Efficient Global Optimization Applied to Multi-Objective Design Optimization of Lift Creating Cylinder Using Plasma Actuators

Masahiro Kanazaki [1,*], Takashi Matsuno[2], Kengo Maeda[2]
and Mitsuhiro Kawazoe[2]
[1] Graduate Scool of System Design, Tokyo Metropolitan University,
6-6 Asahigaoka, Hino,
Tokyo 191-0065, Japan
[2] Graduate School of Engineering, Tottori University,
4-101 Koyama-Minami,
Tottori-shi, Tottori 680-8553, Japan

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Abstract

A Kriging based genetic algorithm (GA) was employed to optimize the parameters of the operating conditions of plasma actuators (PAs). In this study, the multi-objective problem around a circular cylinder was considered. The objective functions are the lift maximization and the drag minimization. Two PAs were installed on the upper and the lower side of the cylinder. This problem was similar to the airfoil design, because the circular has potential to work as airfoil due to the control of flow circulation by the PAs with four design parameters. The aerodynamic performance was assessed by wind tunnel testing to overcome the disadvantages of time-consuming numerical simulations. The developed optimization system explores the optimum waveform of parameters for AC voltage by changing the waveform automatically. Based on these results, optimum designs and global design information were obtained while drastically reducing the number of experiments required compared to a full factorial experiment. An analysis of variance and a scatter plot matrix were introduced for design knowledge discovery. According to the discovered design knowledge, it was found that

*kana@tmu.ac.jp

duty ratios for two PAs are an important parameter to create lift while reducing drag.

Keyword: Plasma actuator; Genetic algorithm; Efficient global optimization; Experimental evaluation.

1 Introduction

Plasma actuators (PAs, shown in Fig. 1) are flow control devices that utilize atmospheric pressure discharge [7][8]; they have gained attention in recent years, because their advantages of being fully electronically driven with no moving parts and having a simple structure and a fast response are potentially ideal for application to subsonic flow control.

Such active flow control devices have potential to control of the circulation around arbitrary objects and produce the lift-creating object even if it is not airfoil geometry.

In this study, the design problem is defined as the optimization of lift creation and drag reduction via flow circulation controlled by the PAs. A circular cylinder model is used as a model and two PAs are installed. Thus, the objective functions considered in this paper are the maximizing lift and the minimizing drag around the circular cylinder. A multi-objective genetic algorithm (MOGA)-based efficient design technique was employed with wind tunnel testing to efficiently find the optimum designs. Through the design case, the applicability of the present wind tunnel testing to the multi-objective/ multi-parameter design problem was also investigated.

Design problems are often solved by GAs based on numerical simulation, such as computational fluid dynamics (CFD) [5]. However, there are several difficulties with solving the flow field around PAs. First, the accuracy of existing simulation methods is still insufficient. Second, the computational cost is very high for design techniques such as GAs. Several days are needed to acquire the results for each case, whereas the actual flow physics finishes in a few seconds.

In MOGA based efficient design technique, Kriging surrogate model was applied to represent the input/output relationship in the experimental data to reduce the experimental cost. This optimization technique, which is called efficient global optimization (EGO) [1][3][4], enables the optimization of global parameters in a small number of experiments while simultaneously obtaining information on the design space. The EGO based on Kriging surrogate model can find efficiently near-global optimum. In this study, Kriging surrogate model based GA performs optimization during a wind tunnel experiment in real time. The design system is automated developing the interface between the optimization and the wind tunnel testing.

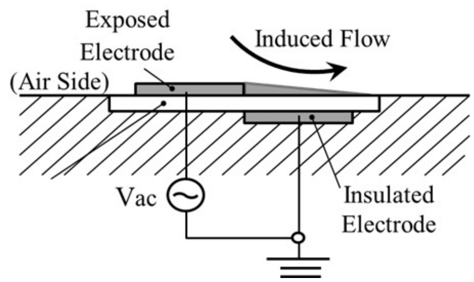


Figure 1: Schematic of plasma actuator.

2 Overview of Active Flow Control by Means of Plasma Actuator

In this research, a PA consisting of an exposed electrode and insulated electrode was used. A nonconductor was placed between the two electrodes, and AC voltage was applied. Fig. 1 shows the setup; this type of PA is called a single dielectric barrier discharge (SDBA) PA. The flow around the PA can be controlled by changing the number and location of PAs and the waveform of the AC voltage. Thus, the optimal technique for solving the design problem has to handle many parameters to acquire the best flow control.

Generic home-style AC voltage has a waveform with a constant frequency. However, several studies have reported that pulse width modulation (PWM) is effective for flow control of PAs. PWM is a drive system that turns the AC voltage on or off, as shown in Fig. 2. The frequency of on/off is defined as the "modulation frequency" (f_{mod}) and is expressed by following equation:

$$f_{\mathrm{mod}} = \frac{1}{T_1} \quad [\mathrm{Hz}] \tag{1}$$

where T_1 is the time of one cycle and T_2 is the time the AC voltage is on. The ratio of T_2 to T_1 is defined as the duty ratio, which is an important parameter for PWM. The duty ratio (D_{cycle}) is expressed by the following equation:

$$D_{\mathrm{cycle}} = 100\frac{T_2}{T_1} \quad [\%] \tag{2}$$

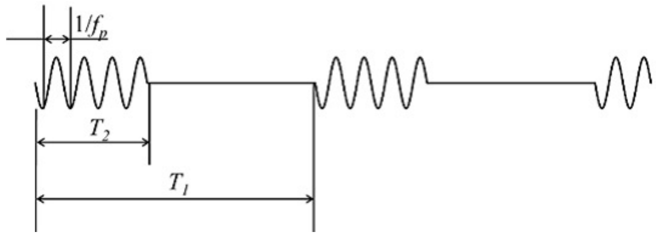


Figure 2: Power supply by means of pulse width modulation (PWM).

3 Design Method: Efficient Global Optimization

3.1 Efficient Global Optimization (EGO)

The optimization procedure (Fig. 4) for PA design consists of the following steps. First, N design samples are selected by Latin hypercube sampling (LHS) [1][3][4][6], which is a space filling method, and then assessed for the construction of an initial Kriging surrogate model. Second, an additional design sample is added, and the design accuracy is improved by constructing a Kriging model based on all $N+1$ samples. Note that the additional sample is selected by using expected improvement (EI) maximization [1][3][4][6]. GA is applied to solve this maximization problem. This process is iterated until the improvement of the objective functions becomes negligible. Through the design procedure proposed in this paper, all samples are evaluated by the wind tunnel testing. Each technique of the optimization procedure is described in detail in the following sections.

3.1.1 Kriging Model

The Kriging models express the value $y(x_i)$ at the unknown design point x_i as

$$y(x_i) = \mu + \epsilon(x_i) \quad (i = 1, 2, ..., m) \tag{3}$$

where m is the number of design variables, μ is a constant of the global model, and $\epsilon(x_i)$ represents a local deviation from the global model. The correlation between $\epsilon(x_i)$ and $\epsilon(x_j)$ is strongly related to the distance between the corresponding points, x_i and x_j. In the Kriging models, the local deviation at an unknown point x is expressed using stochastic processes. Specifically, a number of design points are calculated as sample points and then interpolated using a Gaussian random function as the correlation function to estimate the trend of the stochastic process.

3.1.2 Expected Improvement

Once the models are constructed, the optimum point can be explored using an arbitrary optimizer. However, it is possible to miss the global optimum design, because the approximate model includes uncertainty. Therefore, this study introduced EI values as the criterion. This study solve the lift maximization problem, then EI for maximization problem can be calculated as follows:

$$E[I(x)] = (f_{\max} - \hat{y})\,\Phi\left(\frac{f_{\max} - \hat{y}}{s}\right) + s\phi\left(\frac{f_{\max} - \hat{y}}{s}\right) \tag{4}$$

EI for maximization problem can be calculated as follows:

$$E[I(x)] = (\hat{y} - f_{\min})\,\Phi\left(\frac{\hat{y} - f_{\min}}{s}\right) + s\phi\left(\frac{\hat{y} - f_{\min}}{s}\right) \tag{5}$$

where $f_{\max}$ and $f_{\min}$ are the maximum and the minimum values among sample points, respectively. s is root mean square error (RMSE) and $\hat{y}$ is the value predicted by Eq. 3 at an unknown point x. Φ and ϕ are the standard distribution and normal density, respectively. EI considers the predicted function value and its uncertainty, simultaneously. Therefore, by selecting the point where EI takes the maximum value, as the additional sample point, robust exploration of the global optimum and improvement of the model can be achieved simultaneously as shown in Fig. 4 because this point has a somewhat large probability to become the global optimum. In this study, the maximization of EI is carried out using GA expressed as following section.

3.1.3 Genetic Algorithm

GAs (Fig. 5(a)) was first proposed by Holland in the early 1970s [2] and are based on the evolution of living organisms with regard to adaptation to the environment and the passing on of genetic information to the next generation. GAs can find a global optimum because they do not use function gradients, which often lead to an exact local optimum. Thus, GA is a robust and effective method that can handle highly nonlinear optimization problems involving nondifferentiable objective functions. Owing to this advantage, GAs were applied to this experimental system. The GA used in this study [5] utilizes a real-coded representation, the blended crossover (BLX-α), and the uniform mutation. The selection probability of individuals for the crossover and mutation is expressed as follows:

$$prob = c(1-c)rank1 - 1.0 \tag{6}$$

where $rank$ is the value of fitness ranking among the population.

In BLX-α, children are generated in a range defined by the two parents as shown in Fig. 5(b). The range is often extended equally on both sides as determined by the parameter α.

3.2 Knowledge Discovery Techniques

3.2.1 Analysis of Variance (ANOVA)

In this study, Kriging model based ANOVA [4][1][3][6] is employed to investigate the effect of the design variables to objective functions. Varinace of an surrogate model can be calaulated as,

$$\mu_i(x_i) \equiv \int \cdots \int \hat{y}(x_1, \cdots, x_n) dx_1, \cdots, dx_{i-1}, dx_{i+1}, \cdots, dx_n - \mu \tag{7}$$

where the total mean μ is calculated as

$$\mu \equiv \int \cdots \int \hat{y}(x_1, \cdots, x_n) dx_1, \cdots, dx_n \tag{8}$$

The proportion of the variance attributed to the design variable x_i to the total variance of the model can be expressed as:

$$p \equiv \frac{\int [\mu_i(x_i)]^2 dx}{\int \cdots \int [\hat{y}(x_1 \cdots x_n) - \mu]^2 dx_1 \cdots dx_n} \tag{9}$$

The value obtained by Eq. (9) indicates the sensitivity of an objective function to the variance of a design variable.

3.3 Scatter Plot Matrix (SPM)

The solution and the design space of the multivariable design problem obtained by EGO are observed by the SPM [9] which is one of the data mining, because the Kriging model cannot be visualized directly when the design problem has over four attribute values. SPM arranges two-dimensional scatter plots like a matrix among the objective functions and the design variables and facilitates the investigation of the design problem investigation. Each of the rows and columns is assigned attribute values such as design variables, objective functions, and constraint values. The diagonal elements show mutual same plots. Therefore, it can be said that the SPM shows scatter plots on the upper triangular part of the matrix and the correlation coefficients on the lower triangular part as additional information. modeFrontier$^{\mathrm{TM}}$ver. 4. 4. 2 is employed in this study.

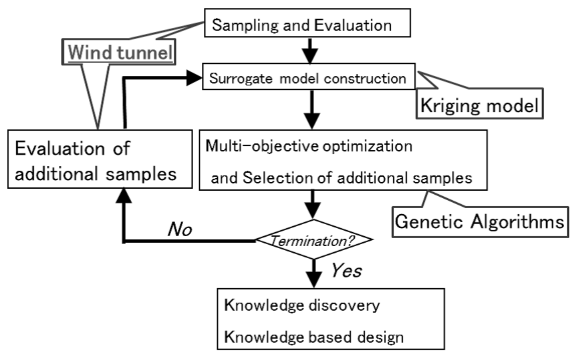


Figure 3: Optimization procedure based on wind tunnel evaluation.

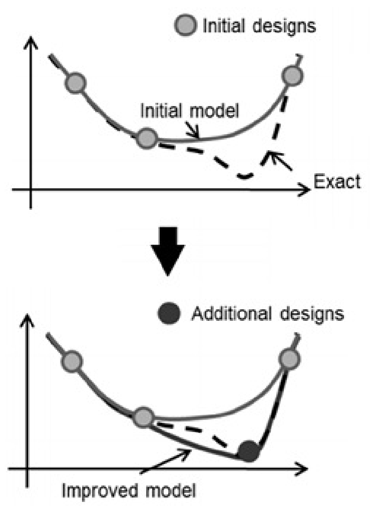


Figure 4: Improvement of the global model by expected improvement (EI) maximization.

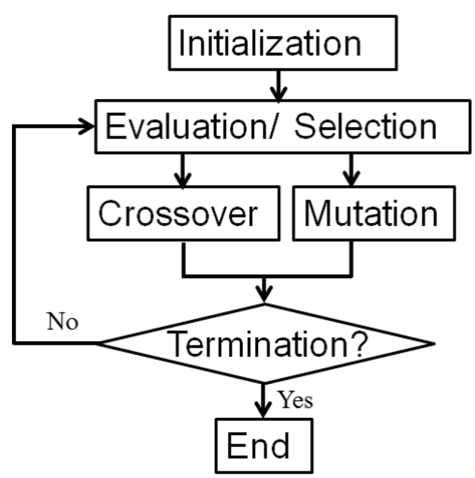


Figure 5: Schematic illustration of genetic algorithm (GA) .

4 Experimental Setup

4.1 Wind Tunnel and Model

The wind tunnel experiments were conducted in the subsonic closed-return wind tunnel of the Aerodynamics Laboratory at Tottori University. The wind tunnel has a closed test section with a 0.70 m $\times$ 1.0 m cross-section and 2.0 m length (Fig. 6). A two-dimensional circular model (105 mm in diameter) was used as shown in Fig. 7. Model was placed on a flat plate and mounted to a support connected to a six-component external balance for measurement of the aerodynamic forces and moments. The output of the balance was amplified and acquired with a data acquisition board (National Instruments PXI-8106). The output signal contains noise from the atmospheric discharge of the plasma actuators. To eliminate this effect, the clean portion of the signal, during which the discharge did not appear, was extracted and used as a "clean" portion of the data.

4.2 PA and Its Power Supply

In this study, two PAs were installed on the surface of the model. PA#1 and PA#2 were installed with mount angles of $\theta 1 = 85.0°$ and $\theta 2 = -85.0°$, respectively, as shown in Fig. 7. The reference waveform of a high-voltage AC input was amplified by a solid-state high-power amplifier; the input power was increased up to 400.0 W with amplitude of 70.0 Vpp. A high-voltage transformer was used to achieve an AC input with amplitude of up to 30 kV at a frequency of 5.0-15.0 kHz. The voltage and current of the AC input were monitored by an oscilloscope along with the reference waveform.

4.3 Integration of Experiment System

Figure 8 shows the schematic illustration of the developed system. EGO is executed in the workstation and receives the experimental data via LabVIEW® from the balance in the wind tunnel. The condition of the AC voltage can be automatically set during the optimization process based on balance measurements.

5 Formulation

In this study, multi-objective/ multi-parameter design problem which has four design variables was considered and the lift creation and drag reduction effect due to circulation control by PAs was investigated. The objective

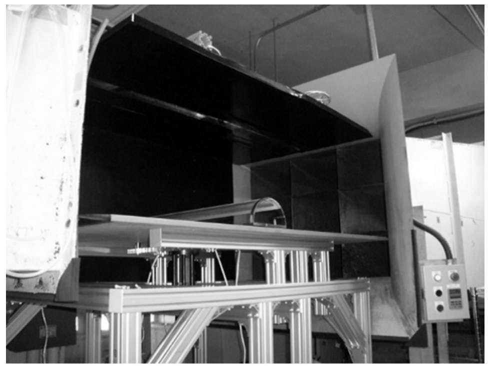


Figure 6: Test section of the wind tunnel.

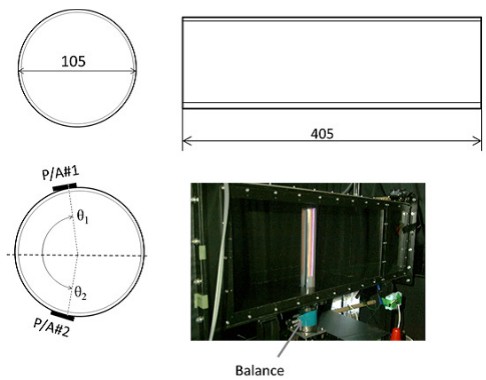


Figure 7: Circular cylinder model and the location of plasma actuators.

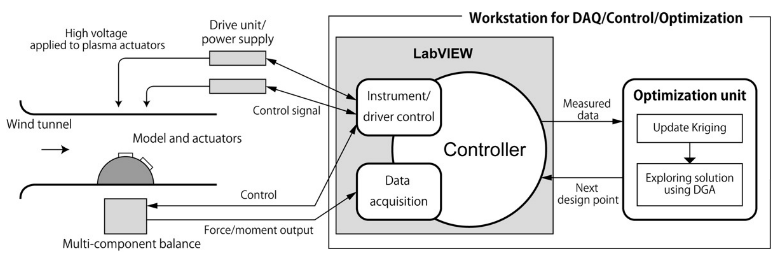


Figure 8: Schematic diagram of the integrated optimization system.

function was maximization of the lift coefficient (C_l) and the minimization of the drag coefficient (C_d)around the circular cylinder model. This design problem can be expressed as follows:

$$\begin{cases} \text{Maximize} \quad C_\mathrm{l} \\ \text{Minimize} \quad C_\mathrm{d} \end{cases} \tag{10}$$

The flow velocity was set to 10.0 m/s. Eq. 10 can be written for the present design problem as follows:

$$\begin{cases} \text{Maximize } EI_{Cl} = (Cl_{\max} - \hat{y})\,\Phi\left(\frac{Cl_{\max}-\hat{y}}{s}\right) + s\phi\left(\frac{Cl_{\max}-\hat{y}}{s}\right) \\ \text{Minimize} \quad EI_{Cd} = (\hat{y} - Cd_{\min})\,\Phi\left(\frac{\hat{y}-Cd_{\min}}{s}\right) + s\phi\left(\frac{\hat{y}-Cd_{\min}}{s}\right) \end{cases} \tag{11}$$

where $Cl_{\max}$ and $Cd_{\min}$ are respectively the maximum C_l and the minimum C_d among sample point, respectively.

The design problem expressed in Eq. (10) was solved by changing four parameters (f_mod, D_cycle1, D_cycle2, ϕ) related to the AC voltage waveform. In this case, two PAs are applied different D_{cycle}; D_cycle1 and D_cycle2, for each design and the difference between D_cycle1 and D_cycle2 is decided by a phase difference ϕ. The design space is defined as follows:

$$\begin{cases} 30.0 \leq f_\mathrm{mod} \leq 200.0 \ [Hz] \\ 0.0 \leq D_\mathrm{cycle1} \leq 50.0 \ [\%] \\ 0.0 \leq D_\mathrm{cycle2} \leq 50.0 \ [\%] \\ -90.0 \leq \phi \leq 90.0 \ [deg.] \end{cases} \tag{12}$$

ϕ is the phase difference between PA#1 and PA#2. Consequently, the time lag can be expressed as ϕ/f_mod.

6 Results

6.1 Design Exploration Result

In this section, the design problem expressed by Eq. (10) is discussed. To construct the initial Kriging model, 15 samples were obtained by LHS. To acquire additional samples, the island GA was executed with the following specifications: BLX-0.5 (α = 0.5), four subpopulations, 16 individuals for each subpopulations(64 individuals generated in total) and 64 generations. The EGO process will be stopped after ten or more additional samples show better function value than that of initial samples [6].

After the objective function was converted, seven additional samples were obtained, for a total of 22 sample designs. Figure 9 shows the history of C_l values for the sampling process. According to the history, the objective function converged well with a small number of samples. Without EGO, a full factorial design of over 1000 samples would be needed to find the global optimum. The proposed system reduces the cost of the wind tunnel testing by over 99

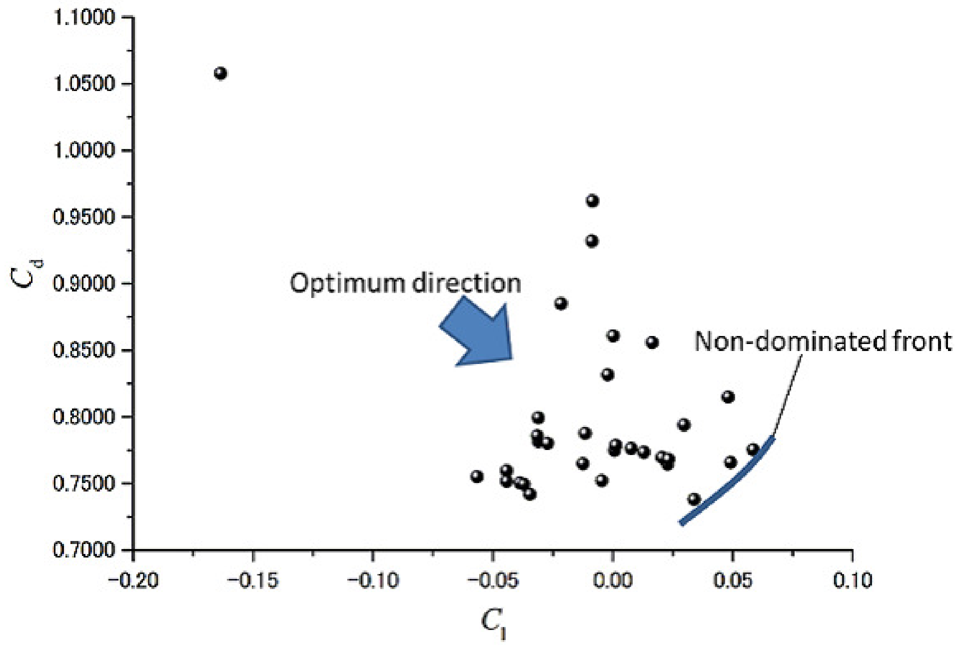
6.2 Design Knowledge by Analysis of Variance

Figure 10(a) shows the main effects and the two-way interaction of the design variables for objective function for C_l. According to Fig. 10(a), f_mod and D_cycle2, which defines the driving condition of PA on the lower side of the cylinder, has a predominant influence on C_l. In addition, two-way interaction of $f_\mathrm{mod} - D_{cycle2}$ is also effective to C_l. These results suggest that the circulation which creates aerodynamic lift around the model is decided by duty ratio PA on the lower side.

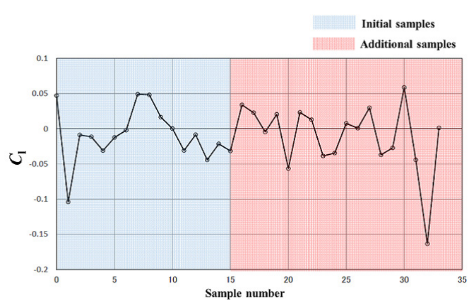
Figure 10(b) the main effects and the two-way interaction of the design variables for objective function for C_d. According to Fig. 10(a), f_mod which defines the driving condition of eaxh PA on the cylinder, has a predominant influence on C_d. It is reasonable result because higher f_mod create higher volume force which can reduce the flow separation. As this result, the drag is affected by f_mod.

6.3 Visualization of Design Problem by SPM

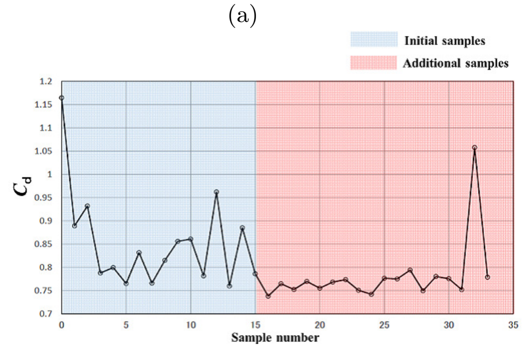
Figure 11 shows the visualization results obtained by SPM, which shows the scatter plot for all parameter combinations. Plots colored by red represent designes which achive higher aerodynamic performance. According to Fig. 11, higher f_mod and D_cycle2 are always required for higher C_l and lower C_d. In addition, C_d and f_mod shows the high correlation (-0.882.) This result suggests that the lower C_d can be carried out with the higher f_mod.



(a)

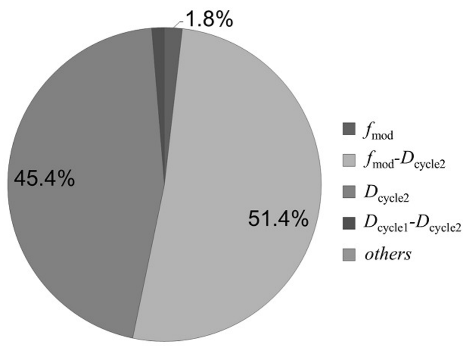


(b)

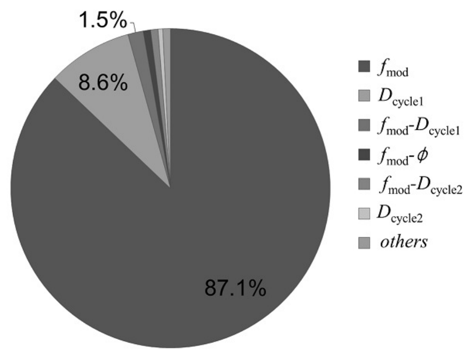


(c)

Figure 9: Solutions of the desgin problems (a)Design result, (b)Progression of objective function with sample number for the C_l and (c)Progression of objective function with sample number for the C_d.



(a)



(b)

Figure 10: ANOVA results.(a)Effect of design variables of the design variables for C_{l} and (b)Effect of design variables of the design variables for C_{d}.

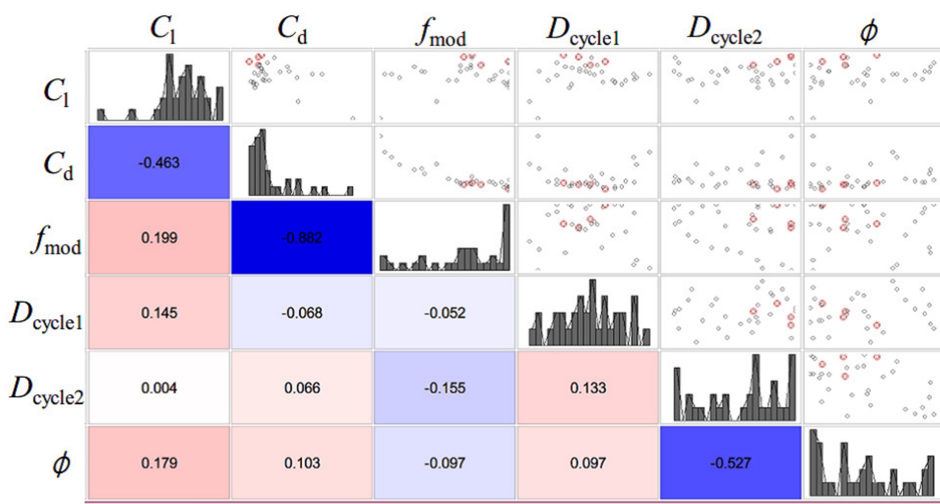


Figure 11: Visualization of the design problem using SPM.

7 Conclusions

Aerodynamic control performance of plasma actuators was optimized using wind tunnel test-based EGO. In this study, the lift-creating cylinder using plasma actuators was considered. This problem was that the circulation around a circular cylinder model was controlled to maximize the lift around the model. In addition, this study also considered the drag minimization around the cylinder, thus the design problem was formulated as the multi-objective problem. The optimization technique is firstly integrated in the operating system of the wind tunnel experiment to enable automation of the data-acquisition/optimization process. Using the developed system, multi-objective design problem (lift maximization/ drag minimization) was solved. After several additional samples are obtained, the analysis of variance and the scatterplot matrix is employed for the knowledge discovery. Using these techniques, it is found that duty ratio and modulation frequency for the plasma actuators installed on the lower surface have the dominant effect for this problem. It is also found that the higher modulation frequency is required for the plasma actuator to minimize the drag.

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