Chinese Journal of Aeronautics 25 (2012) 887-895

Contents lists available at ScienceDirect

Chinese Journal of Aeronautics

journal homepage: www.elsevier.com/locate/cja

Inflatable Wing Design Parameter Optimization Using Orthogonal Testing and Support Vector Machines

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Received 7 February 2012; revised 16 April 2012; accepted 12 June 2012

Abstract

The robust parameter design method is a traditional approach to robust experimental design that seeks to obtain the optimal combination of factors/levels. To overcome some of the defects of the inflatable wing parameter design method, this paper proposes an optimization design scheme based on orthogonal testing and support vector machines (SVMs). Orthogonal testing design is used to estimate the appropriate initial value and variation domain of each variable to decrease the number of iterations and improve the identification accuracy and efficiency. Orthogonal tests consisting of three factors and three levels are designed to analyze the parameters of pressure, uniform applied load and the number of chambers that affect the bending response of inflatable wings. An SVM intelligent model is established and limited orthogonal test swatches are studied. Thus, the precise relationships between each parameter and product quality features, as well the signal-to-noise ratio (SNR), can be obtained. This can guide general technological design optimization.

Keywords: inflatable wing; orthogonal test; design parameter; support vector machines; optimization

1. Introduction

Inflatable wings are becoming increasingly attractive for potential use in the automotive, transportation, aeronautical and aerospace industries, with specific uses including aircraft, unmanned aerial vehicles (UAVs), airships and missile stabilization surfaces. Traditionally, UAVs have a need to stow their wings and control surfaces, but many military and commercial applications have been identified for vehicles whose wings must be stowed in very small volumes. Examples include gun launch or aircraft mounted aerial drop assemblies which have special packaging requirements. The development of these vehicles will require a design that uses deployable wings. One technology that has shown promise in achieving this goal is the inflatable wing, due to its low density, small volume and ease of recyclables.

However, its mechanical properties still do not satisfy the demands of some important application fields. The successful development of this type of wing will also take significant priority in the future. Future requirements include wing designs allowing the greatest possible endurance of platforms used for surveying targets of intelligence interest [1].

Inflatable wings have been demonstrated in many applications over the years. Recent system design challenges have ushered in advances in the areas of materials, manufacturing and configuration that have advanced this technology into a practical form for near term application. Inflatable wings were successfully demonstrated in the 1950s with the Goodyear inflatoplane. Recently, wings have been constructed of composite material that becomes rigid upon exposure to UV light. Information relating to the construction and materials used in these wings can be found in previous papers [2-4]. Flight characteristics, aerodynamic performance, aerodynamic analysis and wind-tunnel testing for inflatable/rigidizable wings are detailed in

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Foundation item: China Space Foundation (CASC0105)

doi: 10.1016/S1000-9361(11)60459-7

Refs. [5]-[6]. Furthermore, several methods have been developed to investigate the bearing capacity of an inflatable wing. W. Wang, et al. [7] analyzed the bearing capacity by considering approaches of mechanics of both materials and structures. Z. F. Wang, et al. [8] presented a prediction method based on BP-artificial neural network to analyze the flexural rigidity of inflatable wings.

The robust parameter design method is a traditional approach for robust experimental design that seeks the optimal combination of factors/levels for the lowest societal cost while fulfilling customer's requirements. Over the past decade, the robust parameter design method has been widely applied to optimize the design parameter problems, which uses orthogonal array (OA) to arrange the experiments and employs signal-to-noise ratio (SNR) to evaluate the performance of the response of each experimental run [9-11]. The goal of this method is to choose the settings of the control factors (parameters) so that the performance of a system (product or process) is insensitive to variation in uncontrollable "noise" variables. In this case, statistically designed experiments and data analysis methods have been used to implement design parameter. The commonly used setup is the product array where the control factors are varied according to a suitably chosen experimental design (control array) and at each setting of the control array, the pre-identified noise variables are systematically varied according to a noise array.

The support vector machine (SVM) is a linear method in a high-dimensional feature space, which is nonlinearly related to the input space [12-13]. Though the linear algorithm works in the high-dimensional feature space, in practice it does not involve any computations in that space due to the usage of kernels; all necessary computations are performed directly in the input space; the combination of optimal parameters can be obtained by fewer steps searching in the parameters space. As an efficient method, orthogonal testing design is merged into the running of SVM, which can improve the precision and has low model complexity.

Traditionally, various mathematical methods, such as linear, nonlinear and dynamic programming, have been developed to solve engineering optimization problems. However, these methods are difficult to optimize inflatable wing design parameter, because of the influence and constriction of many factors. It has become one of the difficult tasks for the inflatable wing design parameter optimization to use mathematics and mechanics models. In order to obtain an optimal technique, a novels optimization design based on robust design parameter is proposed, which incorporates orthogonal testing and SVMs for solving the design parameter of the inflatable wing in this paper. The optimal parameter settings can be referenced in the design of the inflatable wing.

2. Design Methods

Using the design methods based on OAs, the time and cost required to conduct the experiments can be reduced and an appropriate technique that renders an optimal design parameter can be found. On this basis, orthogonal testing and SVMs are introduced to optimize the technique for the inflatable wing.

2.1. Orthogonal testing design

Orthogonal testing design is an optimization method for searching multiple factors and levels [13]. It utilizes an orthogonal table to arrange the experiment scientifically and evaluate multiple factors. The five steps of the Taguchi method used in the present study are as follows:

Step 1 Identification of the objectives. In the first step of the Taguchi method, identifying a specific objective is important. The objective of this work is to determine the optimum values of the design parameters of the inflatable wing.

Step 2 Selection of characteristics. The characteristics are classified into three types: higher is better, nominal is the best and lower is better. There are two objectives in this paper. The first objective is minimizing the deflection; therefore, it is a lower-the-better problem. The second objective is maximizing the SNR, a higher-the-better problem.

Step 3 Selection of the controllable factors and noise factors. The selection of factors to be tested for (in terms of their influences on the quality characteristic) is one of the most important procedures in the Taguchi method. Careless selection of controllable factors and noise factors leads to a false conclusion. After selecting the factors, their desired number of levels is determined. In this paper, the controllable factors are pressure (A), applied load (B) and the number of chambers (C), as depicted in Table 1.

Table 1 Factor level table for an orthogonal test with one of the three factors

Factor	Level 1	Level 2	Level 3
1	A_1	A_2	A_3
2	B_1	B_2	B_3
3	C_1	C_2	C_3

Step 4 Selection of an OA. The sequence of experiments with different combinations of factors and levels is determined by an OA. This array will determine the number of experiments to be performed, ensuring that equal quantities of all levels of factors will be tested. The OAs are an important part of the Taguchi method. There are many different types of that can be used to perform the Taguchi

experiment.

The selection of OA to be used depends predominantly on these items in the order of priority:

1) The number of factors and interactions present.

2) The number of levels for the factors present.

3) The desired experimental resolution or cost limitations.

The orthogonal table L9(3) is used to arrange the experiments. For this reason, L9 is suitable for our study. Three factors are evaluated at each instance, and each factor possesses three levels. A blank column is added to represent the degree of interaction among the three factors, and the testing result is analyzed using the range analysis method. A traditional full factorial design requires either 34 or 81 experiments. In this situation, all major effects and interactions can be estimated. All of these factors result in a high-resolution experiment. Resolution power indicates the clarity with which individual effects of factors and interactions may be evaluated in an experiment [9]. The number of columns of an array represents the maximum number of parameters that can be studied using that array. Note that this design reduces 81 configurations to nine experimental evaluations. This array reduces the total cost of experiments. The total testing time of experiments is shortened significantly by this array. In the literature, L9 OA is generally used for three factors and three levels in Refs. [14]-[20]. Therefore, we have chosen to use L9, which is shown in Table 2. In Table 2, A_i, B_i and C_i are the factor values for the ith test; Y_{ij} is the jth performance value of the ith test, Y_i the average value of the ith test; η_i the value of SNR.

Table 2 L9 OA array with design factors

Sequence	Factor level/line number			Deflection/m				SNR
	A	B	C	Level 1	Level 2	Level 3	The mean	
1	A_1	B_1	C_1	Y_{11}	Y_{12}	Y_{13}	Y_1	η_1
2	A_1	B_2	C_2	Y_{21}	Y_{22}	Y_{23}	Y_2	η_2
3	A_1	B_3	C_3	Y_{31}	Y_{32}	Y_{33}	Y_3	η_3
4	A_2	B_1	C_2	Y_{41}	Y_{42}	Y_{43}	Y_4	η_4
5	A_2	B_2	C_3	Y_{51}	Y_{52}	Y_{53}	Y_5	η_5
6	A_2	B_3	C_1	Y_{61}	Y_{62}	Y_{63}	Y_6	η_6
7	A_3	B_1	C_3	Y_{71}	Y_{72}	Y_{73}	Y_7	η_7
8	A_3	B_2	C_1	Y_{81}	Y_{82}	Y_{83}	Y_8	η_8
9	A_3	B_3	C_2	Y_{91}	Y_{92}	Y_{93}	Y_9	η_9

Step 5 Perform the experiment and analysis. The Taguchi method uses a special design of OA design to study the entire parameter space using only a small number of experiments. The experimental results are then transformed into an SNR. Taguchi recommends the use of SNR to measure the quality characteristics deviating from the desired values. Usually, there are three categories of quality characteristic in the analysis of SNR. The SNR for each level of process parameters is computed based on the SNR analysis. Regardless of the category of the quality characteristic, a greater SNR corresponds to superior quality characteristics. Therefore, the optimal level of the process parameters is the level with the greatest SNR.

2.2. SVMs for design parameter regression

An SVM can be applied not only to classification problems but also to regression problems. Even so, it contains all the major features that characterize maximum margin algorithm: a nonlinear function is learned by a linear learning machine mapping into high dimensional kernel induced feature space. The capacity of the system is controlled by parameters that do not depend on the dimensionality of the feature space. One of the most important ideas in cases of support vector classification and regression is that presenting the solution by means of small subset of training points gives enormous computational advantages. Using the ε-insensitive loss function, we ensure the existence of a global minimum and in the mean time optimization of reliable generalization bound.

In support vector regression (SVR), the input $\boldsymbol{x}=\left[\boldsymbol{x}_1\ \boldsymbol{x}_2 \cdots \boldsymbol{x}_n\right]^{\mathrm{T}}$ is first mapped onto an m-dimensional feature space using some fixed (nonlinear) mapping, and then a linear model is constructed in this feature space. Using mathematical notation, the linear model (in the feature space) $f(\boldsymbol{x},\boldsymbol{\omega})$ is given by

$$f(\boldsymbol{x},\boldsymbol{\omega})=\sum_{j=1}^{m}\omega_j g_j(\boldsymbol{x})+b \tag{1}$$

where $\boldsymbol{\omega}$ is the weight vector, $g_j(\boldsymbol{x})$ $(j=1,2,\cdots,m)$ a set of nonlinear transformations, and b the "bias" term. Often the data are assumed to be zero mean (this can be achieved by pre-processing), so the bias term is dropped. The quality of estimation is measured by the loss function $L(y,f(\boldsymbol{x},\boldsymbol{\omega}))$, where y is the corresponding scalar output (target) value. SVR uses a new type of loss function called the ε-insensitive loss function, proposed by Vapnik:

$$L_\varepsilon(y, f(\boldsymbol{x},\boldsymbol{\omega})) = \begin{cases} 0 & |y - f(\boldsymbol{x},\boldsymbol{\omega})| \le \varepsilon \\ |y - f(\boldsymbol{x},\boldsymbol{\omega})| - \varepsilon & \text{Otherwise} \end{cases} \tag{2}$$

The empirical risk is

$$R_{\text{emp}}(\boldsymbol{\omega}) = \frac{1}{n}\sum_{i=1}^{n} L_\varepsilon(y_i, f(\boldsymbol{x}_i,\boldsymbol{\omega})) \tag{3}$$

In specific terms, for classes $\boldsymbol{\omega}_i$ and classes $\boldsymbol{\omega}_j$, the constructed SVM, denoted by SVM_{ij} can be obtained by solving the following optimization problem [16]:

$$\min \quad \frac{1}{2}(\boldsymbol{\omega}^{ij})^{\text{T}}\boldsymbol{\omega}^{ij} + C\sum_{i=1}^{j}\xi_i^{ij} \tag{4}$$

s.t.

$$\begin{cases} (\boldsymbol{\omega}^{ij})^{\text{T}}\boldsymbol{\varphi}(\boldsymbol{x}_i) + b^{ij} \ge 1 - \xi_i^{ij} & y_i = i \\ (\boldsymbol{\omega}^{ij})^{\text{T}}\boldsymbol{\varphi}(\boldsymbol{x}_i) + b^{ij} \le 1 - \xi_i^{ij} & y_i \ne i \\ \zeta_{ij} \ge 0 \end{cases} \tag{5}$$

where $\boldsymbol{\omega}^{ij}$ is the weight vector, b^{ij} the expression of bias, ζ_i^{ij} slack variable ($\zeta_i^{ij} \ge 0$); $\boldsymbol{\varphi}(\boldsymbol{x}_i)$ the training vector, and C the penalty factor, which punishes the misclassified training examples and appointed by the user. After solving the optimization problem, we can obtain $N(N-1)/2$ decision-making functions:

$$g_{i,j}(\boldsymbol{x}) = (\boldsymbol{\omega}^{ij})^{\text{T}}\boldsymbol{\varphi}(\boldsymbol{x}) + b^{ij} \tag{6}$$

The dual formulation provides the key for extending the SVM to nonlinear functions. The standard dualization method utilizing Lagrange multipliers has been described as follows:

$$L(\boldsymbol{\omega}, b, \xi_i, \xi_j, a_i, a_i^*, \eta_i, \eta_i^*) = \frac{1}{2}\boldsymbol{\omega}\cdot\boldsymbol{\omega} + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) - \sum_{i=1}^{n} a_i(\varepsilon + \xi_i - y_i + \boldsymbol{\omega}\cdot\boldsymbol{x}_i + b) - \sum_{i=1}^{n} a_i^*(\varepsilon + \xi_i^* - y_i + \boldsymbol{\omega}\cdot\boldsymbol{x}_i - b) - C\sum_{i=1}^{n}(\eta_i\xi_i + \eta_i^*\xi_i^*) \tag{7}$$

where a_i and a_i^* ($a_i \ge 0, a_i^* \ge 0$) are Lagrange multipliers, η_i and η_i^* ($\eta_i \ge 0, \eta_i^* \ge 0$) the temporary variables, and the slack variables ξ_i and ξ_j are introduced for the situation that the target value exceeds.

We can determine Lagrange multipliers a, a^* and the weight in the regression function of Eq. (7) as follows:

$$\boldsymbol{\omega} = \sum_{\boldsymbol{x}_i \in S_{\text{SV}}} (a_i - a_i^*)\boldsymbol{x}_i \tag{8}$$

$$f(\boldsymbol{x}) = \boldsymbol{\omega}\cdot\boldsymbol{x} + b = \sum_{\boldsymbol{x}_i \in S_{\text{SV}}} (a_i^* - a_i)(\boldsymbol{x}_i\cdot\boldsymbol{x}) + b \tag{9}$$

A nonlinear mapping can be used to map the data into a high dimensional feature space where linear regression is performed. The SV algorithm can be made nonlinear by simply preprocessing the training patterns $\boldsymbol{x}_i$ by a map $\boldsymbol{\varphi}: \boldsymbol{x} \to \boldsymbol{\zeta}$ into some feature space $\boldsymbol{\zeta}$ and then applying the standard SVR algorithm. The expansion in Eq. (8) becomes

$$\boldsymbol{\omega} = \sum_{i=1}^{n}(a_i - a_i^*)\boldsymbol{\varphi}(\boldsymbol{x}_i) \tag{10}$$

The next step is to perform an SVM to optimize the design parameters of the inflatable wing to obtain the optimal multi-response, as well as the corresponding combination values of the control factors from the space of possible solutions. The parameter bounds and the precision are determined according to the characteristics of the system. The operational steps are given as follows:

Step 1 Finish the orthogonal experiment, collect the patterns from the experimental data, and preprocess the patterns.

Step 2 Detemine the SVM learning model, set model parameters and choose kernel function $k(\cdot)$.

Step 3 Obtain parameters ($a^* - a$ and b) by inputting learning patterns and determine the regression model.

Step 4 Fix the level parameters within certain range, and the parameters form an arithmetic series.

We used SVR to determine the best set of chosen inputs, which describe the deflection and SNR. The following criteria guide the choice of the set of inputs:

1) The number of inputs should be as low as possible.

2) Each input should be highly cross-correlated to the output parameter.

3) The inputs should be weakly cross-correlated to one another.

4) The selected input set should give the best output prediction, which is checked by using statistical analysis metric (e.g., average absolute relative error (AARE), standard deviation).

When choosing the optimal inputs, there is a compromise between the number of inputs and prediction accuracy. Based on different combinations of inputs, a trial-and-error method is used to finalize the input set which gives AARE when exposed to the SVR.

3. Optimization Analysis of Design Parameters Using Two Different Methods

3.1. Experimental apparatus

The experimental apparatus shown in Fig. 1 consists of an inflatable wing by Beihang University, a PLC (S7-220) by Siemens, a flow sensor (APM-450) by Tokyo Meter, a tank, a throttle valve (AS3001F) by SMC, and a data acquisition card (USB-4711A) by

Advantech. The wing profile is based on a NACA 4424 with a 3° incidence angle. The taper ratio is 1, with an aspect ratio of 15.38 and a full span of approximately 2 m. Wing dimensions are shown in Fig. 2. The wing is designed such that internal wing pressure is required to maintain the wing shape. It has a design pressure of 100 kPa, though the wing has been successfully flight tested at values as low as 50 kPa with sufficient wing stiffness for low-speed applications carrying small, low-mass payloads. The present design uses the presence of internal span-wise spars to help maintain structural stiffness at lower internal pressures. The outer restraint areas of the wing and internal spars are constructed from a high-strength fabric. An internal gas-retaining bladder is contained inside the porous external structural restraint. Figure 3 shows the components of the wing.

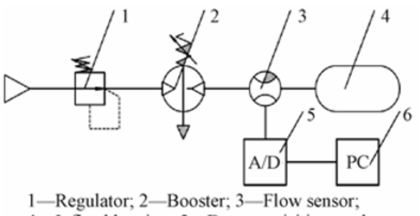


Fig. 1 Configuration of experimental apparatus.

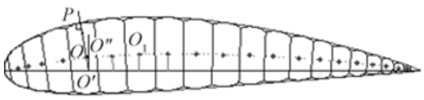


Fig. 2 Inflatable wing dimensions.

Fig. 3 Inflatable wing.

The restraint is composed of a silicone coated plain weave Vectran fabric. The yarns are made from 200×2 ply denier (400 denier total in each yarn) Vectran HS fiber. The breaking strength of the fabric is approximately16 000 kg/m, with a coated fabric weight of 0.29 kg/m^2. The thickness of the restraint is 0.013 inch (1 inch=25.4 mm). The wing is constructed in semi-span sections that can be attached to the aircraft fuselage. The construction of the wings is such that the wings can be stored in volumes much smaller than the deployed wing volume. The inflatable wing, in its packed and deployed configuration, is shown in Fig. 4.

Fig. 4 Inflatable wing in packed and deployed configuration.

3.2. Orthogonal experimental procedure for optimization

Pressure, applied load and the number of chambers are considered as the variables for optimization. The orthogonal table L9(3) was used to arrange the experiments. Their limiting constraints, testing factors and levels are shown in Table 3, where the Level 1 is lower limit and the Level 3 is upper limit.

Table 3 Constraints of process parameters and factor levels for orthogonal test

Factor	Level 1	Level 2	Level 3
Pressure/kPa	50	80	100
Applied load/N	9.8	39.2	58.8
The number of chamber	9	13	17

In this experiment, we first opened the compressed air source, adjusted the regulator and set the pressure to a fixed value. Next, applied the load, making sure that distribution was uniform, and that the pressure of the air was maintained at an approximately fixed value. The last stage was data acquisition and preservation.

Current research efforts are focused on warping an inflatable, non-rigidizable wing to provide lift through wing warping, so the deflection is the most important index. In the Taguchi method, SNR is used to represent quality characteristics, and the largest value of the SNR is required. There are three types of SNR—the lower the better, the higher the better, and the closest to nominal the best. According to the measurement methods above, the orthogonal tests were carried out, and the deflection of an inflatable, rigidizable wing along with the SNR were measured and assessed. An SNR with higher-the-better characteristics can be calculated using Eq. (11):

$$\eta_i = -10\lg\left(\frac{1}{n}\sum_{j=1}^{n} Y_{ij}^2\right) \tag{11}$$

where n the total number of tests.

Experimental values of the deflection of the inflatable wing are listed in Table 4.

Table 4 Experimental results from orthogonal test

Sequence	Deflection/m				SNR
	Level 1	Level 2	Level 3	The mean	
1	0.028 6	0.037 3	0.033 7	0.033 2	24.75
2	0.104 0	0.096 4	0.089 4	0.096 6	15.51
3	0.144 0	0.139 6	0.150 8	0.144 8	12.01
4	0.013 2	0.011 8	0.012 8	0.012 6	33.21
5	0.056 4	0.057 6	0.049 8	0.054 6	20.47
6	0.053 4	0.053 2	0.053 6	0.053 4	22.44
7	0.041 0	0.040 7	0.039 5	0.040 4	23.10
8	0.035 6	0.035 3	0.035 3	0.035 4	24.25
9	0.085 6	0.086 5	0.087 1	0.086 4	16.49

3.3. Parameter optimization using SVM

Based on the above analysis, the input variables such as pressure, applied load and the number of chambers of the flowing medium were finalized to predict the deflection and SNR (Table 1). Table 5 shows some typical data used for the SVR.

To validate the robustness of our approach, the proposed method was evaluated using experimental data from the orthogonal experiment. After many tests, the best values of the regression model parameters of the SVM are set as follows: insensitive factor ε'=0.01, penalty factor C=500. The radial basic function (RBF) kernel is the best choice for this SVM because it is accurate and relatively fast. In this case, the RBF kernel function type with σ=2 (σ is the width of RBF) is chosen as the parameter for the SVM. These parameters are identified as the input for the SVM, and the deflection and SNR are put as targets. The data were then applied to the SVM model described above. The results obtained by using SVM are in agreement with the experimental results obtained from orthogonal test. These results are shown in Table 4.

The regression capability of the SVM algorithm is plotted in Figs. 5-6. The low AARE may be considered to indicate regression performance considering the poor understanding of the slurry flow phenomena and a large data bank for training that comprises various systems.

Table 5 Comparison of the performance of optimum parameters vs non-optimum parameters

Serial No.	A	B	C	Deflection/m		SNR	
				Predicted value	Experimental value	Predicted value	Experimental value
1	50	19.6	13	0.061 5	0.061 7	21.36	21.37
2	79	9.8	9	0.013 2	0.012 6	33.24	33.21
2	80	9.8	9	0.012 3	0.012 4	38.27	38.29
3	81	9.8	9	0.012 9	0.012 6	33.50	35.48
4	100	58.8	13	0.086 4	0.008 65	16.48	16.49

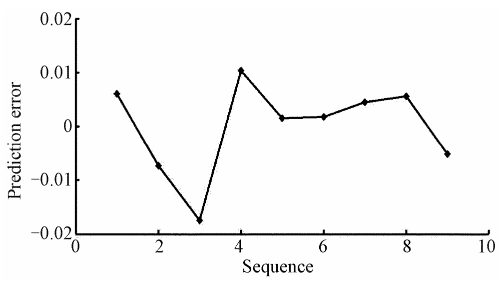


Fig. 5 Deflection error regressed by an SVM-based model.

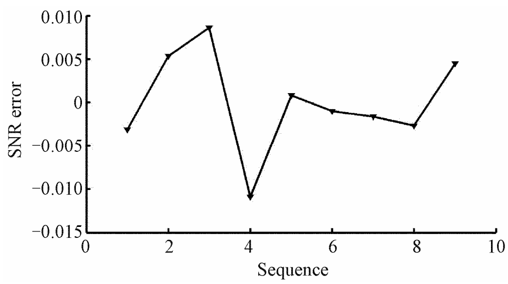


Fig. 6 SNR error regressed by an SVR-based model.

3.4. Results and discussion

Experimental data samples can be processed using the following steps:

Step 1 Calculate each level of the experimental data mean as follows:

$$\begin{cases} K_{A_1}=(Y_1+Y_2+Y_3)/3 \\ K_{A_2}=(Y_4+Y_5+Y_6)/3 \\ K_{A_3}=(Y_1+Y_2+Y_3)/3 \end{cases} \tag{12}$$

$$\begin{cases} K_{B_1}=(Y_1+Y_4+Y_7)/3 \\ K_{B_2}=(Y_2+Y_5+Y_8)/3 \\ K_{B_3}=(Y_3+Y_6+Y_9)/3 \end{cases} \tag{13}$$

$$\begin{cases} K_{C_1}=(Y_1+Y_6+Y_8)/3 \\ K_{C_2}=(Y_2+Y_4+Y_9)/3 \\ K_{C_3}=(Y_3+Y_5+Y_7)/3 \end{cases} \tag{14}$$

Step 2 Calculate each level of the SNR of the mean as follows:

$$\begin{cases} \eta_{A_1} = (\eta_1 + \eta_2 + \eta_3)/3 \\ \eta_{A_2} = (\eta_4 + \eta_5 + \eta_6)/3 \\ \eta_{A_3} = (\eta_7 + \eta_8 + \eta_9)/3 \end{cases} \tag{15}$$

$$\begin{cases} \eta_{B_1} = (\eta_1 + \eta_4 + \eta_7)/3 \\ \eta_{B_2} = (\eta_2 + \eta_5 + \eta_8)/3 \\ \eta_{B_3} = (\eta_3 + \eta_6 + \eta_9)/3 \end{cases} \tag{16}$$

$$\begin{cases} \eta_{C_1} = (\eta_1 + \eta_6 + \eta_8)/3 \\ \eta_{C_2} = (\eta_2 + \eta_4 + \eta_9)/3 \\ \eta_{C_3} = (\eta_3 + \eta_5 + \eta_7)/3 \end{cases} \tag{17}$$

Step 3 Calculate the extreme difference of each level of the experiment data.

Step 4 Draw experimental results with each factor as a variety relation diagram.

According to Table 3, the following conclusions can be made: 1) the mean experimental data at each level: K_{A_1}=0.091 3 m, K_{A_2}=0.040 2 m, K_{A_3}=0.054 0 m, K_{B_1}=0.028 7 m, K_{B_2}=0.063 2 m, K_{B_3}=0.094 8 m, K_{C_1}=0.040 6 m, K_{C_2}=0.065 2 m, K_{C_3}=0.079 9 m. Each level of the experimental data of extreme difference: R_{K_A}=0.051 1, R_{K_B}=0.066 1, R_{K_C} =0.066 1; 2) Each level of the SNR of the mean: η_{A_1}= 17.42, η_{A_2}=25.37, η_{A_3}=21.28, η_{B_1}=27.02, η_{B_2}=20.07, η_{B_3}=20.08, η_{C_1}= 23.81, η_{C_2}=21.73, η_{C_3}=18.53. Each level of the experimental SNR data of extreme difference: R_{η_A}=7.95, R_{η_B}=6.95, R_{η_B}=5.28.

The optimized results can be correlated with the inflatable wings of orthogonal testing specimens. The optimum condition of design parameters is given as $A_2B_1C_1$ and the optimum values of the parameters for minimizing the deflection condition are given as follows: A_2=80 kPa, B_1=9.8 N and C_1 =9. This is clearly observed from Table 3 and Fig. 7.

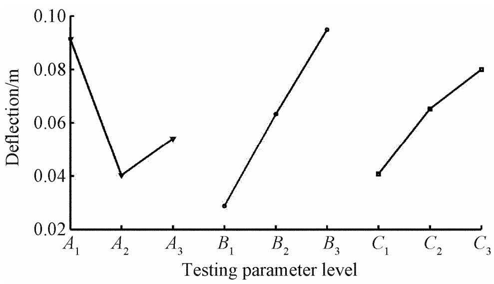


Fig. 7 Effects of inflatable wing parameter levels on deflection.

From Table 4 and Fig. 8, the optimum condition of design parameters is $A_2B_1C_1$ and the optimum values of the parameters for maximizing the SNR condition are given as follows: A_2=80 kPa, B_1=9.8 N and C_1 =9.

We compared the experimental results and calculated results in terms of pressure, applied load and the number of chambers.

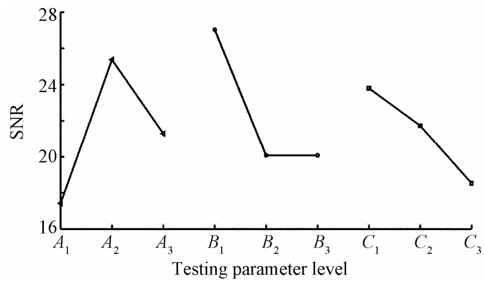
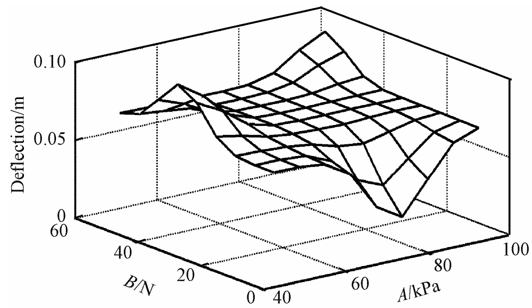


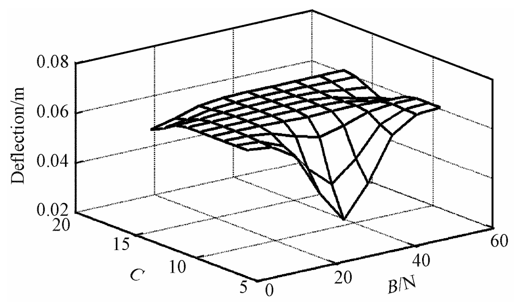
Fig. 8 Effects of inflatable wing parameter levels on SNR.

To find the optimal deflection and SNR while simultaneously varying all parameters, we extended deflection and SNR plots of our previous work by one more parameter. These results of the experiments are shown in Fig. 9. We varied A over its entire range, $A\in$ [50 100] kPa, and $B\in$ {9.8, 15.925, 22.05, 28.175, 34.3, 40.425, 46.55, 52.675, 58.8} N. We used $C\in$ {9, 10, 11, 12, 13, 14, 15, 16, 17}. Each surface shows two different parameters for a different deflection and SNR.

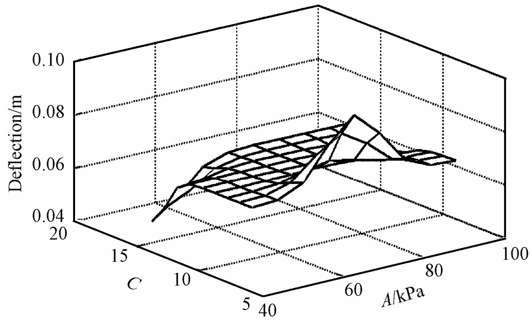
Table 5 compares the values of the SVR with the experimental value. In general, the performance of the SVM prediction of that deflection and SNR can be evaluated from the results. It can be shown that SVM takes less time and has less cost. In terms of speed and accuracy, the SVM performs better than the OA. This feature is particularly important when used in real-time. In order to validate the proposed approach, confirmation tests were conducted with the use of the levels of optimal design parameters and non-optimum parameters, each of which contains the deflection and SNR with a predicted value and an experimental value. The results show that the levels of design parameters affect the performance of the inflatable wing, and the levels of optimal design parameters are the best combination.



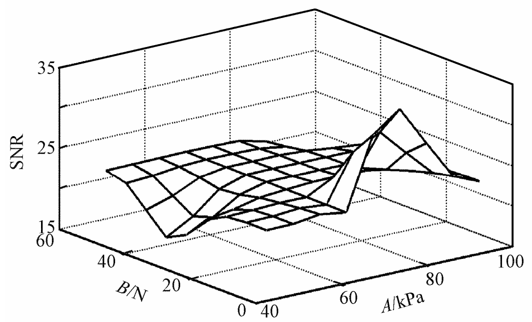
(a) Deflection variation plotted against A and B for C=13



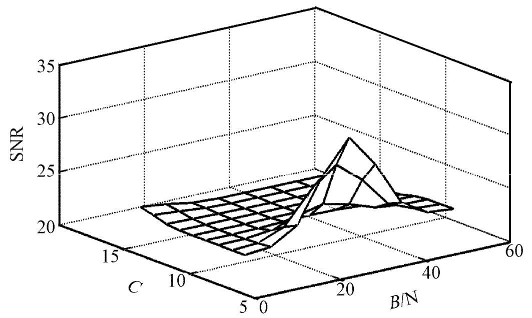
(b) Deflection variation plotted against B and C for A=75 kPa



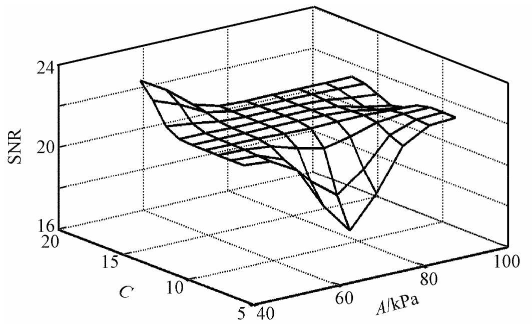
(c) Deflection variation plotted against A and C for B=34.3 N



(d) SNR variation plotted against A and B for C=13



(e) SNR variation plotted against B and C for A=75 kPa



(f) SNR variation plotted against A and C for B=34.3 N

Fig. 9 Regression surfaces of the deflection and SNR.

4. Conclusions

1) This experiment is rapidly and effectively completed using orthogonal method to experimental design. The experimental results show that among all the factors that affect the performance of the inflatable wing, the pressure is the most important, followed by the applied load and the number of chamber.

2) The optimum factors for the lowest deflection and largest value of SNR are given as $A_2B_1C_1$, and the optimum values of the parameters are given as follows: A_2=80 kPa, B_1=9.8 N and C_1 =9. Because performing all the experiments would be time-consuming and costly, the orthogonal test method is successfully applied to the present work, with a very limited number of experiments and short duration of time.

3) The SVM is more complete and accurate than the orthogonal testing in determining the bearing capacity of an inflatable wing. The low AARE of the prediction capability of the SVM algorithm is 0.18%. To optimize design values, the precise relationship between SNRs can be obtained.

4) Simulated and measured models have been developed to validate the SVM approach. The experimental results show that the presented model not only simplifies the measurement procedure, but also improves computation efficiency with high accuracy of the measured results.

Acknowledgement

The authors would like to thank WANG Wei for his valuable help in the experiments.

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