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Improving Efficiency in Engineering Design Using Augmented D-Optimal Designs 'Synthetic Jet' Design Optimization Study

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IMPROVING EFFICIENCY IN ENGINEERING DESIGN USING AUGMENTED D-OPTIMAL DESIGNS: 'SYNTHETIC JET' DESIGN OPTIMIZATION STUDY

by

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ABSTRACT

IMPROVING EFFICIENCY IN ENGINEERING DESIGN USING AUGMENTED D-OPTIMAL DESIGNS: 'SYNTHETIC JET' DESIGN OPTIMIZATION STUDY

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The purpose of this thesis is to study the efficiency of several "design of experiments" (DOE) approaches used for the analysis and optimization of engineering designs. A literature review is conducted to study various "design of experiments" methods and the advantages and limitations of each method are discussed.

As an application, Augmented D-Optimal designs are utilized for a design study of 'synthetic jet'.

With the objective of improving efficiency and providing a minimum point experimental design model, computer-aided D-optimal method is preferred for this study. For setting up the design of the experiments and for performing the analysis of results, the "DOE" software-JMP is used.

In flow control studies, performance of the system is generally reached by the use of computerized analysis programs. In this study, the experiments are performed using a NASA-developed flow simulation program, CFL3D (Computational Fluids Laboratory 3-Dimensional flow solver). The D-optimal design in this study is enhanced by applying the augmentation method. For augmenting the design, additional experiments are statistically placed in the model. During the analysis of outputs of the experiments, logarithmic

transformation is used for better fitting the data to the formation of mathematical model.

Results indicate that utilizing the augmented D-Optimal designs have led to improving efficiency significantly in the design, analysis and optimization studies performed in this thesis.

Members of Advisory Committee: Dr. Rafael Landaeta (Member)
Dr. C. Ariel Pinto (Member)

To my Mother İclal Erdogan and to my Father Fuat Erdogan

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CHAPTER 1

INTRODUCTION

1.1. Background

Design optimization is essential in the design and evaluation of products or processes in view of the fact that it has an important impact on quality, performance and cost. The objective in design optimization is to search the design space efficiently to determine the values of design variables that optimize performance characteristics subject to system constraints [1]. In various aerospace studies such as a “synthetic jet” design, the experiments are generally performed by the use of computer programs that use complex algorithms which may need a long time to run the experiments.

Sir Ronald Fisher is accepted to be the pioneer of statistical experimental design. He used DOE method in agricultural studies. Since Fisher, numerous methods have been developed by other researchers. In this study, some common methods are reviewed from the recent literature. These methods include OFAT (one-factor-at a time) approach, full factorial design, fractional factorial design, response surface model design (central composite designs and Box-Behnken designs), D- optimal designs and ‘augmentation of experiment’ design techniques.

OFAT (one-factor-at a time) approach seems the least efficient one of the methods reviewed. However, it is widely used in parametric design studies. The OFAT approach does not take the interactions into consideration between parameters or between disciplines in a multidisciplinary design study. Thus, it may produce sub-optimal results.

Full factorial designs take all the possible combinations of design parameters and levels and interactions into account. However, the number of experiments increases drastically as the number of parameters increases, especially with multiple levels. Execution of high numbers of experiments may be significantly expensive and time consuming.

Fractional factorial designs use the fractions of full factorial designs and estimate main effects and some interactions proportional to a fraction ratio. Namely, fractional factorial design is a systematically arranged subset of the full factorial design.

Response surface designs and optimal designs are efficient methods of DOE.

To explore the relationship between design parameters and performance characteristics, building a mathematical model is the approach of response surface designs. In this approach, design analyses are performed at statistically selected points specified by an experimental design matrix. The resulting data from the experiments construct response surface approximation models using multivariate least-squares regression analysis [2].

In this study, Optimality criteria for the above approaches and its different forms are briefly reviewed. Then, D-optimal criterion is studied in more detail since they appear to have the most promise in improving efficiency in design, analysis and optimization for aerospace systems.

For the application part of the study, minimum point D- optimal design method is applied to a 'synthetic jet' design study since it may be the appropriate design method for the case.

Another point studied is 'augmentation'. Augmentation allows the designer to statistically add runs to original model to improve the efficiency of the predetermined design. After performing experiments, the statistical results may be improved by the use of logarithmic transformations in model building. The fitness of the model and the statistical values of the analysis of main and interaction effects may be improved. Consequently, a better mathematical model that approximates the response surface may be constructed. When the appropriate transformations are performed, better statistical values can be obtained. Consequently, the optimum parameter values and a better mathematical model can be achieved thanks to the transformation methods.

1.2. Purpose of the Study

The purpose of this study is to utilize minimum point experimental designs, specifically D-optimal designs, for computer-aided design optimization applied to the design of "synthetic jet" used in the aerospace industry.

In the aerospace field, the design effort may be costly and time consuming. In this research, minimum point, D-optimal, experimental design is utilized to reduce the design effort and improve efficiency. The method is applied to a 'synthetic jet', design case study. The approach provides minimum point designs in an efficient and flexible way.

1.3. Research Question

There are limited numbers of applications of the D-optimal experimental design methods in the aerospace field. In addition, this approach utilizes augmentation of experimental data by adding points to a pre-selected minimum point D-optimal design. This may save significant amounts of computing time, and may allow including points that are of special interest and may lead to a better assessment of model accuracy. This research proposes to study how the augmented D-optimal designs would be applicable to a 'synthetic jet' design to improve the design efficiency.

1.4. Scope of the Research

This research comprises the following assumptions:

- In spite of using a computer simulation programs, the execution of experiments for the design of a 'synthetic jet' takes a long time.
- The selection of the method should use minimum points of design. In other words, the minimum number of experiments should be performed for the most efficient design in terms of cost and efficiency.
- By augmenting the design, there may be added terms to the original model which may lead to new optimal test runs with regards to this expanded model.
- Transformation of the results of the experiments to another form may be beneficial in terms of fitness of the model.

For better understanding the nature of design of experiments (DOE), the following methods are reviewed:

- OFAT- one factor at a time
- Full factorial designs
- Fractional factorial designs
- Response surface designs

- D- optimal designs
- Augmentation of D-Optimal Designs

For the application of the design of the experiments, JMP [3] computer software is used to perform statistical analyses and generate D-Optimal experimental designs. This program is also used for the analysis and optimization of outputs obtained after performing the experiments. Implementation of experiments for the design of 'synthetic jet' is performed using CFL3D (Computational Fluids Laboratory 3-Dimensional flow solver), a computer program developed by NASA Langley Research Center.

CHAPTER 2

LITERATURE REVIEW

2.1. Design of Experiments (DOE)

Definitions of DOE:

DOE is a statistical technique that allows to determine the best experiments to run for fitting a particular mathematical model [4].

DOE is a branch of applied statistics dealing with planning, conducting, analyzing and interpreting controlled tests for evaluating the factors that control the values of a parameter or a group of parameters [5].

Sir Ronald Fisher, in the 1920s, developed the techniques of factorial Design of Experiments. He is accepted to be the pioneer of statistical experimental design. He applied these techniques to agricultural experiments.

In an experiment, one intentionally changes one or more parameters (or factors) with the purpose of observing the effect that the changes have on response variables. The design of experiments (*DOE*) is an efficient procedure for planning experiments in order that the data obtained may be analyzed to get valid and objective conclusions.

2.2. Benefits of DOE

Design of experiments (DOE), used in many industrial sectors, can be applied to most of the product and process design applications at research, development and production phases.

In a competitive market it is crucial to obtain products/processes of high quality and low cost. After performing the design, it may be very expensive to redesign or make major changes in case of undesired conditions. A major part of the life cycle cost of a product occurs in the design phase. If this cost is optimized by providing the quality, that would give a great opportunity in terms of competitiveness. There are many engineers unaware or lacking knowledge of design of experiments. An efficient way of performing a design with low cost and high quality is 'design of experiment' methods [6].

The advantage of DOE is that it provides an *organized* approach; this way it is easier to address experimental problems whether they are simple or complex. Once the experimental objectives are determined, the best fitting experimental design method may be selected and successively, a set of experiments can be designed in terms of objectives.

It is obvious that DOE requires a lesser number of experiments than any other techniques. "Since these few experiments belong to an experimental plan, they are mutually connected and thereby linked in a logical and theoretically favorable manner" [6].

Thus, by means of DOE, one obtains more useful and more precise information about the studied system since the joint influence of all factors is assessed. Once the fitness of the model is verified, the effects of the parameters are evaluated using regression analyses for setting up a math model [6].

Steps for Implementation of DOE

1. Define the product or process to be studied.
2. Identify main function- state the problem.
3. Determine the response(s) - Y and identify the quality characteristics to be observed.

4. Determine the Measurement System for the response(s).
5. Identify main factors – Xi.
6. Determine the levels for the selected factors.
7. Select the experimental design.
8. Design the matrix experiment and define data analysis methods.
9. Conduct the experiments according to the design and collect data.
10. Analyze the results and draw conclusions.
11. Determine optimum levels.
12. Document the new settings and run a confirmation experiment [7] [8].

Figure 1 shows the relationship between design factors, response(s), and noise factors in a design.

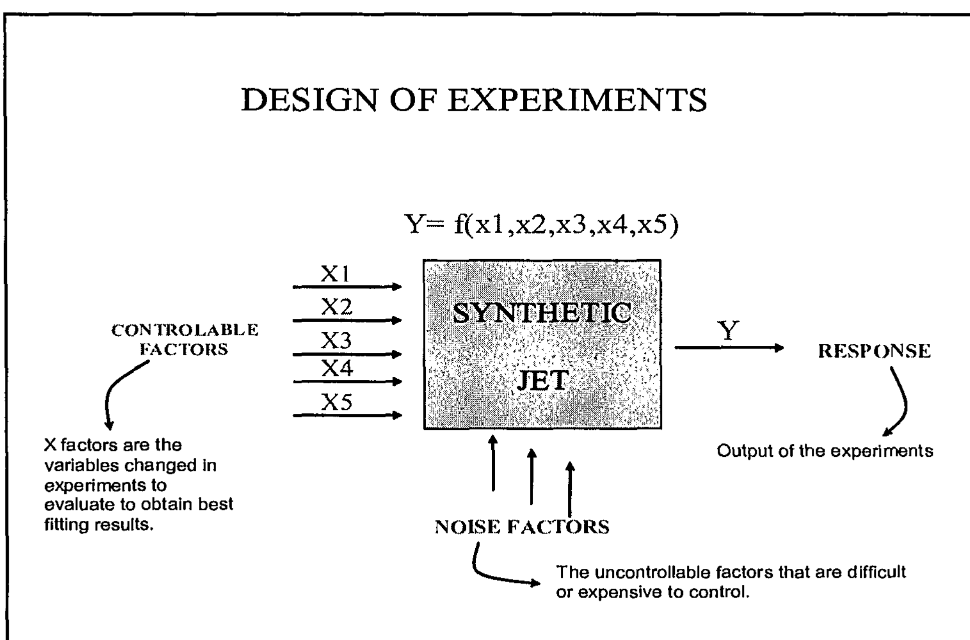

Figure 1. Factors –Response(s) in DOE

2.3. Selecting the Design Method

The number of variables and the objective(s) of the experiments identify the selection of the experimental design. According to the objectives, the classification of methods can be reviewed in five categories [9]:

- **Comparative Objective**:

If the primary aim of the design is to make a decision about one important parameter among all the parameters, comparative design may be a good choice. For different levels of this primary parameter, the changes in the response are observed and then it can be decided whether it has significant effect to the design or not.

- **Screening Objective**:

Among many parameters, if the few important ones are to be screened out, screening design which is also called 'the main effect design' is suitable for the purpose.

- **Response Surface Objective**:

If the interactions and quadratic terms of the parameters are to be observed, the response surface method giving the shape of the surface can be used for the design. In most designs there exist interactions between parameters and sometimes non-linearity in parameter(s). In these cases, RSM designs are useful [9].

- **Mixture Objective**:

If the factors are proportions of a mixture, for finding the "best" proportions of the factors in order to get optimum response, mixture designs may be appropriate choices.

- **Regression Model Objective**:

If the goal is to make the mathematical model of the factors and estimate the parameters without bias and with minimized variance, the regression is useful.

Randomized designs are comparative objective designs, full factorial or fractional factorial designs are screening objective designs and central composite designs and Box-Behnken designs are response surface objective designs [9].

2.4. Common DOE Methods

The DOE methods below have been reviewed for the purpose of literature review. The advantages and disadvantages of each are be discussed. These methods are:

- OFAT- one factor at a time
- Full factorial design
- Fractional factorial design
- Response surface model (Central Composite Design and Box-behnken Design)
- D- optimal design
- Augmentation of D-Optimal Designs

2.4.1. One Factor At a Time Approach

The One Factor At a Time (OFAT) approach refers to changing only one factor at each experiment for finding the best value of each factor. It is very simple approach to understand and to apply.

The OFAT method consists of selecting a baseline set of levels for each factor, followed by successively varying each factor over its range with the other factors staying constant at the baseline level. After completion of all the tests, a series of graphs are generally constructed showing how the response variables are affected by varying each factor while all other factors stay constant. The OFAT approach is regarded as healthier than the trial-and-error approach of experimentation, and has been perceived by some as a scientific method. Despite the fact that this approach is used frequently, it has some significant limitations:

Limitations of OFAT Approach

- The major disadvantage of the OFAT strategy is that it doesn't consider any possible factor interactions.
- Compared to the factorial design, it is less efficient and may require more trials.
- Limited use of test data.
- Unable to generate reproducibility of results -not balanced.
- Biased information on each level.

If it is assumed that the effects of the factors are independent, then one can model the result by changing several factors at once, and can find the optimal strategy which consists of the best combination of the factors.

However, in most engineering experiments, interactions between factors exist and as OFAT doesn't respond to the interactions, there may be poor and sometimes disastrous results.

This method is believed to be a standard, systematic, and accepted method of design experimentation by many people including experienced engineers. However, OFAT is a poor approach, consequently one needs a better design such as factorial design, which takes interactions in to consideration [10].

2.4.2. Factorial Design

The One factor at a time technique of experimentation was actually outdated in the 1920s with the discovery of much more efficient methods of experimentation using factorial designs by Sir Ronald A. Fisher. These studies by Fisher further developed by including fractional factorial designs, orthogonal arrays, and response surface methodology [10].

The factorial design approach has the following advantages over varying one factor at a time:

- A better precision is obtained for estimating the overall main factor effects.
- All factors may be simultaneously varied to deal with interactions and maximize efficiency.
- All or a fraction of interactions between different parameters can be taken into consideration.

- Inclusion of additional factors may extend the validity of conclusions extracted [11].
- The experiments may be performed in a random order for maximizing accuracy and reduce the probability of incorrect conclusions [10].

2.4.2.1. Full Factorial Design

"A design, in which all factor combinations appear with every setting of every other factor, is a full factorial design"[12]. In other words, full factorial designs measure the response of every possible combination of factors and factor levels. These responses are analyzed for providing information about each main effect and each interaction effect [13].

Full factorial designs are ideal from a mathematical point of view, because they make minimal assumptions about the factor interactions, assuming their existance [14].

However, the sample size grows exponentially with the number of factors. As can be seen in table 1, when the number of investigated factors is 5 or greater, a full factorial design requires a large number of runs and is not efficient. This is the most conservative design approach, but testing all combinations becomes too expensive and time-consuming with five or more factors [13]. It is recommended that a fractional factorial design be used for 5 or more factors when the experimental effort is high [12].

The sample size is the product of the number of levels and factors. For instance, a full factorial experiment with five factors at three-level has $3^5 = 243$ runs [3].

A sample size of factorial designs with only two-level factors is a power of two. "When there are three factors, the factorial design points are at the vertices of a cube. For more factors, the design points are the vertices of a hypercube" [3].

In Table 1, it can be concluded that full factorial designs are not so efficient, especially for 3^k designs.

Number of	2^k	3^k
2	4	9
3	8	27
4	16	81
5	32	243
6	64	729
7	128	2187

Table 1: Number of Runs for a 2^k and 3^k Full Factorial Design

2.4.2.2. Fractional Factorial Designs

Fractional factorial design is "a factorial experiment in which only an adequately chosen fraction of the treatment combinations required for the complete factorial experiment is selected to be run" [15] [12].

Fractional factorial design includes only a fraction of the corners of a hypercube and typically fits interaction models that include only 2-factor interactions.

Fractional factorial designs use only a portion (fraction) of the full factorial design to estimate main effects and lower order interactions [6]. This design is a carefully arranged subset of a full factorial design and includes selected combinations of factors and levels [13].

In a full factorial design, the number of experiments increases drastically as the number of factors increases. The solution to this problem is using a fraction of the runs designated by the full factorial design. It reduces the total number of runs required. Generally, it is preferred to choose a fraction such as ½, ¼, etc. of the runs required for the full factorial design. Various strategies are used which ensure an appropriate choice of runs [12].

A disadvantage of fractional factorial approach is the possibility of confounding interaction effects with main effects [16].

By decreasing the number of runs, a fractional factorial DOE is not able to evaluate the impact of some of the factors independently. Usually, higher-order interactions are confounded with main effects or lower-order interactions, because there tends to be a hierarchy in strength of interactions. In terms of absolute magnitude, 2-factor interactions tend to be larger than 3-factor interactions, 3-factor interactions tend to be larger than 4-factor interactions and so on. As higher order interactions are rare, it can be assumed that their effect is minimal and that the observed effect is caused by the main effects or lower-level interactions [13].

2.4.3. Response Surface Model

Response surface methodology (RSM) is one of the most common methods pertaining to developing, improving and searching or hunting for an optimum of a running system by using mathematical and statistical techniques in Design Optimization, and also is employed to design, develop, and formulize new products. The application of RSM is applicable in the industrial world, especially when several input variables potentially influence some quality characteristic or performance measures of the product or process. By using RSM, one can find the local maximum response variable, which means that there could be more than one peak in the function, and one of them may be greater than the response variable (Y) [41]. Response surface methodology was developed in the early 1950s by Box and Wilson and by Box and Hunter, and later by Cornell [42].

In response surface models, the experiments are designed to estimate interactions and even quadratic effects, and consequently give us an idea about the shape of the response surface that we are inspecting. Therefore, they are called response surface method (RSM) designs [9].

"Under some circumstances, a model involving only main effects and interactions may be appropriate to describe a response surface when:

- Analysis of the results revealed no evidence of "pure quadratic" curvature in the response of interest (i.e., the response at the center approximately equals the average of the responses at the factorial runs).

- The design matrix originally used included the limits of the factor settings available to run the process.

In other circumstances, a complete description of the process behavior may require a quadratic or cubic model" [12].

Quadratic model

$$y = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + b_{12}x_1x_2 + b_{13}x_1x_3 + b_{23}x_2x_3 + b_{11}x_1^2 + b_{22}x_2^2 + b_{33}x_3^2$$

(Equation 1)

Cubic model

$$\begin{aligned} y = \text{quadratic model} &+ b_{123}x_1x_2x_3 + b_{112}x_1^2x_2 + b_{113}x_1^2x_3 + b_{122}x_1x_2^2 \\ &+ b_{133}x_1x_3^2 + b_{223}x_2^2x_3 + b_{233}x_2x_3^2 + b_{111}x_1^3 + b_{222}x_2^3 + b_{333}x_3^3 \end{aligned}$$

(Equation 2)

These equations refer to full models, including all possible terms, but generally all the terms are not needed in applications [12].

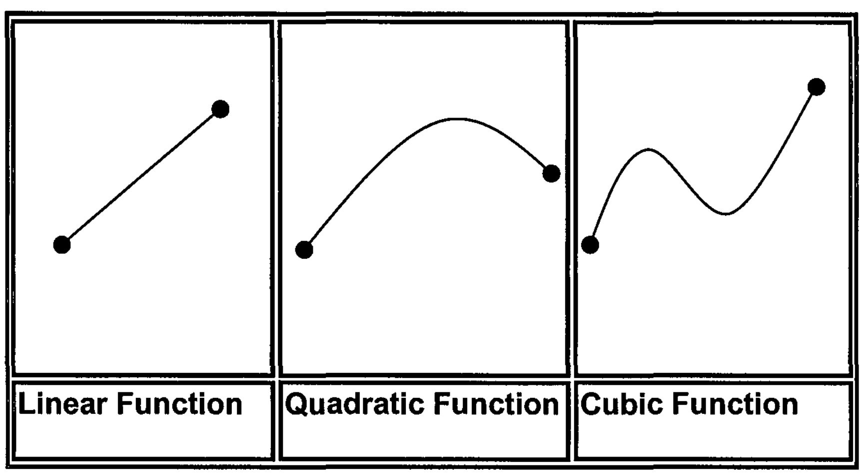

Figure2: Linear-Quadratic and Cubic Functions

2.4.3.1 Regression Analysis and RSM

Regression analysis is a statistical technique which is used to find relationships between input parameters in order to predict future values. In the experiments, several input parameters (X_1, X_2, X_3, etc.) are imposed to the subjects in order to influence the response(s)-Y. The response variables are dependent to the input parameters. In other words, changing one input parameter causes change in the response variable. The parameters can be either qualitative or quantitative. In regression, input parameters and response variables are called the regressor variables and the dependent variable respectively. Given a collection of data from the experiment, regression analysis may be employed to get a mathematical equation which shows the relationship in the quantitative way.

There is a relationship between regression analysis and RSM. The basic regression model is the linear regression model (the first-order model is $Y = b_0 + b_1X_1 + ... + b_kX_k + \varepsilon$ where ε is normally distributed with mean zero and the linear regression coefficients are b_k) which describes a very simple response surface. In some cases, if one considers maximizing yield, or minimizing defects, using simple linear and interaction models are not proper. These systems are considered as curvature having a local maximum, and then a model such as the second-order model is

$$Y = b_0 + \sum_{i=1}^{k} b_i x_i + \sum b_{ii} x_i^2 + \sum \sum_{i \le j}^{k} b_{ij} x_i x_j + \varepsilon \qquad \text{Equation 3}$$

$$Y = b_0 + b_1 x_1 + b_2 x_2 + b_{11} x_1^2 + b_{22} x_2^2 + \varepsilon \qquad \text{Equation 4}$$

where b_iX_i denote linear terms for all factors, $b_{ii}X_i^2$ denote squared terms for all factors, and ε is the error term. These models are called response surface designs.

The applications of RSM include designing the experiment, selecting the input parameters, getting the relationship between the response and input parameters through a mathematical equation by using regression analysis, and optimizing the response variable by optimization techniques.

2.4.3.2. RSM Designs

The first step in RSM is finding an approximation for the true relationship between the response and the input variables, since the form of the relationship between them is unknown. Suppose the response variable is defined as Y, and the response function, f, as the complex form, then the model is

$$Y= f(x_1 , x_2 ,...... x_k)+ \varepsilon \qquad \text{Equation 5}$$

where $x_1, x_2, ..., x_k$ denote the k control parameters and ε is the error vector.

In RSM, the two most common designs are central composite design and Box-Behnken design. The inputs may be at three or five distinct levels in these designs. However all combinations of these levels do not appear in the design [9].

The following designs are used to produce specific response surface designs:

- **Central Composite Designs (CCD)**

It is common to use CCD in quadratic response surface modeling for design of experiments. It was first introduced by Box and Wilson and is used to estimate the unknown parameter vector.

In CCD designs, one starts with an imbedded factorial or fractional factorial design with center points and then adds "star" points in order to estimate curvature [9]. In CCD, if there are k factors, then the number of star points equals to 2k, and in the design, the new low and high extreme values are represented by star points for each factor [17].

In CCD, the number of design parameters should be small in order to have a practical CCD since it contains factorial designs. However, one should reduce the trial number by reducing the factorial part in case the number of design parameters is large.

The advantages of CCD:

1. Efficient.
2. The numbers of experimental design points are significantly less than required by Taguchi's three-level orthogonal array and three-level full or fractional factorial designs.
3. All parameter interactions can be captured.
4. Second order non linearity (quadratic) can be captured [7].

Limitations of CCD:

1. In some cases, the number of design points must be kept to an absolute minimum (conducting a design study may be expensive).
2. CCD matrices may contain row(s) with parameter value combinations resulting in unfeasible solutions (excluding a row destroys orthogonality).
3. A second order (quadratic) approximation model may be inadequate in highly nonlinear cases [third order (cubic) or higher order polynomials may have to be utilized for an accurate representation] [7].

- **Box-Behnken Design (BBD)**

For fitting a full quadratic RSM, this type of design is an efficient three level design. It is based on the construction of balanced incomplete block designs. The difference between CCD and BBD is that three evenly spaced levels are achieved by BBD. It was introduced by Box and Behnken in 1960 [12].

2.4.4. Computer-Aided Designs

In many cases, standard designs respond to the purposes and can be constructed with several statistical software packages. However, sometimes they are not appropriate or practical. These classical designs may be inappropriate in some situations. According to *Engineering Statistics Handbook* [12], they do not work where:

1. "The required blocking structure or blocking size of the experimental situation does not fit into a standard blocked design.
2. Not all combinations of the factor settings are feasible, or for some other reason the region of experimentation is constrained or irregularly shaped.
3. A classical design needs to be 'repaired'. This can happen due to improper planning with the original design treatment combinations containing forbidden or unreachable combinations that were not considered before the design was generated.
4. A nonlinear model is appropriate.
5. A quadratic or response surface design is required in the presence of qualitative factors.

6. The factors in the experiment include both components of a mixture and other process parameters.
7. There are multiple sources of variation leading to nested or hierarchical data structures and restrictions on what can be randomized.
8. A standard fractional factorial design requires too many treatment combinations for the given amount of time and/or resources" [12].

If the situations above exist, computer-aided designs work better. Moreover, in some situations, computer-aided designs may be the only option.

Computer-aided designs are designs generated from a computer algorithm. Experimental designs which are generated on the basis of a particular optimality criterion are referred to as computer-aided designs. They are generally optimal for a particular model. The computer algorithms generate the design runs by choosing from a candidate set of possible combinations. This candidate set includes all the possible combinations that can be taken into consideration in an experiment [12].

In table 2, numbers of runs for full factorial design, 3-level orthogonal design, CCD design and D-optimal design are shown. It can be seen that D-optimal experimental design requires the least number of experiments as compared to the others.

NUMBER OF FACTORS	FULL FACTORIAL DESIGN (3^k)	3-LEVEL ORTHOGONAL ARRAY	CCD DESIGN	D-OPTIMAL DESIGN
3	27	27	15	10
4	81	81	25	15
5	243	81	43	21
6	729	-------	77	28
7	2187	-------	143	36
EQUATION	3^n		2^n+2n+1	$(n+1)(n+2)/2$

Table 2: Numbers of Runs for Most Common Models

2.4.5. DOE Using Minimum Point Designs

"A design is called 'minimum point' when the number of design points is exactly equal to the number of terms in the model to be fitted" [40]. Minimum point design methods generate efficient and flexible experimental designs. These powerful design approaches enable a designer to compute a proper design which can be conducted with minimum numbers of observations. These parameters can be either qualitative or quantitative. In addition, the optimal method can fit any type of model whether it is linear or nonlinear [18].

Characteristics of Minimum Point D-Optimal Designs:

- They may be used in place of CCD when there are a large number of parameters and point design effort is very expensive.
- They work well in initial screening situations.
- Number of design points can be reduced to minimum.
- Second order or cubic response surface polynomials can be constructed.
- May lead to poor coverage of the region of interest.

- Design matrices containing row(s) resulting in unfeasible solutions can be avoided [7].
- Unlike standard classical designs such as factorials and fractional factorials, minimum point design matrices are usually not orthogonal and effect estimates are correlated [12].
- No degrees of freedom left to estimate fitted model accuracy.

Standard factorial or fractional factorial designs may require too many runs for the amount of resources or time allowed for some experiments. In Chapter 3, D-optimal model is explained in detail.

Optimality Criteria

There are various forms of optimality criteria that are used to select the points for a design. The definitions of the optimal designs below come from the *Engineering Statistics Handbook* [12].

"D-Optimality

The most common criterion is the D-optimality, which seeks to maximize |X'X|, the determinant of the information matrix X'X of the design. This criterion results in minimizing the generalized variance of the parameter estimates based on a pre-specified model.

A-Optimality

Another criterion is the A-optimality, which seeks to minimize the trace of the inverse of the information matrix. This criterion results in minimizing the average variance of the parameter estimates based on a pre-specified model.

G-Optimality

A third criterion is the G-optimality, which seeks to minimize the maximum response variance, i.e., minimize max. $[d=x'(X'X)^{-1}x]$, over a specified set of design points.

V-Optimality

A fourth criterion is V-optimality, which seeks to minimize the average prediction variance over a specified set of design points" [12].

2.4.6. Augmented Designs

By augmenting the design, it is possible to add runs using a model having more terms than the original model. Adding runs to a design is efficient because one can achieve response surface objectives by changing a linear model to a full quadratic model. For instance, suppose one starts with a two-factor, two-level four-experiment design. If one adds quadratic terms and five new points to the model, there can be generated the 3 by 3 full factorial as the augmented optimal design by means of DOE software. D-optimal augmentation is a powerful tool for sequential design via which there can be added terms to the original model and the optimal new test runs with regard to this expanded model can be found. It is also possible to group the two sets of experimental runs into separate blocks that optimally blocks the second set with respect to the first [3].

The augment designer in JMP [3] software modifies an existing design data table, supporting an iterative process. It gives the following choices:

"• Replicate the design a specified number of times.

• Add center points.

• Allows doing statistical analysis extensively for minimum point designs.

• Create a fold over design.

• Add axial points together with center points to transform a screening design to a response surface design.

• Add runs to the design using a model that can have more terms than the original model" [3].

2.5. Data Transformation

Transformations are a remedy in the case of having problem with the data as outliers, failures of normality (e.g.skewness), and unequal variation. The most common and recommended transformations are shown graphically in Figure 3.

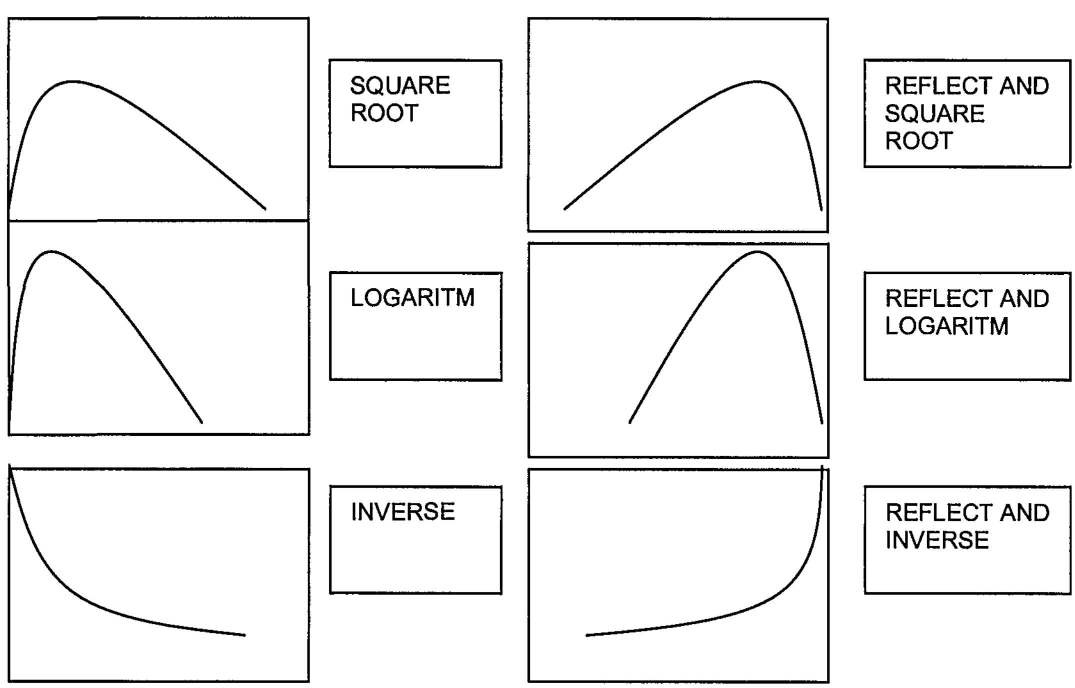

Figure 3. Common Transformation Forms [19]

To find the most appropriate transformation form for the selected data, the steps below are followed:

- Choosing one of transformation forms.
- Then applying it to the actual data set.
- Checking whether the new data set is distributed normally or near-normally.
- If not, picking another transformation until the data set has the fewest outliers or zero skewness [19].

Some terms related with the transformation are outlier, skewness and Heteroscedasticity. Outlier is a single observation "far away" from the rest of the data [20]. Skewness is the measure of the degree of the distribution for asymmetrical distributions. There are two types of skewness as left-skewed and right-skewed which has the tail widely spread apart at the left side and the right side respectively. If the two tails are equal, it is considered symmetric and to have zero skewness [21]. Heteroscedasticity is the unequal variation of data.

➢ **Log Transformation**

Log Transformation is one of the common transformations. If there are problems with the data like skewed data, outliers and heteroscedasticity (unequal variation), the log transformation is one of the convenient transformations to apply, but does not guarantee to solve these problems. In order to do log transformation, three steps are followed:

1. Taking the logarithm of each data value.

2. Analyzing the resulting data.

3. Transforming the results back [15].

If a variable is skewed to the right as shown clearly in Figure 4, log transformation is used to produce a data set closer to symmetric. If the variable is symmetric or skewed to the left, log transformation may not be a good idea to apply.

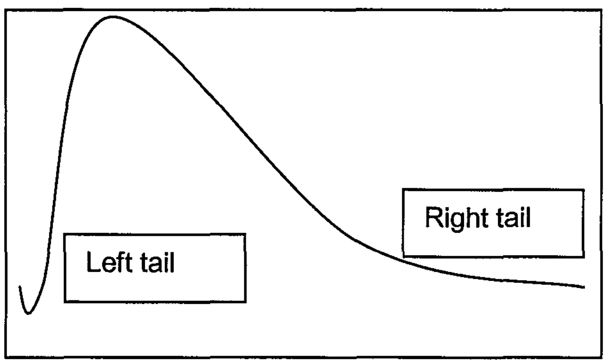

Figure 4. Right Skewed Distribution

If there are outliers on the high end, log transformation can be used to solve the problem. Log transformation squeezes the larger values, so it might help the high ended outliers. But it is not proper to use log transformation if there are outliers on the low end. If there is an unequal variation problem in the data, tests and confidence intervals may not be true. In this case, log transformation is convenient to apply. The log transformation equalizes the variation by squeezing the groups with the larger standard deviations [22][23].

2.6. Summary of Literature Review

Various DOE methods were studied in this chapter. These methods are put in order in terms of their complexity and efficiency. These methods are OFAT- one factor at a time method, full factorial design, fractional factorial design, response surface model (CCD-central composite design and box-behnken design), D- optimal design and augmentation of optimality criterion.

The OFAT approach works only when there is no interaction between parameters of the model. However in most cases, interactions exist. Ignorance of these interactions prevents the designer from reaching to optimal values and setting up a proper mathematical model.

The full factorial method uses all main and interaction effects, but works well only when the number of parameters and level of each parameter are low. Otherwise time and cost of the design may be prohibitive and inefficient.

The fractional factorial design uses a fraction of full factorial design assuming that some quadratic effects are of the less importance.

The response surface model (RSM) is a second-order model which uses all two-parameter interactions and captures the curvature or nonlinearities. Therefore, RSM gives an idea about the shape of the response surface of the design. Using this design method, optimal design setting may be found and consequently the design may be improved, the problems and weak points of the design may be determined, and the design may become more robust. Two most common RSM designs are 'CCD-central composite design' and 'Box-Behnken design'.

There are various optimality criteria. The definition of D, A, G, and V optimality criteria are given. Then, D-optimality criterion is explained. D-optimal criteria which is the most common one, has several advantages. Therefore, it was used for the application of this research. Minimum point design is selected for the application and the augmentation is applied to the selected design.

2.7. Contributions

The purpose of this study is to do several contributions to the application of minimum point design of experiments. These contributions are:

2.7.1. Augmentation

With the purpose of constructing minimum point D-optimal design, the least number of experiments is selected. However, by using augmentation method, the selected D-optimal design can be improved. Thus, it can be possible to apply the choices mentioned in section 2.4.6.

2.7.2. Transformation

In JMP [3], after acquiring the results of the experiments, the fit of the model can be performed for analysis of the results. In case there is a lack in the fittness of the model, the desired math model may not be achieved. The transformation technique provides better fitting of the model by converting the results of the experiments to different forms. By transforming result data, better analysis values may be attained. Common transformation forms are square root transformation, inverse transformation and logarithmic transformation. The aim is to form a better mathematical model by testing each transformation form.

2.7.3. Application in Aerospace Field to the 'synthetic jet' design

There is limited number of studies using DOE methods for the design in aerospace. Synthetic jet is an active control device which controls the air flow on any surface. The design studies on 'synthetic jet' are quite new and the optimization of this device is not defined properly.

There is nonlinearity and strong interactions between design parameters of 'synthetic jet'. The statistical DOE approach to this design would be quite efficient. Applying the augmented minimum point D-optimal design method to this design problem may be a proper approach than the OFAT currently used by some. Efficiency and fitness will be evaluated.

CHAPTER 3

METHODOLOGY

APPLICATION OF D-OPTIMAL METHOD TO 'SYNTHETIC JET' DESIGN

3.1. Synthetic Jet

Synthetic jet is a device which controls the air flow on any surface. While active control methods require an expenditure of energy, the main advantage of synthetic jet is that it can respond rapidly to the changes in the flow surface with low energy. Despite the fact that continuous-blowing and suction have side effects, intermittent blowing and suction in the form of synthetic jet have shown their effectiveness in controlling the flow separation [24].

Flow control methods are classified in terms of the expenditure of energy. Passive or active flow control devices are used to control the flow on a surface. With the help of these devices, a considerable treatment on the flow area may be acquired. The passive control devices control the flow without external energy expenditure. There has been much research about passive control devices. Passive techniques can be in different forms;

- Changing the shape geometrically to control the pressure gradient.
- Using mechanical vortex generators for controlling the separation.
- Using longitudinal riblets or grooves on the flow surface to reduce drag [25].

The studies about active control devices are relatively new. Active devices use external energy or auxiliary power to affect the flow area. The 'synthetic jet' is an active flow control device and can be used on any surface where flow exists. There have been studies on devices which controls the flow by only absorbing or only blowing the air. However, the 'synthetic jet' which is used in our design of experiments study, both absorbs and blows the air respectively.

"Synthetic jets are composed entirely of entrained ambient fluid synthesized by the formation of a time-harmonic train of vortices that are created at the sharp edges of an orifice of an enclosed cavity" [24]. The usage purpose of the 'synthetic jet' is to control the air flow on any surface. Here, the word control either means decreasing or increasing the effect of the vortices.

Figure 5 shows the main parts of a 'synthetic jet'. The device draws the fluid into its cavity and than blows it out in sequence. The membrane at the bottom which is a piezoelectric part of the synthetic jet moves periodically up and down. At the orifice, the net mass flux is zero since all the air drawn is pushed by the oscillation of the membrane.

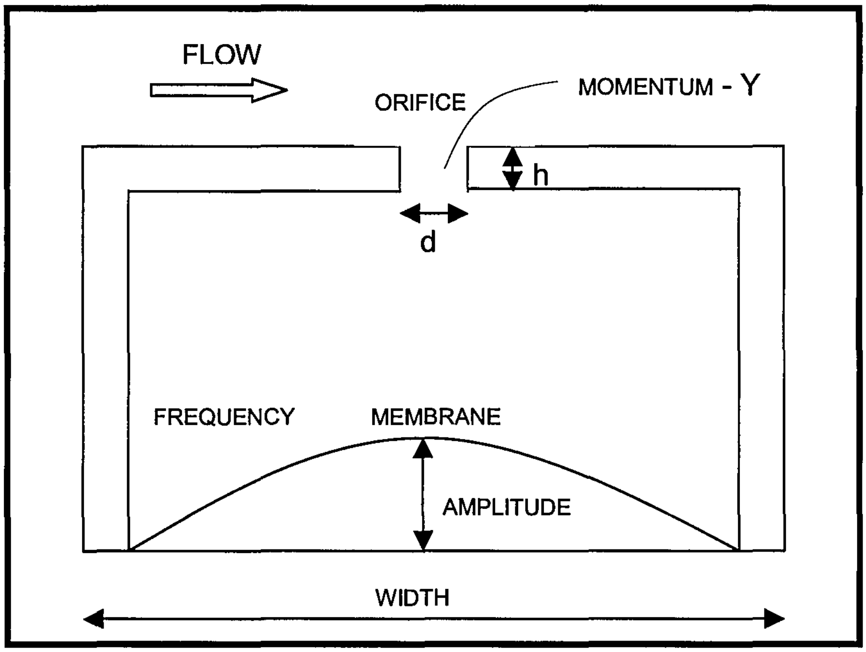

Figure 5. Synthetic Jet

The main parameters having an effect on the performance of synthetic jet design are in table 4. The goal of this study is to find maximum momentum value by changing these main parameters with D-optimal design. These parameters are displacement frequency of the membrane, displacement range of the membrane (amplitude), width of the cavity, width of the orifice and height of the cavity. The changes in the measures of these parameters give different amount of flow displacement from the cavity. In this study, the purpose of the design is to maximize the momentum value generated by the 'synthetic jet'. For each parameter, it was determined three levels and the different combinations of parameters were designed for the experimentation by the use of the software.

3.2. Statement Of The 'Synthetic Jet' Design Problem

The studies about synthetic jets are rather new and the design phase of this device may need time-consuming studies and plenty of experiments. To find the optimal values of parameters, the "one factor at a time approach" or the full factorial approach is not appropriate. The major limitation of OFAT approach is that it does not consider any possible factor interaction. Full factorial designs require high number of experiments unless the number of parameters is small. The limitations of common DOE methods were mentioned previously in chapter 2.

Since this study requires minimum point experimental design, applying the D-optimal method might be a good choice.

3.3. Determination of the Response – Y, And The Quality Characteristics To Be Observed

The purpose of this study was to maximize the momentum value generated by synthetic jet. On behalf of generating maximum momentum by consuming minimum energy, the design parameters were needed to be optimized. For enabling the 'synthetic jet' to generate maximum momentum, the five parameters: width of the synthetic jet, width of the orifice, height of the orifice, amplitude and frequency are set into the design in order to get their optimum values.

3.4. Main Factors and Feasible Ranges

There are five main parameters affecting the output value (momentum of the synthetic jet). Among these parameters, the most complex one seems to be the frequency as it does not change linearly. So, it was determined to conduct some experiments to find the global maximum value and to select the range of frequency. During the execution of these pre-experiments, the values of other four parameters were kept fixed at mid-values while changing frequency values. The table 3 and figure 4 show the frequency values acquired from the experiments conducted for this purpose.

Rank	Frequency	Momentum	Rank	Frequency	Momentum
1	50	0,5862	16	800	110,75
2	100	4,90149	17	850	123,953
3	150	30,0603	18	900	99,7321
4	200	28,0291	19	950	105,215
5	250	23,0771	20	1000	113,382
6	300	32,4175	21	1100	93,1196
7	350	49,6327	22	1200	59,6707
8	400	57,0544	23	1300	48,5596
9	450	49,4609	24	1400	44,5394
10	500	64,5708	25	1500	34,6157
11	550	80,876	26	1600	23,8932
12	600	100,75	27	1700	22,3652
13	650	88,8147	28	1800	21,252
14	700	108,181	29	1900	12,0854
15	750	141,336	30	2000	11,9202

Table 3. Momentum Values for Different Frequency Values

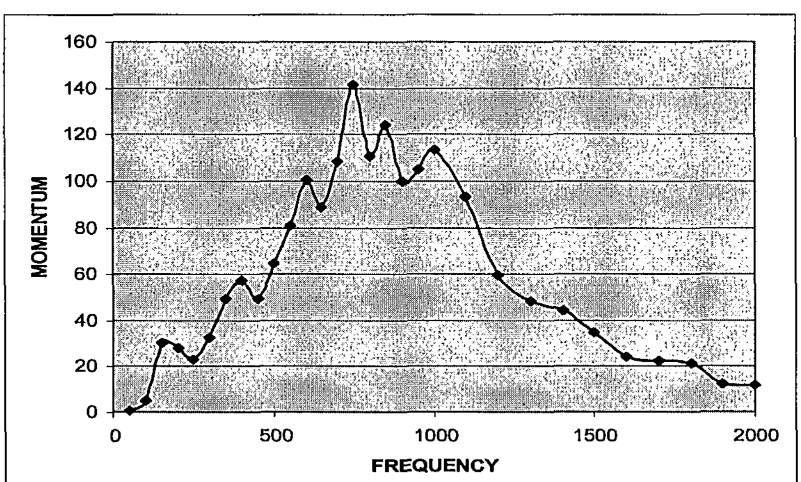

Figure 6. Frequency- Momentum

Since the purpose of the study was to maximize the momentum, the momentum values were tested between 50 Hz and 2000 Hz frequency values. As shown in figure 5, among several local maximums, the global maximum was obtained at 750 Hz resulting as 141,336 kg.m/sec^2 momentum value. According to these results, the frequency range was determined between 300 Hz and 1300 Hz. For the accuracy of the design of experiments of synthetic jet, these pre-experiments are necessary and beneficial in order to arrange the parameter range robustly.

As opposed to 243 experiments required for full factorial design, five synthetic jet parameters and 15 two-parameter interactions were studied at three levels by conducting 21 design experiments. By adding eight runs for the augmentation and by adding 1 center point, the total number of experiments reached to 30. The aim here is to determine the best values of the design parameters that maximize the momentum value. The five design parameters are given in table 4.

PARAMETERS	RANGES LOW	HIGH
WIDTH	15	25
AMPLITUDE	0,2	0,8
ORIFICE HEIGHT	0,4	1,6
ORIFICE WIDTH	0,4	1,6
FREQUENCY	300 Hz	1300 Hz

Table 4, Ranges of Parameters

3.5. Determination of the Levels for the Selected Factors

The equation 6 represents the construction of a second-order response model for the D-optimal design.

$$Y=b_0+\sum b_i x_i+\sum b_{ii} x_i{}^2+\sum\sum b_{ij} x_i x_j \qquad \text{Equation 6}$$

Using the custom design tool of JMP [3] software, an augmented D-optimal experimental design was constructed with 30 experiments. In this design matrix, the five parameters were studied at three levels (values). These levels were represented in coded form by, (-1), 0 and (+1). To illustrate, (-1) for amplitude represents to 0.2 (lower bound); 0 represents to 0.5 (mid value); and +1 represents to 0.8 (upper bound). For the conduction of the experiments, these coded values were transformed into actual parameter values.

	WIDTH	AMPLITUDE	ORIFICE HEIGHT	ORIFICE WIDTH	FREQUENCY
-1	15	0.2	0.4	0.4	300
0	20	0.5	1	1	800
1	25	0.8	1.6	1.6	1300

Table 5. Coded Values of Parameters

3.6. Measurement System for the Response(s)

There are 3 types of measurement systems, these are:

1- Computer models (simulation)

2- Set of equations

3- Actual hardware experiments

In this study, a computer program CFL3D was used for the simulation of the experiments.

➢ **CFL3D**

The CFL3D is a Reynolds-Averaged thin-layer Navier-Stokes flow solver for solving 2-D or 3-D flows on structured grids. It was developed in the 1980's in the Computational Fluids Laboratory at NASA Langley Research Center. The name of the code is an acronym for the Computational Fluids Laboratory 3-Dimensional flow solver. This program solves the time-dependent conservation law form of the Reynolds-averaged Navier-Stokes equations [26].

To avoid units of measurement such as feet, meters, pounds, grams, etc. while coding the equations, the CFL3D solves the Nervier-Stokes equations nondimensionally. Flow-field parameters are nondimensionalized by reference values. For example, all points on a synthetic jet may be nondimensionalized by the length of the orifice [26].

3.7. Selection of the Experimental Design

For the design of the experiments, the D-optimal model was selected. If the number of design points is equal to the number of terms in the model to be fitted it refers to "minimum point design". Since the number of design points can be reduced with this model to minimum, it can be a good choice when the number of variables tends to be large. By using the D-optimal model, it is possible to observe quadratic and cubic response surface polynomials. Besides, the design matrices of D-optimal design are usually not orthogonal and the estimates of effects are correlated and also, the design matrices containing unfeasible rows can be avoided.

The second order approximation model which was used for the synthetic jet design takes non-linearity (square terms) and interactions (cross terms) into account to better explore the design space.

These approximation models can be used to determine the effect of varying design parameter values on momentum value. Another major advantage of this approach is that, while doing sensitivity analysis, it does not require re-analyzing the entire system after changing any parameter value in the model [27].

The math model of the design was constructed based on the equation 6 representing the second-order approximation model.

$$Y=b_o+\sum b_i x_i+\sum b_{ii} x_i^{2}+\sum\sum b_{ij} x_i x_j \qquad \text{Equation 6}$$

In equation 6 the x_i terms represent the input variables which influence the response Y. The b_o, b_i, and b_{ij} are the estimated regression coefficients. The cross terms represent two-parameter interactions and the square terms represent second-order non-linearity. Design parameters should be studied at least at three levels for constructing a second-order model in order to estimate the coefficients in the model. Therefore, 3^n factorial experiments may be necessary [28] [40].

In contrast to full factorial design, the second-order approximation model can be constructed efficiently by utilizing minimum point D-optimal experimental design. In the regression analysis, the predicted response variable(Y) is obtained in the most accurate way by the given input variables (X) with the equation called the least squares regression equation. This model estimates the minimum generalized variance of coefficients. For constructing a quadratic model by using minimum point designs, D-optimality criterion which leads to minimized variance of the least squares estimates, is a proper approach [28].

To simply explain the logic of D-optimal method, the estimation of the coefficients using least squares regression analysis of a linear approximation model, is shown below.

$$y = b_0 + \sum b_i x_i \qquad \text{Equation 7}$$

The matrix notation of equation 7 can be displayed as:

$$Y = XB + e \qquad \text{Equation 8}$$

In equation (8) Y represents the vector of observations, e is the vector of errors, X is the design matrix and B is the vector of model coefficients (b_0 and b_i). "The design matrix is a set of combinations of the values of the coded variables, which specifies the settings of the design parameters to be performed during experimentation. B can be estimated by using the least squares method as" [27]:

$$B = (X'X)^{-1} X'Y \qquad \text{Equation 9}$$

A measure of accuracy of the column of estimators B is the variance-covariance matrix that is defined as [28].

$$V(B) = \sigma^2 (X'X)^{-1} \qquad \text{Equation 10}$$

In equation 10, σ^2 represents the variance of the error. $V(B)$ matrix is the statistical measure of the goodness of the fit. $V(B)$ is a function of

$(X'X)^{-1}$ and consequently, to improve the quality of the fit $(X'X)^{-1}$ should be minimized. Statistically minimizing $(X'X)^{-1}$ is equivalent to maximizing the determinant of $(X'X)$ [40]. Thus, generating a design matrix enabling us to construct a good least squares approximation model, translates to maximizing the determinant of the $X'X$ matrix. Experimental designs which maximize $|X'X|$ are referred to as D-optimal designs. "D" is the symbol of the determinant of the $X'X$ matrix of the model [28] [40]. This analysis can easily be extended to the quadratic model given by equation 6, with the same conclusion for D-optimality.

3.8. Design of the Matrix Experiment

The matrix was designed as minimum point D-optimal model with 21 experiments. Eight experiments for augmenting the design and one center point were added to the design. Thus, the total number of experiments came up to 30. The design in table 6 was formed by the aid of software.

WIDTH	do/hc	FREQ.	AMPL.	ho/hc
1	1	1	-1	-1
1	1	1	0	0
-1	1	-1	-1	-1
1	1	-1	-1	1
0	-1	-1	-1	-1
-1	-1	-1	1	-1
1	-1	1	1	-1
0	1	0	0	-1
-1	-1	1	-1	-1
-1	1	1	-1	1
-1	-1	-1	-1	1
1	-1	0	-1	0
1	-1	-1	1	1
-1	1	-1	1	1
-1	1	1	1	-1
1	0	0	1	1
1	0	-1	0	-1
0	0	1	-1	0
-1	-1	1	1	1
1	-1	1	-1	1
1	1	-1	1	-1
-1	0	-1	0	0
1	1	1	1	1
-1	1	0	-1	1
1	-1	-1	-1	-1
0	-1	1	0	1
0	1	-1	1	0
0	0	1	1	-1
-1	-1	0	1	0
0	0	0	0	0

Table 6. Five Parameter Augmented D-Optimal Experimental Design

3.9. Data Analysis Method and Computerized Analysis Code Used

➢ **JMP**

JMP [3] is software which performs simple and complex statistical analyses. It links statistics with graphics to explore, understand, and visualize the data. It also allows the user to click on any point in a graph, and see the resultant data point highlighted in the data table, and other graphs.

JMP [3] software provides a wide-ranging set of statistical tools like design of experiments and statistical quality control. It can work with a wide range of data formats, such as text files, Microsoft Excel files, SAS datasets, and ODBC(open database connectivity)-compliant databases [29].

A cost-beneficial one of the methods for quality improvement and productivity may be the statistical design of experiments. The aim of experimental design is to characterize, predict, and then cost effectively improve the behavior of any product or process. JMP [3] software's custom designer is a good way to describe the design process and create a design that works for any situation. When using the custom designer, after entering the process variables and constraints, JMP [3] tailors a design which suits to that unique case. This approach requires less experience and expertise supporting the statistical design of experiments. With custom design, any type and any number of factors can be studied. It is also possible to control the number of runs, being any number greater than or equal to the number of unknowns of the model. This makes custom design flexible and cost effective [3]. For these reasons, this software was selected for this study.

3.10. Conduction of the Experiments

The experiments were conducted by using NASA-developed CFL3D (Computational Fluids Laboratory 3-Dimensional flow solver) [26]. Old Dominion University, Aerospace Engineering Department's Computer Laboratory was used for this purpose. The results of the experiments are in table 7.

	WIDTH	do/hc	FREQ.	AMPL.	ho/hc	RESULTS
1	25	0,4	300	0,8	1,6	58,16926
2	25	1	800	0,8	1,6	227,3849
3	15	0,4	300	0,8	0,4	83,69798
4	25	0,4	1300	0,8	0,4	75,47368
5	20	0,4	300	0,2	0,4	16,21742
6	15	1,6	300	0,2	0,4	9,525087
7	25	1,6	300	0,2	1,6	11,28429
8	20	1	300	0,8	1	122,4258
9	15	0,4	300	0,2	1,6	12,24956
10	15	0,4	1300	0,8	1,6	83,73629
11	15	0,4	1300	0,2	0,4	20,81844
12	25	0,4	800	0,2	1	20,64893
13	25	1,6	1300	0,2	0,4	14,51937
14	15	1,6	1300	0,8	0,4	358,615
15	15	1,6	300	0,8	1,6	51,17152
16	25	1,6	1300	0,5	1	59,83274
17	25	1	300	0,5	0,4	83,04012
18	20	0,4	800	0,5	1,6	55,09334
19	15	1,6	1300	0,2	1,6	19,38202
20	25	0,4	1300	0,2	1,6	5,221729
21	25	1,6	300	0,8	0,4	106,7702
22	15	1	800	0,5	0,4	98,38415
23	25	1,6	1300	0,8	1,6	98,51434
24	15	0,4	1300	0,8	1	90,05769
25	25	0,4	300	0,2	0,4	18,85215
26	20	1	1300	0,2	1,6	10,75915
27	20	1,6	800	0,8	0,4	260,5051
28	20	1,6	300	0,5	1,6	32,73228
29	15	1,6	800	0,2	1	69,8165
30	20	1	800	0,5	1	156,4131

Table 7. D-optimal Design with Actual Values and Results of Experiment

The pictorial demonstrations of the results for three experiments are in figure 7. These three experiments are the 14^{th}, 30^{th}, and 7^{th} experiments and are arranged from top to down in terms of the amount of momentum created in synthetic jet. The yield in 14th experiment is the highest one as 358,615kg.m/sn^2, the 30th experiment which is the center point, yielded as 1564131 kg.m/sn^2 momentum value and the 7th experiment's result is 11,28429 kg.m/sn^2.

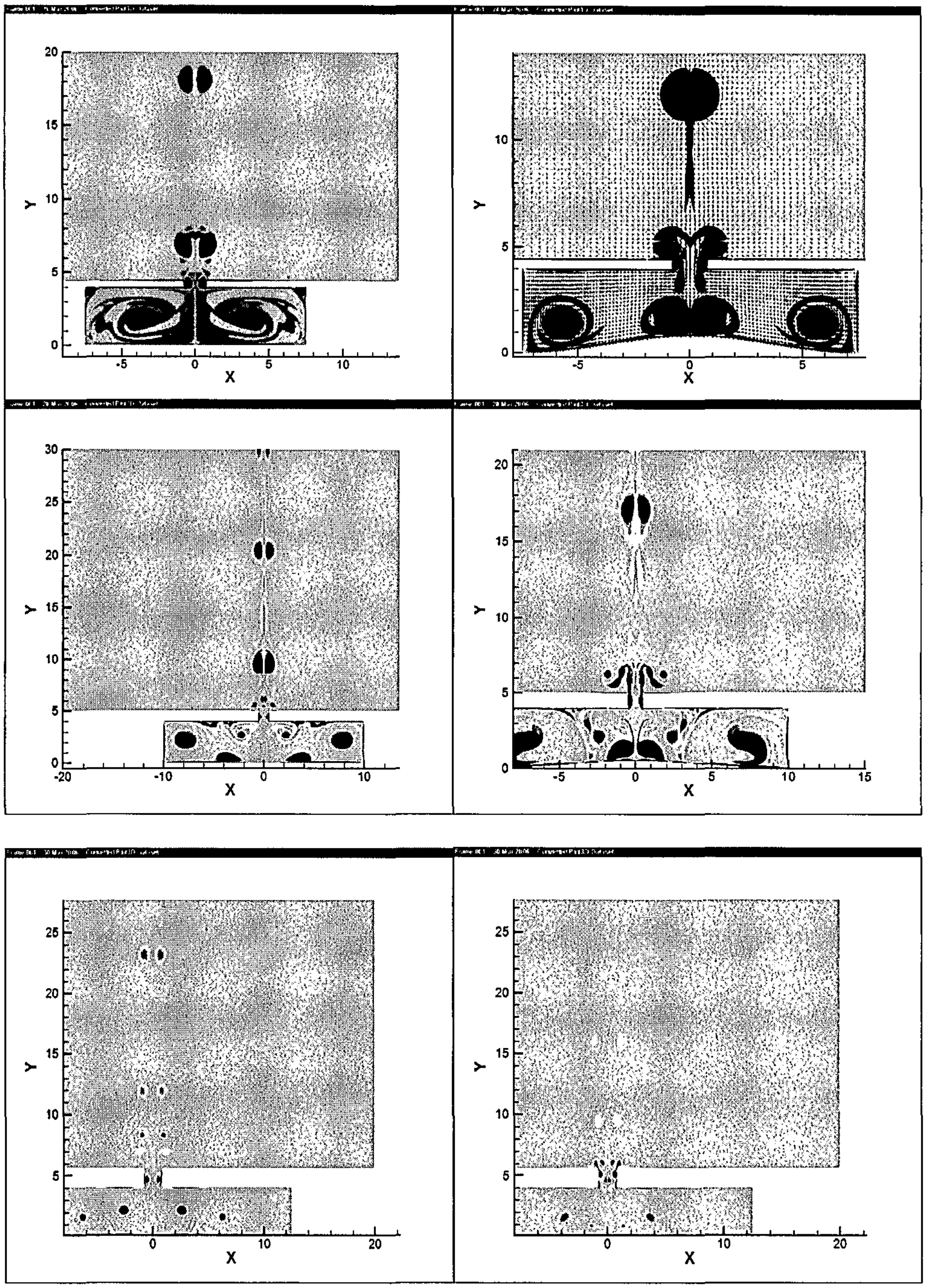

Figure 7. the pictorial demonstration of the momentum created by synthetic jet

CHAPTER 4

ANALYSIS & RESULTS

4.1. Analysis

After getting the output values (momentum) of the experiments as in table 8, the model was fitted with the results by using 'analyze' tool of JMP [3].

Results of the		Experiments	
1	58,16926	**16**	59,83274
2	227,3849	**17**	83,04012
3	83,69798	**18**	55,09334
4	75,47368	**19**	19,38202
5	16,21742	**20**	5,221729
6	9,525087	**21**	106,7702
7	11,28429	**22**	98,38415
8	122,4258	**23**	98,51434
9	12,24956	**24**	90,05769
10	83,73629	**25**	18,85215
11	20,81844	**26**	10,75915
12	20,64893	**27**	260,5051
13	14,51937	**28**	32,73228
14	358,615	**29**	69,8165
15	51,17152	**30**	156,4131

Table 8. The Actual Results of Experiments

The result tables and figures of the analysis acquired using software are in appendix A. These are actual by predicted chart, summary of fit table, analysis of variance table, parameter estimates table, scaled estimates table and prediction profiler table.

The contours showing the change of the results are plotted and illustrated in different shades in figure 8. The result contours were plotted by taking the amplitude as 1 and by changing frequency and width of the orifice which are the most dominant parameters.mIn figure 9 similarly, the amplitude and frequency are the changing parameters while width is taken as 1.

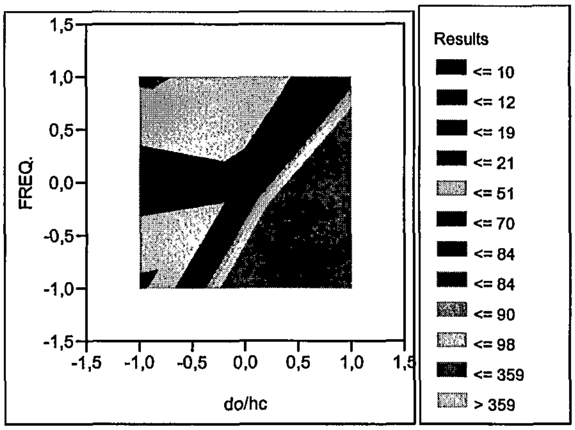

Figure 8. Contour Plot for Results AMPL=1

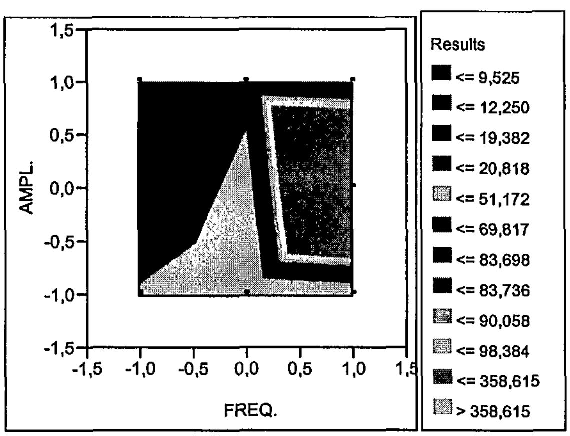

Figure 9. Contour Plot for Results WIDTH=1

4.1.1. Construction of the Math Model and Estimation of Optimal Parameter Values

Using the analysis tables in Appendix A which were derived from JMP [3], the second-order response surface math model and the design of the parameter values that optimize the response were calculated.

Term	Estimate
Intercept	125,77134
WIDTH	-7,871838
do/hc	53,904522
FREQ.	-16,22137
AMPL.	23,68415
ho/hc	17,997165
(WIDTH-0,03333)*(WIDTH-0,03333)	-11,65854
(WIDTH-0,03333)*do/hc	-7,255338
do/hc*do/hc	26,820486
(WIDTH-0,03333)*FREQ.	14,909413
do/hc*FREQ.	-14,14407
FREQ.*FREQ.	7,8448763
(WIDTH-0,03333)*AMPL.	-10,05746
do/hc*AMPL.	18,77267
FREQ.*AMPL.	-15,21522
AMPL.*AMPL.	-43,95075
(WIDTH-0,03333)*(ho/hc+0,03333)	-19,81922
do/hc*(ho/hc+0,03333)	20,747031
FREQ.*(ho/hc+0,03333)	-12,80102
AMPL.*(ho/hc+0,03333)	19,662471
(ho/hc+0,03333)*(ho/hc+0,03333)	-41,47709

Table 9. Estimate Coefficients

WIDTH	-1
do/hc	1
FREQ.	-1
AMPL.	1
ho/hc	1
Y	336,4148

Table 10. Parameter Values That Optimize the Model

The second-order math model of the design was formed by using equation6. The 'b' coefficients obtained from the parametric estimate coefficients table (table 9) and coded values of parameters assigned to table 10 are used for the formation of the math model. For maximization of response-Y, the 'solver' tool of excel was used. Between (-1) and (+1) parameter ranges, by changing each parameter and using the formula below, the optimum parameter values and momentum value were obtained.

$$Y=b_o+\sum b_i x_i+\sum b_{ii} x_i^{2}+\sum\sum b_{ij} x_i x_j \qquad \text{Equation 6}$$

The second-order math model of the design is;

Y=125,7713+(-7,87184)*(width)+ 53,90452*(do/hc)+ -16,2214*(freq)+ 23,68415*(amp)+17,99717*(ho/hc)+(-11,6585)*(width)*(width)+(-7,25534)* (width)*(do/hc)+26,82049*(do/hc)*(do/hc)+14,90941*(width)*(freq)+(14,1441)* (do/hc)*(freq)+7,844876*(freq)*(freq)+(-10,05)*(width)*(amp)+18,77267* (do/hc)*(amp)+(15,2152)*(freq)*(amp)+(43,9508)*(amp)*(amp)+(19,8192)*(wi dth)*(ho/hc)+20,74703*(do/hc)*(ho/hc)+12,801*(freq)*(ho/hc)+19,66247*(amp)* (ho/hc)+(-41,4771)* (ho/hc) * (ho/hc)

Y= 336,4148

The purpose of the study was to maximize the momentum generated by the synthetic jet. According to the optimum values of parameters, the maximized result of math model is 336,4148 kg.m/sec^2. The result of the experiment which shows the center point (the experiment that takes center point values of the design parameters) of the design is 156,41 kg.m/sec^2. Regarding to center value, 336,4148 kg.m/sec^2 is pretty good. This shows that the model was improved more than double. The coded parameter values of the 14th experiment match the optimum parameter values acquired by the 'solver'. Consequently, it is not required to do a confirmation experiment and 358,615 can be accepted as the confirmed value of 336,4148 kg.m/sec^2.

However, the math model might be improved by applying transformation technique to the result data.

First, the type of transformation to be used should be decided on. According to the results of the experiments, the mean and the median of the results are 77.7104 and 59.001 respectively. Since the mean is greater than the median, there is an outlier as seen in figure 10 and the data set is skewed to the right.

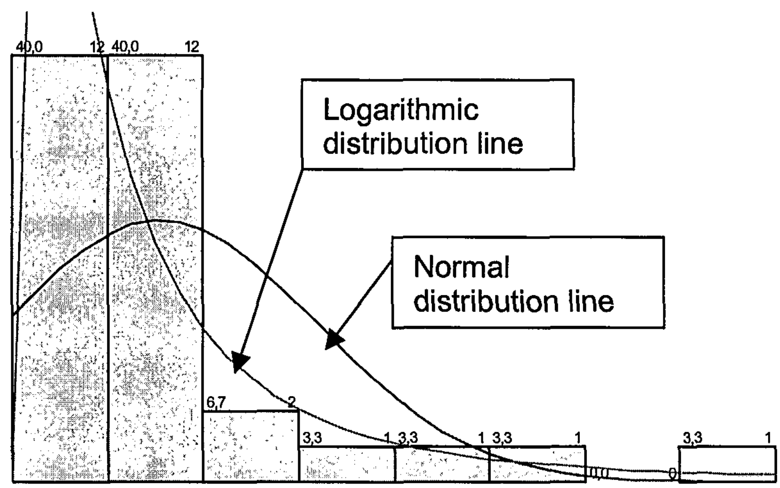

Figure 10. Histogram of the Actual Predicted Results

When the skewness is to the right, log transformation is appropriate. By using log transformation, it is possible to get the new results as distributed normally or near-normally. For this purpose, the logarithm of each data value was taken as in table 11 and the histogram of these logarithmic data was formed as in figure 11.

	ln(y)		
1	4,063357	**16**	4,091553
2	5,426644	**17**	4,419324
3	4,427215	**18**	4,009029
4	4,323784	**19**	2,964346
5	2,786086	**20**	1,652829
6	2,253929	**21**	4,670679
7	2,423411	**22**	4,58888
8	4,807505	**23**	4,590202
9	2,50549	**24**	4,50045
10	4,427672	**25**	2,936627
11	3,035839	**26**	2,375757
12	3,027664	**27**	5,562622
13	2,675484	**28**	3,488362
14	5,882249	**29**	4,24587
15	3,935183	**30**	5,052501

Table 11. The Logarithmic New Data

The new transformed data set has the mean as 3.83 which is slightly equal to the median as 4.07. This means that the new histogram is roughly a symmetrical distribution as shown in figure 11.

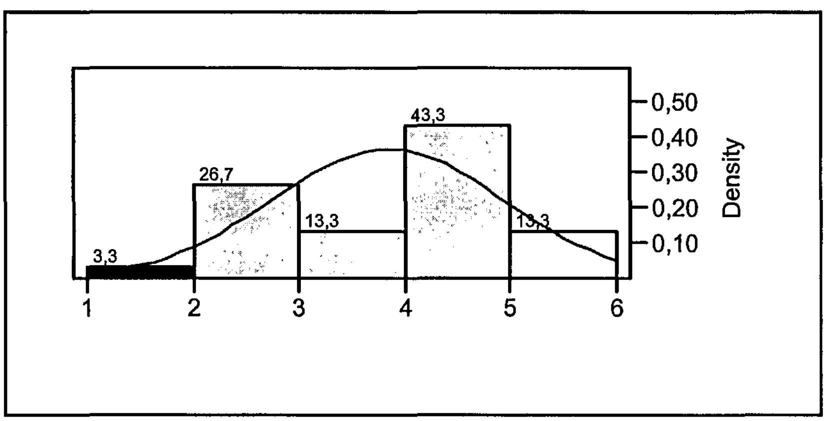

Figure 11. Histogram of Logarithmic Data

As can be seen in Figure 11, the new data has no outlier, and is roughly symmetrical. With new logarithmic values, the analyses were performed once again and new analysis tables and figures of logarithmic data were obtained [Appendix A]. By the use of these tables, the new math model was formed.

The estimate values of parameters which were transformed to logarithmic form in table 12, are the ones maximizing the response Y. These optimum values were obtained by running 'solver' in excel. The response value 6,021353472 was in the logarithmic form. For getting the actual value, the exponent of this logarithmic value was calculated as 412,1360329.

$\ln(Y)= 6{,}021353472$

$e^{\ln Y} = e^{6{,}021353472}$

$Y= 412{,}1360329$

WIDTH	-1	15
do/hc	1	0,676593
REQ.	-0,38838687	1,258343
AMPL.	0,588642814	1,6
ho/hc	0,430572498	605,8066
Y	6,021353472	
EXP(Y)	412,1360329	139,784

Table 12. Logarithmic Parameters that Optimize the Model

The estimated Y value derived from the optimization as 412,1360329 kg.m/sn^2 is considerably a good value. The highest momentum result of the experiments was 358,615 kg.m/sn^2. The estimated value 412,1360329 kg.m/sn^2 versus this highest result shows that a good improvement was acquired by the help of transformation. This means that the math model of the design would provide a better fitting model after transformation. However, a confirmation run is required for observing the fitness of the mathematical model. Only after this confirmation experiment the accuracy of the math model can be evaluated.

4.2. Verification

➢ Running a Confirmation Experiment

The optimized parameter values were transformed into actual values and a confirmation run was performed. The result value was obtained as 139,784 kg.m/sn^2. This value is very low in proportion to 412,1360329, in other words the result is not as high as predicted with the math model. There may be two reasons of this lack of accuracy of the model.

- There might be another parameter affecting the performance of the synthetic jet than those studied. The parameters thought to be the most important ones were chosen for the design. However, there might be another strong parameter which is not included into the model.
- Another reason might be the discontinuous topology of the response surface. This application was applied to the 'synthetic jet' design which includes nonlinear parametric values. For that reason, the interactions and quadratic effects were taken in to consideration for covering nonlinearity, but the math model did not fit well to the surface. This may be because of the discontinuous topology of the response surface. In case of discontinuity, some parts of the surface may be indeterminate and the predictions can be accurate only at specific areas of the surface.

4.3. Summary

Design of experiments (DOE) is a beneficial statistical set of methods that allows the designer to optimize various products or processes.

There are several DOE methods in literature. The usual ones have been reviewed and advantages and limitations of each method were explained. These methods are OFAT- one factor at a time approach, full factorial design fractional factorial design, response surface model [central composite design (CCD) and Box-Behnken design], D-optimal design and augmentation of optimality criterion.

This research demonstrates that application of augmented D-optimal design method to the 'synthetic jet' design is a time and cost efficient and especially a powerful tool for the optimization of the design.

The D-optimal method is a computer-aided design based on optimality criterion. For this study D-optimal method was used since it mainly enables to construct minimum point experimental designs.

In this study two different computer programs were used. The JMP [3] software which enables statistical design and analysis applications was used for the design of the experiments and the analysis of the results. The CFL3D (computational Fluids Laboratory 3-Dimensional flow solver) computer algorithm [26], developed by NASA- Langley Research center was used for the execution of the experiments.

The design was prepared by the use of the JMP [3] and the experiments were conducted using the CFL3D. The results of experiments were evaluated in 'analyze' tool of the JMP [3]. Using the data derived from analysis, the math model was set up and optimum values of parameters and the optimum result of math model were found. These optimum values were evaluated as being high enough in terms of improving the design more than double. However, statistical analysis values of the model were not high enough to fit well the model.

For improving statistical values, the transformation method was applied to the result data. By the use of logarithmic transformation, the skewness of the distribution of result data was made near normal distribution and the regression data was improved considerably. However, the result of the confirmation run did not match with the new math model. The possible reasons for this incompatibility are explained in section 4.2. The most probable one of these reasons is that the response surface of the data was of discontinuous topology. This means that the math model works well only at specific points scattered on the response surface.

In spite of the discontinious topology, a good momentum value which is more than double of the center point value of the design could be reached using augmented minimum point D-optimal methods.

4.4. Contributions, Conclusions Future Work Potential Application

4.4.1. Contributions

With this study, it was aimed to make several contributions by applying D-optimal design of experiments method to the design of the “synthetic jet”.

4.4.1.1. Application in Aerospace to the ‘Synthetic Jet’ Design

For controlling the air flow, a great quantity of studies on passive control methods have been applied for years. Active control methods are rather new.

Synthetic jet is an active control device which controls the air flow on any surface. The design studies on 'synthetic jet' are being conducted for only a few years.

It was determined that statistical approach to this design would be quite efficient in terms of time and efficency. Instead of doing random experiments at high number of runs, statistics based augmented minimum point D-optimal method yielded a good model .

4.4.1.2. Augmentation

In addition to 21 experiments required for the minimum point D- optimal design, by adding eight more experiments and a center point, the design was augmented with the purpose of improving its efficiency. By this way, a more robust and flexible design was acquired and after getting the results of experiments, the augmentation allowed to do improved analysis.

4.4.1.3. Transformation

In the first results table, the statistical indicators such as R-square, adjusted R-square and p-value were not high enough to make a good estimate. The mathematical model was setup according to these values and then optimized using 'solver'. The result of the optimized math model was 336,4148 which is a higher value of the results of experiments except one. But the aim here was to get good statistical values and to form a math model that yield a higher value than the results of the experiments. For that reason, with the purpose of increasing the fitness of the design with improved statistical values and consequently acquiring a higher output, the data were transformed to logarithmic form and the analyses were performed in this form. By means of this transformation, a better fitting model was acquired. By using the new logarithmic values, 412,1360329 kg. m/sn^2 momentum value could be reached.

4.4.2. Conclusions

Several methods of DOE (design of experiments) have been reviewed in terms of their basic principles, limitations and advantages prior to the selection of the application method.

Experiments for the synthetic jet design study take a long computer time since they are conducted by complex computer algorithms. Consequently, applying minimum number of runs was the main constraint for this study. Regarding to literature review and taking the constraints and objectives in to consideration, it was thought that the minimum point D-optimal design was more appropriate than others for this case. D-optimal designs give flexibility in choosing the number of experiments. However, when the number is minimum, the resulting design is saturated which means that there are no degrees of freedom for error. To avoid this limitation, the model was improved by applying augmentation to the minimum point D-optimal design.

An augmented minimum point D-optimal design was applied to the design of synthetic jet and the results have shown that the model has been improved more than double in proportion to the center point of the design.

Despite having a good result, it was considered that a better prediction model might be acquired since the statistical result data did not show a strong fit. For the purpose of improving the fitness of the model, logarithmic transformation was applied to the result data of the experiments. The skewness of the distribution was chanced and a higher statistical accuracy was achieved with logarithmic transformation. The new prediction of the response value turned to be higher. However, the confirmation run didn't yield a result as predicted in the math model. The main cause of this difference is evaluated that the response surface of the model might be of discontinuous topology. In this topology the model fits to the response surface only at some narrow parts. Except these parts, it does not give meaningful results.

Another cause might be the extinction of a strong parameter in the model. For preventing the probability of not including a strong parameter into design, a 2-stage design is considered to be useful as explained in future work potential application.

4.4.3. Future Work Potential Application

The main parameters were selected among many parameters in terms of the degree of their effect. However, there may exist a missed important parameter and its absence may cause the failure of the model. To be able to include all important parameters, a slightly different approach may be applied. This approach refers to separating the design into two stages; analyzing the parameters in 2-level with few experiments and after that switching to 3-level design. It is not efficient to include many parameters at 3-level design as it requires a lot of experiments. However, at 2-level it may be possible to include more parameters with less number of experiments in proportion to 3-level design. After performing 2-level design experiments and analysis, the stronger ones can be selected for 3-level experimental design. Thus, the parameters can be chosen not based on prediction or on expert judgment but according to the experimental analysis.

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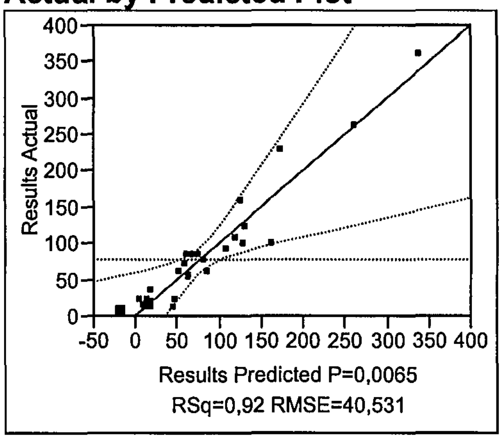
APPENDIX A

Analysis Tables

This appendix includes the tables of the analysis for normal and logarithmic transformed data. Both include: actual by predicted figure, summary of fit table, analysis of variance table, parameter estimates table, scaled estimates table and prediction profiler table.

Analysis Tables for Normal Data

Actual by Predicted Plot



Summary of Fit

RSquare	0,923436
RSquare Adj	0,753294
Root Mean Square Error	40,53053
Mean of Response	77,7104
Observations (or Sum Wgts)	30

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	20	178315,74	8915,79	5,4274
Error	9	14784,51	1642,72	Prob > F
C. Total	29	193100,25		0,0065

Parameter Estimates

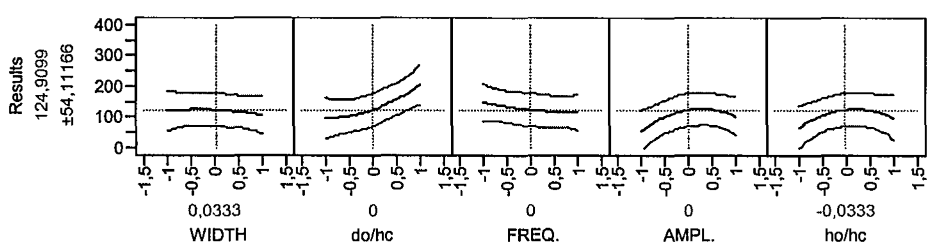
Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	125,77134	23,96328	5,25	0,0005
WIDTH	-7,871838	8,714192	-0,90	0,3899
do/hc	53,904522	8,576381	6,29	0,0001
FREQ.	-16,22137	8,521106	-1,90	0,0894
AMPL.	23,68415	8,571243	2,76	0,0220
ho/hc	17,997165	8,92823	2,02	0,0746
WIDTH*WIDTH	-11,65854	20,09483	-0,58	0,5760
(WIDTH)*do/hc	-7,255338	9,437221	-0,77	0,4617
do/hc*do/hc	26,820486	21,78015	1,23	0,2494
WIDTH*FREQ.	14,909413	9,660238	1,54	0,1571
do/hc*FREQ.	-14,14407	9,335353	-1,52	0,1640
FREQ.*FREQ.	7,8448763	20,35825	0,39	0,7089
WIDTH*AMPL.	-10,05746	9,590979	-1,05	0,3217
do/hc*AMPL.	18,77267	9,40336	2,00	0,0770
FREQ.*AMPL.	-15,21522	9,454465	-1,61	0,1420
AMPL.*AMPL.	-43,95075	22,5532	-1,95	0,0831
WIDTH*ho/hc	-19,81922	9,556157	-2,07	0,0679
do/hc*ho/hc	20,747031	9,515577	2,18	0,0571
FREQ.*ho/hc	-12,80102	9,536166	-1,34	0,2124
AMPL.*ho/hc	19,662471	9,314043	2,11	0,0640
ho/hc*ho/hc	-41,47709	21,78883	-1,90	0,0894

Scaled Estimates

Continuous factors centered by mean, scaled by range/2

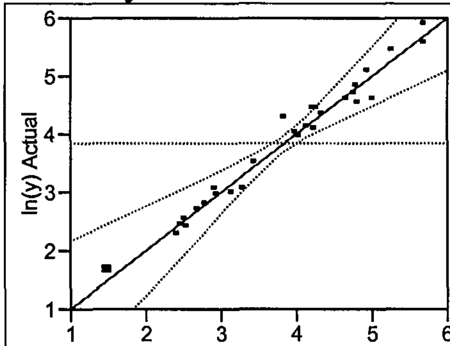
Term	Scaled Estimate	Plot Estimate	Std Error	t Ratio	Prob>|t|
Intercept	124,90904		23,92034	5,22	0,0005
WIDTH	-7,871838		8,714192	-0,90	0,3899
do/hc	53,904522		8,576381	6,29	0,0001
FREQ.	-16,22137		8,521106	-1,90	0,0894
AMPL.	23,68415		8,571243	2,76	0,0220
ho/hc	17,997165		8,92823	2,02	0,0746
WIDTH*WIDTH	-11,65854		20,09483	-0,58	0,5760
WIDTH*do/hc	-7,255338		9,437221	-0,77	0,4617
do/hc*do/hc	26,820486		21,78015	1,23	0,2494
WIDTH*FREQ.	14,909413		9,660238	1,54	0,1571
do/hc*FREQ.	-14,14407		9,335353	-1,52	0,1640
FREQ.*FREQ.	7,8448763		20,35825	0,39	0,7089
WIDTH*AMPL.	-10,05746		9,590979	-1,05	0,3217
do/hc*AMPL.	18,77267		9,40336	2,00	0,0770
FREQ.*AMPL.	-15,21522		9,454465	-1,61	0,1420
AMPL.*AMPL.	-43,95075		22,5532	-1,95	0,0831
WIDTH*ho/hc	-19,81922		9,556157	-2,07	0,0679
do/hc*ho/hc	20,747031		9,515577	2,18	0,0571
FREQ.*ho/hc	-12,80102		9,536166	-1,34	0,2124
AMPL.*ho/hc	19,662471		9,314043	2,11	0,0640
(ho/hc*ho/hc	-41,47709		21,78883	-1,90	0,0894

Prediction Profiler



Analysis Tables for Logarithmic Data

Actual by Predicted Plot



ln(y) Predicted P<.0001
RSq=0,97 RMSE=0,3116

Summary of Fit

RSquare	0,974749
RSquare Adj	0,918635
Root Mean Square Error	0,311561
Mean of Response	3,838351
Observations (or Sum Wgts)	30

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	20	33,724267	1,68621	17,3710
Error	9	0,873633	0,09707	Prob > F
C. Total	29	34,597900		<,0001

Parameter Estimates

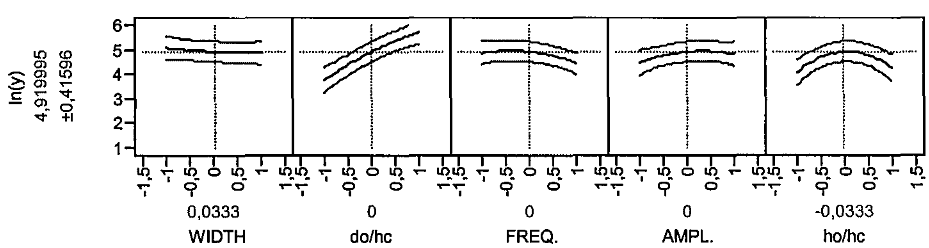
Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	4,9276565	0,184208	26,75	<,0001
WIDTH	-0,092125	0,066987	-1,38	0,2023
do/hc	0,9783403	0,065927	14,84	<,0001
FREQ.	-0,200574	0,065502	-3,06	0,0135
AMPL.	0,1736159	0,065888	2,64	0,0271
ho/hc	0,1379362	0,068632	2,01	0,0754
WIDTH*WIDTH	0,054344	0,15447	0,35	0,7331
WIDTH*do/hc	0,0739049	0,072545	1,02	0,3349
do/hc*do/hc	-0,170937	0,167426	-1,02	0,3339
WIDTH*FREQ.	-0,034355	0,074259	-0,46	0,6546
do/hc*FREQ.	-0,030692	0,071762	-0,43	0,6789
FREQ.*FREQ.	-0,25462	0,156495	-1,63	0,1382
WIDTH*AMPL.	0,0152994	0,073727	0,21	0,8402
do/hc*AMPL.	0,0747933	0,072284	1,03	0,3278
FREQ.*AMPL.	0,0408482	0,072677	0,56	0,5878
AMPL.*AMPL.	-0,264933	0,173368	-1,53	0,1608
WIDTH*ho/hc	-0,249477	0,073459	-3,40	0,0079
do/hc*ho/hc	0,1090492	0,073147	1,49	0,1702
FREQ.*ho/hc	-0,057867	0,073305	-0,79	0,4502
AMPL.*ho/hc	0,2198397	0,071598	3,07	0,0133
ho/hc*ho/hc	-0,752886	0,167492	-4,50	0,0015

Scaled Estimates

Continuous factors centered by mean, scaled by range/2

Term	Scaled Estimate	Plot Estimate	Std Error	t Ratio	Prob>|t|
Intercept	4,9199878		0,183877	26,76	<,0001
WIDTH	-0,092125		0,066987	-1,38	0,2023
do/hc	0,9783403		0,065927	14,84	<,0001
FREQ.	-0,200574		0,065502	-3,06	0,0135
AMPL.	0,1736159		0,065888	2,64	0,0271
ho/hc	0,1379362		0,068632	2,01	0,0754
WIDTH*WIDTH	0,054344		0,15447	0,35	0,7331
WIDTH*do/hc	0,0739049		0,072545	1,02	0,3349
do/hc*do/hc	-0,170937		0,167426	-1,02	0,3339
WIDTH*FREQ.	-0,034355		0,074259	-0,46	0,6546
do/hc*FREQ.	-0,030692		0,071762	-0,43	0,6789
FREQ.*FREQ.	-0,25462		0,156495	-1,63	0,1382
WIDTH*AMPL.	0,0152994		0,073727	0,21	0,8402
do/hc*AMPL.	0,0747933		0,072284	1,03	0,3278
FREQ.*AMPL.	0,0408482		0,072677	0,56	0,5878
AMPL.*AMPL.	-0,264933		0,173368	-1,53	0,1608
WIDTH*ho/hc	-0,249477		0,073459	-3,40	0,0079
do/hc*ho/hc	0,1090492		0,073147	1,49	0,1702
FREQ.*ho/hc	-0,057867		0,073305	-0,79	0,4502
AMPL.*ho/hc	0,2198397		0,071598	3,07	0,0133
(ho/hc*ho/hc	-0,752886		0,167492	-4,50	0,0015

Prediction Profiler



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