32nd Congress of the International Council of the Aeronautical Sciences
September 6-10, 2021
Pudong Shangri-La, Shanghai, China

RESEARCH OF PROPULSION-SYSTEM-SURROGATE-MODELING METHOD USING INFILL CRITERION SAMPLES

Dongchen Wang[1], Bifeng Song[1], Haifeng Wang[1] & Jun Jiao[2]

[1]Department of Aeronautics, Northwestern Polytechnical University, Xi'An 710012, China
[2]Institute of Engineering Thermophysics, Chinese Academy of Sciences, Beijing 100190, China

Abstract

An accurate model of propulsion system is important to high altitude aircraft design. However, traditional approaches predicting propeller performance are often time-consuming. In this paper, a surrogate modeling method using infill criterion samples was chosen to refine the design process and reduce the time consumption. The results of this study show that the combination of infill criteria based surrogate model method and low-fidelity simulation can achieve comparable accuracy (average error of 5%) in prediction with the traditional approaches.

Keywords: Surrogate model; Infill criterion; Design of experiments; High altitude aircraft propeller design

1. Introduction

High Altitude Long Endurance(HALE) aircraft such as solar powered stratospheric airships and Unmanned Aerial Vehicle(UAV) have been the focused area for years and electric propulsion system is one of the most important issue.

Aircraft overall design schemes are strongly related to the accuracy of propeller performance solving process. A variety of methods are used to calculate propeller performances, most of which are time-consuming and computationally expensive.

In view of improving performance and reducing research and development time, surrogate model technology emerges as the requirement of the present time and has gradually become an important branch and key technology of aircraft overall design [1, 2].The surrogate model method deals with the relationship between input parameters and response of complex structures of systems [3]. Generally speaking, larger number of samples often lead to higher fidelity of surrogate models. Thus, determination of the number of samples are important.

In recent years, there are many studies on surrogate models investigating methods to reach higher fidelity with less samples.

Leifur Leifsson and Slawomir Koziel developed an optimization procedure based on kriging interpolation of the low-fidelity model data enhanced by space-mapping correction exploiting a few high-fidelity training points [4]. Han and Gortz6 proposed a Hierarchical Kriging (HK) method, using Mean-Squared-Error (MSE) estimation to refine the sample points scheme [5]. They also combined direct Gradient-Enhanced Kriging (GEK) and a newly developed Generalized Hybrid Bridge Function (GHBF) to improve the efficiency and accuracy of the existing Variable-Fidelity Modeling (VFM) approach [6]. Multi-fidelity samples based surrogate modeling methods using infill criterion are extensively applied in optimal design work [7–9].

This paper applied infill criterion to propeller modeling process. Two sets of different fidelity samples are acquired for propeller model construction and evaluation. The low-fidelity sample set is applied to construction of the initial surrogate model. And the high-fidelity sample set is utilized in evaluation the accuracy of surrogate models. When the surrogate models' accuracy cannot reach the demand, a new set of low- fidelity samples are generated by infill criterion and added to the surrogate model.

2. Surrogate model iteration based on sequential design

An ordinary surrogate model is constructed with a one-shot approach in which the samples are generated at once. Due to the lack of prior information, it is often hard to determine the size of the sample set. To avoid the case that too few samples are evaluated to obtain an accurate model(under-sampling), an easier way of generating and evaluating more samples than required(over-sampling) is often applied, which means wasting computational resources [10, 11]. Thus, sequential design approach is applied to turn the surrogate model construction into an iterative process. The acquired samples and the constructed model from previous iterations are analyzed in order to intelligently select locations for new samples using infill criteria. As a result, the risk of over- or under-sampling is avoided [12–17].

2.1 Overview

This paper uses SUMO toolbox to conduct the modeling iteration process. The flow chart is shown in Figure 1. Step 1, two sets of samples are chosen. One is the initial sample set, generated by design of experiment method, for model construction and the other is manually picked for model evaluation. Step 2, low-fidelity sample response value is acquired through low-fidelity simulator (scripts based on blade-element momentum theory). For every sample, the chord and torsion angle distribution are optimized to obtain the best efficiency as the response value. And kriging surrogate model is constructed after acquiring the response value. Step 3, high-fidelity sample response value is acquired through high-fidelity simulator (high-accuracy computational fluid dynamics tools). Some of these samples' high-fidelity response value is validated by experiments. Step 4, error of the surrogate model is evaluated by comparing the high-fidelity samples and the surrogate model prediction. If the termination condition (model average error 5%) is reached, the current surrogate model is accepted. If not, go to step5, and repeat the updating cycle of sample infill(step5)-construction(step2)-evaluation(step4). Step 5, apply infill criterion to the surrogate model. The infill criterion would generate and add extra samples to the low-fidelity sample set by exploring the design space and exploiting the existed samples.

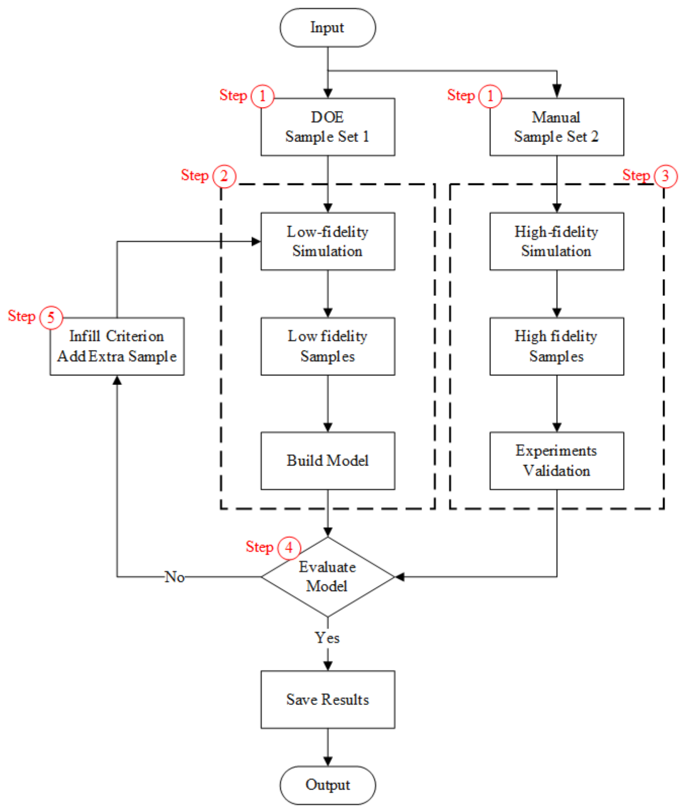

Figure 1 – Flow chart of surrogate model iteration

2.2 Design of experiments

Design of experiments (DoE) is a technique for planning samples and analyzing the information obtained. The technique allows using a minimum number of samples, in which several design variables are varied systematically and simultaneously, to obtain sufficient information. A sampling plan that is well-distributed but not regular across the design space is essential for building a surrogate model [3]. In this paper, Latin hypercube sampling method is applied to propeller surrogate model and full factorial sampling is applied to motor surrogate model.

Latin hypercube sampling is a method of sampling that can spread samples uniform in all of the design space. Building a Latin hypercube can be done by splitting the design space into equal size bins. Samples are placed in the bins in a way that no other sample should exist in any direction of bins axis [18, 19].

Design variables of propeller are the input power P_p, the rotation speed N_p and diameter D.The range of design variables are shown in Table 1: Propeller input power varies from 10 to 30kW, rotational speed varies from 200 to 500 r/min, and diameter varies from 4 to 6m. The range of design variables is narrow due to the constraint relationship among design variables. For example, a propeller of high input power and high rotational speed would be too thin and slender; and a propeller of high input power and low rotational speed would be too thick [20]. Thus, this paper chose a narrow range of design variables to guarantee the surrogate model construction.

Table 1 – Range of variables of propeller surrogate model

Design variable	Value	
	Lower boundary	Upper boundary
P_p [kW]	10	30
N_p [r/min]	200	500
D [m]	4	6

The design space was stratificated and the Latin Hypercube Sampling (LHS) method was implemented within each layer to generate the initial sampling scheme as shown in Figure 2. This initial sampling scheme includes 20 points generated by LHS method and 8 corner points.

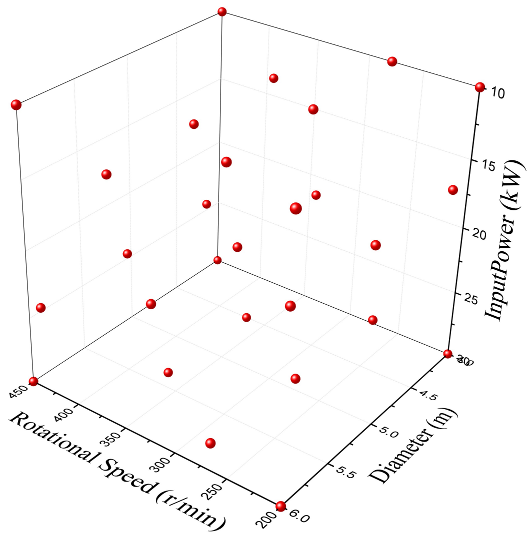

Figure 2 – Initial propeller sample scheme

Generally speaking, full factorial design is often applied in motor design work. Thus, infill criterion is not needed. Range of motor design variables and sampling scheme are shown in Table 2 and Figure 3.

Table 2 – Range of variables of motor surrogate model

Design variable	Value	
	Lower boundary	Upper boundary
P_p [kW]	5	30
N_p [r/min]	300	1500

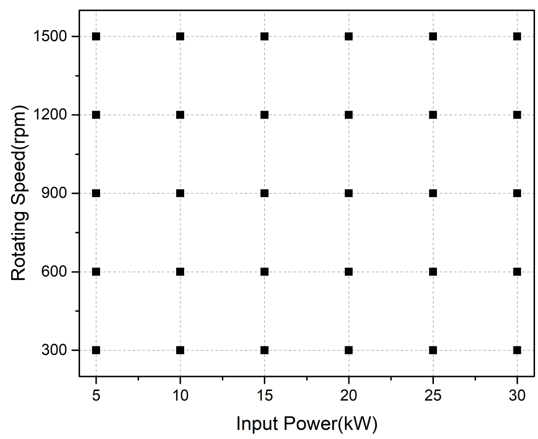

Figure 3 – Motor sample scheme

Besides, this paper manually picked some typical cases as extra propeller samples instead of using sampling algorithm to generate them randomly. High fidelity Computational Fluid Dynamics(CFD) method is applied to these samples and experiments are carried out to verify the fidelity.

2.3 Infill criteria

Infill criteria must find the balance between exploration and exploitation [21]. Exploration is not only the act of filling the design space as evenly as possible but also the exploration of the design space to identify and mark the most important areas like steep slopes and optima. On the other hand, exploitation is the act using existed samples and their evaluations to guide the sampling process. Exploitation method would prefer to sample near optima, possible discontinuities and other identified key areas in design space. LOLA-Voronoi method [22] is a hybrid infill criterion which balances exploration and exploitation.

The Local Linear Approximation (LOLA) sampling algorithm estimates and the gradient measures the nonlinearity around the existed samples [23]. Take a n-dimensional case as example, the gradient of a function $f : \mathbb{R}^d \to \mathbb{R}$ is defined as:

$$\nabla f = \left(\frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2}, \cdots, \frac{\partial f}{\partial x_n} \right) \tag{1}$$

The gradient of the function at a given point $p_0 \in \mathbb{R}^d$ in the design space has the property of representing the beat local linear approximation for f at p_0:

$$f(p) = f(p_0) + \nabla f_{p_0}(p - p_0) \tag{2}$$

Because the gradient of the given point p_0 is often unknown, the LOLA algorithm estimates the gradient of the nearby region around the given point p_0. For those region that are highly nonlinear, new samples are selected in them.

The Voronoi algorithm uses Voronoi diagram to describe sampling density and suggests adding samples in interesting regions which were previously discovered. Take a 2-dimensional (Euclidean plane Q) case as example, a distance function d and a finite set of points $\{p_1, p_2, \cdots, p_n\}$ is given. For a point p_k, its corresponding Voronoi cell R_k consists every point q in Euclidean plane whose distance $d(q, p_k)$ is less than or equal to any other p_j.

$$R_k = \left\{ q \in Q \middle| d(q, p_k) \leq d(q, p_j), \quad j \neq k \right\} \tag{3}$$

Each such cell is obtained from the intersection of half-spaces, and hence it is a (convex) polyhedron [24], as shown in Figure 4 .
The line segments of the Voronoi diagram are all the points in the plane that are equidistant to the two nearest sites. The Voronoi vertices (nodes) are the points equidistant to three (or more) sites. The Voronoi algorithm would select new samples in the larger Voronoi cells in order to achieve equal distribution of samples.

Figure 4 – Voronoi Diagram [25]

3. Propeller surrogate model iteration

The LOLA-Voronoi method generates 10 new samples at every updating cycle until the termination condition(model average error 5%) is reached. The final propeller sample diagram is shown in Figure 5, red points are the initial samples generated by DoE method and the green ones are generated by LOLA-Voronoi method. The efficiency surrogate model of the propeller is shown in Figure 6. It should be noted that the z axis of propeller samples (Figure 5) and propeller model (Figure 6) are different. The z axis of the model is the propeller sample response value (efficiency), and the design variable input power is represented as three slices.
It's easy to see that the added samples are centered around the optima, which is the combination of proper diameter, rotational speed and input power parameter.

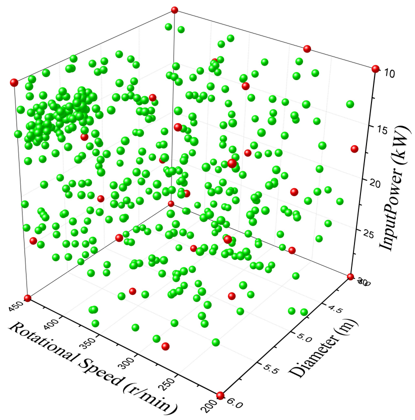

Figure 5 – Final propeller sample scheme

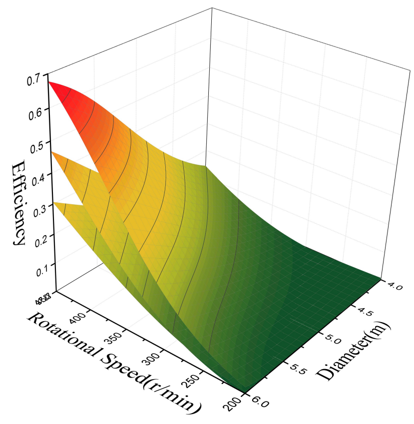

Figure 6 – Propeller model

4. High-fidelity simulator verification

To evaluate the surrogate model with high-fidelity sample response value, the high-fidelity simulator itself must be validated at first. Thus, experiments were carried out to verify the accuracy of high-fidelity simulator.

A scaled propeller model has been tested in wind tunnel, the photo and experiment results are shown in Figure 7and Figure 8.The maximum error of the high-fidelity simulation is 7.6% and average error is 3.7%.

After validation, the high-fidelity samples are used to evaluate the surrogate model. Surrogate model prediction and high-fidelity response value are compared and the average error is calculated. If the termination condition(model average error 5%) is reached, the surrogate model would be accepted.

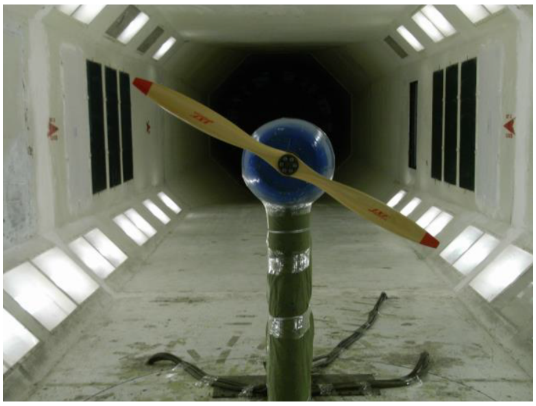

Figure 7 – Scaled propeller wind tunnel experiment

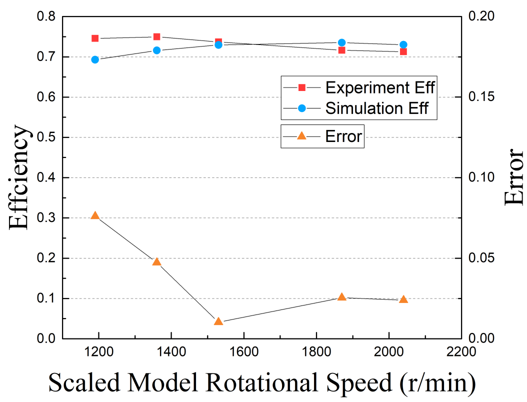

Figure 8 – Experiment results and error

5. Conclusions

In this paper, surrogate model method is applied to propeller performance evaluation to avoid large amount of time-consuming and computationally expensive calculation. Besides, infill criterion is applied to the modeling process to further reduce the calculation cost.

The results of this study show that the combination of infill criterion based surrogate model method and low-fidelity simulation can achieve comparable accuracy (average error of 5%) in prediction with the traditional approaches. Only a few high-fidelity simulations are needed for evaluation, after being validated by experiments.

6. Copyright Statement

References

[1] Alexandrov, Natalia M., and M. Yousuff Hussaini, eds. *Multidisciplinary design optimization: State of the art*. 1st edition, Siam Journal on Control Optimization, 1997.

[2] Song, C. , X. Yang , and W. Song . Multi-infill strategy for kriging models used in variable fidelity optimization. *Chinese Journal of Aeronautics*, Vol. 31, No. 144, pp 34-42, 2018.

[3] X Wang, Ni, B., Zeng, L., and Liu, Y. An adaptive sampling strategy for construction of surrogate aerodynamic model. *Aerospace Science and Technology*, Vol. 112, 106594, 2021.

[4] Leifsson, L. , S. Koziel , and Y. A. Tesfahunegn . Multiobjective Aerodynamic Optimization by Variable-Fidelity Models and Response Surface Surrogates. *AIAA Journal*, Vol. 52, No.2, pp 531-541, 2016.

[5] Han, Z. H. , and S. Goertz . Hierarchical Kriging Model for Variable-Fidelity Surrogate Modeling. *AIAA Journal*, Vol. 50, No.9, pp 1885-1896, 2012

[6] Han Z H, Goertz S, Zimmermann R. Improving variable-fidelity surrogate modeling via gradient-enhanced kriging and a generalized hybrid bridge function. *Aerospace Science Technology*, Vol.25, No.1, pp 177-189, 2013

[7] Siegler, J. , Ren, J. , Leifsson, L. , Koziel, S. , Bekasiewicz, A. Supersonic Airfoil Shape Optimization by Variable-fidelity Models and Manifold Mapping. *Procedia Computer Science*, Vol.80, pp 1103-1113, 2016

[8] Moore, J. , Stanford, B. , Mcclung, A. , and Beran, P. Variable-Fidelity Kinematic Optimization of a Two-Dimensional Hovering Wing. *49th AIAA Aerospace Sciences Meeting including the New Horizons Forum and Aerospace Exposition*, pp 1245, 2011.

[9] Kwon, H. I. , Yi, S. , Choi, S. , and Kim, K. Design of efficient propellers using variable-fidelity aerodynamic analysis and multilevel optimization. *Journal of Propulsion Power*, Vol.31, No.4, pp 1-16, 2015

[10] Gorissen D, Crombecq K, Couckuyt I, Demeester P, Dhaene T. A surrogate modeling and adaptive sampling toolbox for computer based design. *Journal of Machine Learning Research*, Vol.11, No.1, pp 2051-2055, 2010

[11] Deschrijver, D., Crombecq, K., Nguyen, H. M., and Dhaene, T. Adaptive sampling algorithm for macromodeling of parameterized s-Parameter responses. *IEEE Transactions on Microwave Theory and Techniques*, Vol.59, No.1, pp 39-45, 2010

[12] Anderson, Terry, ed. *The theory and practice of online learning*. 2nd edition, Athabasca University Press, 2008.

[13] Aernouts, J., Couckuyt, I., Crombecq, K., and Dirckx, J. J. Elastic characterization of membranes with a complex shape using point indentation measurements and inverse modelling. *International Journal of Engineering Science*, Vol.48, No.6, pp 599-611, 2010

[14] Stephens, D. W., Gorissen, D., Crombecq, K., Dhaene, T.Surrogate based sensitivity analysis of process equipment. *Applied Mathematical Modelling*, Vol.35, No.4, pp 1676-1687, 2011

[15] Koziel S, Leifsson L. *Surrogate-based modeling and optimization*. 1st edition, New York: Springer, 2013.

[16] Deschrijver D, Vanhee F, Pissoort D, Dhaene T. Automated nearfield scanning algorithm for the EMC analysis of electronic devices. *IEEE Trans Electromagn Compat*, Vol.54, No.3, pp 502-510, 2015

[17] Aerts, S., Deschrijver, D., Joseph, W., Verloock, L., Goeminne, F., Martens, L., and Dhaene, T. Exposure

assessment of mobile phone base station radiation in an outdoor environment using sequential surrogate modeling. *Bioelectromagnetics*, Vol.34, No.4, pp 300-311, 2013

[18] Nestor V. Queipo and Raphael T. Haftka and Wei Shyy and Tushar Goel and Rajkumar Vaidyanathan and P. Kevin Tucker. Surrogate-based analysis and optimization. *Progress in Aerospace Sciences*, Vol.41, No.1, pp 1-28, 2005

[19] Palar, P. S. , T. Tsuchiya , and G. T. Parks . Multi-fidelity non-intrusive polynomial chaos based on regression. *Computer Methods in Applied Mechanics and Engineering*, Vol.305, pp 579-606, 2016

[20] Liu PQ. *Theory and application of air propeller*. 1st edition, Beijing: Beihang University Press, 2006.

[21] Crombecq K, Gorissen D, Deschrijver D, Dhaene T. A novel hybrid sequential design strategy for global surrogate modelling of computer experiments. *SIAM Journal on Scientific Computing*, Vol.33, No.4, pp 1948-1974, 2011

[22] van der Herten, J., Couckuyt, I., Deschrijver, D., and Dhaene, T. A fuzzy hybrid sequential design strategy for global surrogate modeling of high-dimensional computer experiments. *SIAM Journal on Scientific Computing*, Vol.37, No.2, pp 1020-1039, 2015

[23] Hachisuka, W. Jarosz, R. Weistroffer, K. Dale, G. Humphreys, M. Zwicker, and H. Wann Jensen. Multidimensional adaptive sampling and reconstruction for ray tracing. *ACM Trans. Graphics*, pp 1-10, 2008

[24] Boyd S, Boyd S P, Vandenberghe L. *Convex optimization*. 1st edition, Cambridge university press, 2004.

[25] Figure Author: Balu.ertl.*https://en.wikipedia.org/wiki/File:Euclidean*$_{V}oronoi_{d}iagram.svg$.

7. Contact Author Email Address

Dongchen Wang: wangdongchen@mail.nwpu.edu.cn