

**DEVELOPMENT OF AN AUTOMATED CFD-BASED OPTIMIZATION
WORKFLOW FOR AUTOMOTIVE AERODYNAMIC APPLICATION**

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in fulfillment of the requirement for the degree of
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DECLARATION

I declare that this project entitled “Development of An Automated CFD-Based Optimization Workflow for Automotive Aerodynamic Application” is the result of my own work except as cited in the references


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APPROVAL

I hereby declare that I have read this project report and in my opinion this report is sufficient in terms of scope and quality for the award of the degree of Bachelor of Mechanical Engineering (Design And Innovation).

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Date : 13/06/2017

ABSTRACT

Aerodynamic design plays an important role in the field of automotive application as it might become one of the main elements that can contribute to sustainable development in the future by improving the fuel efficiency. As a result, a powerful optimization tool or workflow is required to optimize the complicated configurations of parameters related to aerodynamic automotive application. The purpose of this project is to develop a CFD-based optimization workflow to automate an optimization process of aerodynamic automotive application. Three cases which related to the aerodynamic parameters in automotive application are applied with a sequence of optimization methods, Screening method followed by Non-Linear Programming Quadratic Lagrangian (NLPQL) method in order to verify the workflow. The three cases are the design of airfoil shape with the minimum total drag coefficient, the angle of attack of NACA 0012 airfoil profile with maximum downforce generated and the effect of AoA of rear spoiler against the drag and lift coefficient on a 3D Ahmed Model. Before the application of the optimization workflow, the models in three cases need to be meshed and simulated by specific settings and boundary condition. Next, the cases are applied with Screening followed by NLPQL optimizations methods to determine the optimal solution. The optimal results from the workflow of optimization processes are compared to the result from previous findings and proved that Screening followed by NLPQL optimization methods is a good approach of workflow to resolve optimization problems that related to aerodynamic automotive application automatically.

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LIST OF ABBEREVATIONS

CFD	Computational Fluid Dynamics
DOE	Design of Experiment
NLPQL	Non-Linear Programming by Quadratic Lagrangian
SQP	Sequential quadratic programming
KKT	Karush-Kuhn-Tucker
MDF	Multiple Discipline Feasible method
NSGA-II	Non-dominated Sorting Genetic Algorithm II
MISQP	Mixed-Integer Sequential Quadratic Programming
RSM	Response Surface Methodology
AGA	Approximate Evaluation
AoA	Angle of Attack
SIMPLE	Semi-Implicit Method for Pressure-Linked Equations
NACA	National Advisory Committee for Aeronautics

LIST OF SYMBOL

y	=	Objective function
x	=	Design variable
h	=	Constraint function
y_{k+1}	=	design point with $k+1$
y_k	=	design point
α_k	=	step size
d_k	=	direction of given point y_k
3D	=	3-Dimensional
2D	=	2-Dimensional

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

CFD engineers might face time consuming problem while optimizing a design due to consideration of many procedures. The optimizing process will become more complicated when the design come in a complex shape or including a large number of computations into it. However, there are some alternative ways which can obtain the optimized design automatically by using certain type of CFD software. ANSYS simulation software is one of the most effective and powerful tool to carry out the optimization process automatically. The optimization methods can be run by ANSYS simulation software are Design of Experiment (DOE), Genetic Algorithm, Multi-Objective Genetic Algorithm, Screening, Non-Linear Programming by Quadratic Lagrangian (NLPQL), Adjoint Solver and others. ANSYS simulation software can also interface with others software such as OptiSlag, MATLAB, Sculptor and Sigma Technology (YY. Perng, 2011).

Shape optimization plays an important role in designing aerodynamic device for road vehicles. Downforce on motorsports were first bringing in by Michael May in year 1956 and people only started to concern about the aerodynamic lift at speed in year 1960 (McBeath. S, 2011). Thus, some device has been developed to reduce the lift and drag coefficient and increase the downforce of the car. Examples of the devices are front spoiler, rear spoiler, dive plates, air dam and others. There is another device which can use to generate downforce named Splitters. Splitters can increase the static pressure of the upper body of the car by generate a downforce on the surface of the splitters when the air flow

through it. Besides that, rear spoiler also considered as a popular embodies which have been studied by many researchers in order to improve downforce of a car. Meanwhile, there are many parameters of the rear spoiler can be analyzed and each of them will affect the effectiveness of a rear spoiler. Parameters that can be studied are length of inverted wing, thickness of span, angle of attack, leading edge radius (L.E), camber, number of element of wing and installation of end plate (McBeath. S, 2011).

In a general term, aerodynamic device of a road vehicle requires a shape optimization tool to analyze and improve their performance by changing the dimensions and geometric shape of the device.

1.2 PROBLEM STATEMENT

Normally, optimizing process is time consuming because the optimum point could be hard to determine. For an example, optimum angle of attack of rear spoiler can be obtained from the graph of lift coefficient against angle of attack with 0°, 4°, 8°, 12°, and 16°. However, the optimum angle of attack might fall between the angle of attack stated in the graph and another optimization process needs to be done with smaller interval in order to obtain the optimum design point. This process will consume a lot of time since the time taken to run the calculation on the analysis is very long. As a result of this, some tool or function of ANSYS simulation software has to be discovered so that the optimized parameter can be obtained automatically from the analysis. This method can be known as optimization algorithms that capable to determine the actual optimal solution for any linear or non-linear problems.

1.3 OBJECTIVES

The objectives of this project are:

1. To develop a CFD-based workflow and guidelines to automate an optimization process for automotive aerodynamic applications.
2. To reduce the time taken that required to obtain the accurate optimal solution for CFD-based analysis related to automotive aerodynamic application.

1.4 SCOPE

The scopes of this project are:

1. Optimization workflow only studied by using analysis that related to automotive aerodynamic applications in this project.
2. ANSYS simulation software must be included in the workflow of optimization method.

CHAPTER 2

LITERATURE REVIEW

2.1 Optimization

2.1.1 Definition

Optimization can be clarified as a process to find the maximum or minimum value of a function based on the given objective function. In the field of engineering systems, engineers make their decisions based on the main goal which is minimize the input resources or maximize the profit of the output results. Thus, these decisions can be indicated as a function of certain design variables and optimization method is applicable for these cases based on the aim of the given function (Ajaykumar, 2005).

2.1.2 Statement of Optimization Problem

Most of the engineering problems come up with restricted minimization or maximization. For instances, aerofoil shape of rear spoiler attached on the road vehicles is designed based on the minimum drag produced subject to constraints on downforce generated by the rear spoiler. The constrained problems in the case can be expressed as shown as below in a general non-linear programming form:

Minimize $y(x)$;

Subject to $h(x) \leq 0$, $x=1, 2, 3, 4, 5$

where x referred as real value design variables, y referred as objective function and h is referred as constraint function (Ajaykumar, 2005).

The design space of an optimization problem can be defined as an n -dimensional Cartesian coordinate space with the axis represents the design variable, $x = 1, 2, 3, 4, 5$. The design variables x that satisfied the constraint function will form a constraint surface inside the coordinate space. The constraint surface will be separated into $h(x) < 0$ and $h(x) > 0$. Design points on the constraint surface $h(x) = 0$ means it satisfied the constraint function critically. The design points belong to the region $h(x) < 0$ is reliable and acceptable whereas the design points belong to the $h(x) > 0$ is unreliable and unacceptable. Thus, the best design points will be chosen among the points that fall in the region that is reliable and acceptable (Ajaykumar, 2005).

2.1.3 Optimization method

Based on the fact of time consuming development cycle, different types of optimization methodology has been invented to overcome the situation. The advantages of optimization method is the possession of manage many design variables based on shape modification of certain geometry (Ajaykumar, 2005).

The optimization can be categorized in to mathematical programming techniques, stochastic process techniques and statistical methods. Mathematical Programming Techniques included calculus methods, linear or non-linear programming, genetic algorithm, geometric programming, sequential or non-sequential quadratic programming etc (Ajaykumar, 2005).

2.1.3.1 Sequential quadratic programming (SQP)

Sequential quadratic programming solved the optimization problem by using Newton's method and Karush-Kuhn-Tucker (KKT). This method determine the improve design points by using the equation shown as below:

$$y_{k+1} = y_k + \alpha_k d_k$$

Where

d_k =direction of given point y_k

α_k =step size

The tasks of searching the direction vector of the given y_k and step size are included in the iterations run by sequential quadratic programming. Meanwhile, there is also an optimization tool in MATLAB named 'fmincon' works based on the concept of sequential quadratic programming (Ajaykumar, 2005).

Non-Linear Programming by Quadratic Lagrangian is one of the examples of sequential quadratic programming (SQP) method which can be used to resolve continuous parameters optimization problem with different objective function and different constraints. This method runs by using quadratic approximation of Lagrangian function and linearization of the constraints (Schitt, 1986)

Based on the journal "A study of airfoil parameterization, modelling, and optimization based on the computational fluid dynamics method", the NLPQL method is incorporate with MIGA (Multi-Island Genetic Algorithm) to improve the lift to drag ratio of NACA 0012 airfoil profile. The CFD solver is used to combine with the mathematical optimization method to obtain the best point in this optimization problem. The problem at first defined and solved by Response Surface Methodology and proceeds to MIGA

optimization method. The database will be produced by MATLAB and post processing by using FLUENT. The values of lift and drag are obtained and lift to drag ratio is calculated. Next, the result is proceed to the second stage of the optimization method which is NLPQL is used to select the best design point based on the result from the MIGA optimization method. The lift to drag ratio has been improved by 62.32% based on the initial shape of the airfoil at the end of this study. The study also shown that the combination of NLPQL and MIGA can perform a better optimization process than using the methods separately (Zhang, 2016).

There is another journal with title “Multidisciplinary Design Optimization of Solid Launch Vehicle Using Hybrid Algorithm” proposed a combination of optimization algorithm method to obtain an optimum multidisciplinary design of solid launch vehicle. The proposed method is related to the combination of Genetic Algorithm and Sequential Quadratic Programming method. The conceptual design of this study is conceived by using Multiple Discipline Feasible method (MDF). It stated that MDF is an optimization approach to achieve the objectives with certain disciplinary analyses and limited constraints. The designs of the vehicle included are structure, aerodynamics, propulsion, and trajectory disciplines. The MDF method is carried out by using the proposed hybrid optimization method, combination of Non-dominated Sorting Genetic Algorithm II (NSGA-II) and Non-Linear Programming Sequential Lagrangian (NLPQL) (Zahar, 2010).

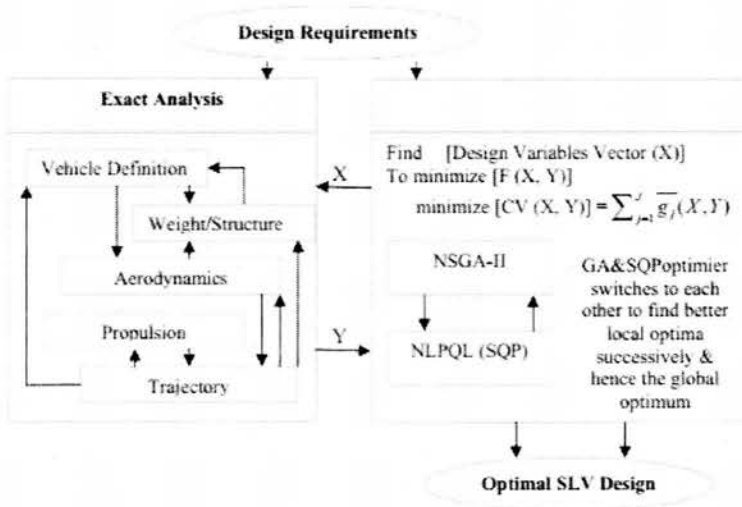


Figure 2.1: The proposed hybrid optimization workflow used in the Multiple Disciplines Feasible formulation (MDF) in the study of Solid Launch Vehicle (Zahar, 2010)

The proposed hybrid optimization is run by using a population of 10 members at first and run for 100 generations in NSGA-II method. Next, a randomly selected solution will be chosen and search for the local optimal solution by using NLPQL. After that, the solutions switched back to the NSGA-II and continue with the next population of 10 members. The procedures are repeated until the optimal result can be obtained. However for the conventional optimization method, a population size of 50 members is chosen and run for 150 generations in NSGA-II. The solutions will be chosen randomly from the result and continue with the application of NLPQL method until the optimal result is obtained (Zahar, 2010).