of the parameters is investigated by using ANSYS. An ANSYS Fluent software package is utilized to simulate the viscous gas flow-field in the nozzle; the Response Surface Methodology (RSM) applied for the reason of performing a multi-objective optimization.

Keywords: optimization, DOE, RSM, MOGA, convergence.

INTRODUCTION

The development of high-speed computers has revolutionized the world. They have been changed our ways of thinking and have generated an impact in every facet of our daily lives. Problems hitherto unsolvable have come under the purview of computer solution. Over the past half-century, we have witnessed the rise in the new methodology for attacking complex problems.

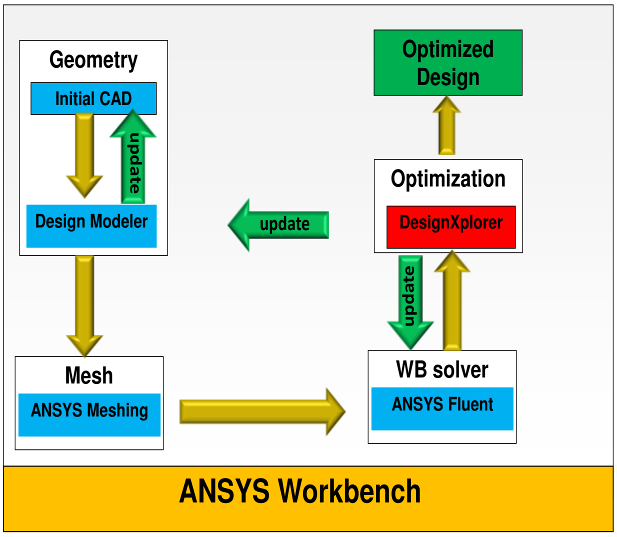

Figure-1. Workflow for optimization.

DESIGN OF EXPERIMENTS (DOE)

An important aspect of RSM is the design of experiments (Box and Draper, 1987), usually abbreviated as DoE. These strategies were originally developed for the model fitting of physical experiments, but can also be applied to numerical experiments. In Design of Experiments the target is the selection of points with that the response should be evaluated.

Most of the criteria for optimal design of experiments are associated with the mathematical model of the process. Generally, these mathematical models are polynomials with an unknown structure, so the corresponding experiments are designed only for every particular problem. The choice of the design of experiments can have a large influence on the accuracy of the approximation and the cost of constructing the response surface.

In a traditional DoE, screening experiments are performed in the early stages of the process, when it is likely that many of the design variables initially considered have little or no effect on the response. The purpose is to identify the design variables that have large effects for further investigation.

RESPONSE SURFACE METHODOLOGY (RSM)

Response surface methodology (RSM) is a statistical technique in which smooth functions, typically polynomials, are used to model an objective function. Throughout this work, ANSYS program is used to generate response surfaces. For response surface analysis, you can choose from three sampling methods: Central composite design, Box Behnken matrix, Optimal Space Filling and user-defined. In this work the central composite design method is used.

CENTRAL COMPOSITE DESIGN (CCD)

Central Composite Design (CCD) is the default DOE type. It provides a screening set to determine the overall trends of the meta-model to better guide the choice of options in Optimal Space-Filling Design. The generated design point's location for the method is based on the central composite design. N is the number of input parameters and f is Factorial number. In this, no of design variables are N=2, the total no of design points is = $1+2\times N+2^{(N-f)}=1+4+4=9$

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Table-1. CCD Design Points for the specified two input design parameters.

Table of Schematic B2: Design of Experiments (Central Co

	A	B	C
1	Name	P7 - outlet	P6 - Inletangle
2	1	30	65
3	2	10	65
4	3	50	65
5	4	30	50
6	5	30	80
7	6	10	50
8	7	50	50
9	8	10	80
10	9	50	80

MULTI-OBJECTIVE OPTIMIZATION

Multi-objective Optimization Mathematically, a multi-objective problem consists of optimizing (i.e., minimizing or maximizing) several objectives simultaneously, with a number of inequality or equality constraints. The Multi-objective optimization, which is also called multi criteria optimization or vector optimization, has been defined as verdict a vector of decision variables fulfilling constraints to reach adequate values to all objective functions. The general Multi objective Optimization Problem (MOP) can be formally defined as: Find the vector $\vec{x}^{*} = [x^{*}1, x^{*}2, \ldots, x^{*}n]^T$ which will satisfy the m inequality constraints: $g_i(\vec{x}) \geq 0$ $i = 1, 2, \ldots, m$, The p equality constraints $h_i(\vec{x}) = 0$ $i = 1, 2, \ldots, p$ and will optimize the vector function $\vec{f}(\vec{x}) = [f_1(\vec{x}), f_2(\vec{x}), \ldots, f_k(\vec{x})]^T$. In these problems, there are several objectives (a vector of objectives) to be optimized (minimized or maximized) simultaneously. These objectives often conflict with each other so that improving one of them will deteriorate another. Therefore, there is no single optimal solution as the best with respect to all the objective functions. Instead, there is a set of optimal solutions, known as Pareto optimal solutions or Pareto front (Pareto, 1896) for multi-objective optimization problems. The concept of Pareto front or set of optimal solutions in the space of objective functions in multi-objective optimization problems (MOPs)

MULTI-OBJECTIVE GENETIC ALGORITHM (MOGA)

To attain the optimal parameters of nozzle, an integrated method that combine genetic algorithm with CFD simulation analysis is set forward. The integrated method not only shortens the system design, it also extends optimization technique to realize the potential of computer based design automation.

The Pareto ranking done by a fast, non-dominated sorting method and this is an order of magnitude faster than traditional Pareto ranking methods. The penalty functions and Lagrange multipliers are not needed because the constraint handling uses the same non-dominance principle as the objectives. This ensures the feasible solutions are ranked higher than the infeasible solutions.

First Pareto front solutions are archived by separate internal sample sets and this is different from the developing sample set. This ensures Pareto front patterns already available from earlier iterations minimally disrupted. The selection pressure can be (and, consequently, the elitism of the process) to avoid premature convergence by altering the parameter **Percent Pareto**.

The concept of Pareto dominance is importance in multi-objective optimization, objectives and constraints are mutually conflicting particularly where some or all. In such case, no single point yields the "greatest" value for all objectives and constraints. The greatest solutions, often called a Pareto set, are group of solutions such that choose any one of them in a position of another will constantly give up quality for at least one objective or constraint, while improving at least one other.

Unfortunately, the Pareto optimum almost always gives not a single solution, but a set of solutions. Usually Pareto optimality is spoken of as being global or local depending on the neighborhood of the solutions X, and in this case, almost all traditional algorithms can at best guarantee a local Pareto optimality. However, this MOGA-based system, which incorporates global Pareto filters, yields the global Pareto front. The **Maximum Allowable Pareto Percentage** criterion looks for a percentage that represents a specified ratio of Pareto points per Number of Samples per Iteration. When this percentage is reached, the optimization is converged.

CONVERGENCE CRITERIA

The iterative process is repeated until the change in the variable from the one iteration to the next becomes so small that the solution can be considered converged. At convergence: Discrete conservation equations like momentum, energy, etc. are maintained to be a specified tolerance in all cells. The results are no longer altered with additional iterations & Mass, momentum, energy and scalar balances are obtained. Residuals measure imbalance (or error) in conservation equations the convergence of the simulations is said to be achieved when all the residuals reach the required convergence criteria. These convergence criteria are found by monitoring. The convergence criterion for the continuity equation, momentum, k and epsilon equations are $1E^{-4}$ and it is set to $1E^{-6}$ for Energy equation.

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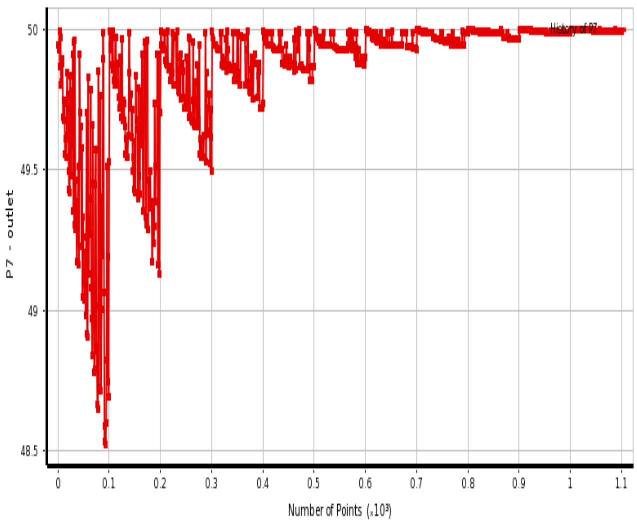
RESULT AND DISCUSSIONS

	A	B
1	Property	Value
2	⊟ General	
3	Component ID	Optimization
4	Directory Name	GDO
5	⊟ Notes	
6	Notes	
7	⊟ Design Points	
8	Preserve Design Points After DX Run	☐
9	⊟ Failed Design Points Management	
10	Number of Retries	0
11	⊟ Optimization	
12	Optimization Method	MOGA
13	Number of Initial Samples	10000
14	Number of Samples Per Iteration	100
15	Maximum Allowable Pareto Percentage	70
16	Maximum Number of Iterations	20
17	Maximum Number of Candidates	3
18	Verify Candidate Points	☐
19	⊟ Optimization Status	
20	Converged	Yes
21	Pareto Percentage	1
22	Number of Iterations	11
23	Number of Evaluations	10719
24	Number of Failures	0
25	Size of Generated Sample Set	100
26	Number of Candidates	3

Figure-2. Multi-objective genetic algorithm.

The MOGA method (Multi-Objective Genetic Algorithm) is a variant of the popular NSGA-II (Non-dominated Sorted Genetic Algorithm-II) and based on controlled elitism concepts. It supports multiple objectives and constraints and aims at finding the global optimum. It is limited to continuous input parameters. Initially generate 10000 samples, 100 samples per iteration and find 3 candidates in a maximum of 20 iterations. It converged after 10719 evaluations.



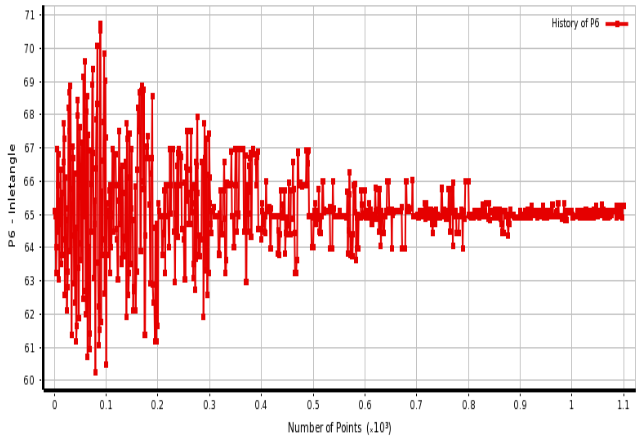


Figure-3. Outlet and inlet angle convergence.

CONCLUSIONS

Multi objective Genetic algorithms have been successfully used for optimization of nozzle and the convergence of the simulation for Pareto based optimization. This paper has been presented to multi-objective optimization, aims to help the user to speed up the choice of correct parameters and ensuring simultaneously convergence of the CFD model. The purpose is to recognize the optimal designs of supersonic nozzles that perform utmost equality of thermodynamic and flow-field properties respect to their average values at nozzle exit. This work has established the effectiveness of Multi-Objective Optimization techniques in convergence and optimization of nozzle.

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APPENDICES

Appendix-A. Pressure velocity contours.