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Integration of Systems Engineering into Weather-Climate Model Optimization

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1. Introduction

In the meteorological model development, tuning is often applied to improve model performance. As tremendous efforts being made to press simulations closer to nature, climate-weather models are getting increasingly sophisticated (more physical, chemical and biological processes, higher horizontal and vertical resolutions, and complex interactions with added degrees of freedom). Because of resource constraints, it is impractical to conduct all tests to find the optimum configuration, causing progresses retarded helplessly. The urgency for model optimization has become another prominent issue in systems engineering since the Earth System Modeling Framework (ESMF) project launched to build a flexible software infrastructure to increase portability, interoperability, and code reuse.

The Orthogonal Array Test (OAT), a systems engineering approach of fractional factorial design, is widely used in industrial and agricultural production and proven to be effective to deal with multiple factors, levels and interactions with reliability and sensitivity analysis. It has been very successful in system configuration, parameter level selection and tolerance design etc. (SSTES 1975, Taguchi 1984)

In this introductory presentation for the meteorological community, the basic principles of OAT design are illustrated, followed by the way of statistical analysis to determine dominant factors, significant interactions and percent contribution by individual component. Its ensemble capability to evaluate inherent variations and noises is also demonstrated. Finally, flexible designs to meet special application needs are briefly explored.

2. Fractional factorial design

The most strateforward optimization strategy is to run a separate experiment for each factor and take on all possible combinations of levels across all factors, while the obvious difficulty would be the prohibitively large number of experiments if the factors are numerous for a sophisticated system. It would be ideal to study more factors in a single experiment. The fractional factorial design emerges as the times require to select a limited number of experiments which produce the most information.

3. Orthogonal Array Testing

The philosophy of the OAT approach is to design the product quality inspection into the production process, not to make it after the product being made. The results of one experiment directs the choice of factors in succeeding experiments. The OAT estimates the effects of control factors on the response mean and variation, making products robust that are insensitive to external environment

Being an orthogonal array, its columns are mutually orthogonal by definition. In a column, each level occurs an equal number of times. The OAT has its advantages to alow non-quantitative factors and enable ensemble practice to measure inherent variations. By analysis of the outcome, it determines the dominant factors and significant interactions, as well as the percent contribution of each factor/interaction to the performance result. The minimum number of experiments would be expected to find the optimium configuration.

3.1 Methodology

Following is a brief illustration of technical procedures via a hypothetical example.

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3.1.1 Experimental design

The purpose of this experiment is to find the optimum configuration of a GCM in respect of four factors in consideration, *i.e.* A- cloud, B- surface boundary layer, C- model initialization, and D- resolution. Each factor has two levels. For example, A- cloud could have two different parameterization schemes, so does B- surface boundary layer, C- initialization process and D- resolution based on the research focus. The experiment target would be a specific performance measure (y_i), *e.g.* skill score *etc.*

To make a design, the $L_8(2^7)$ table (Table 1, rows 1-8) is used. (Note $L_n(E^f)$, where n (= (E - 1) x f + 1= 8) is the number of experiments, f (= 7) the maximum number of factors that the table can accommodate, and E (=2) the number of levels inspected.) Factors A, B, C and D are assigned to the 1st, 2nd, 3rd and 7th column, respectively. The 3rd column is used for examining the importance of interaction between A and B (AxB) according to the principle of design. Subsequently, eight experiments can be performed taking the level assigned for each factor. The last column records the experiment results.

Table 1 Orthogonal array $L_8(2^7)$ and factors assignment

Factor / Exp.	1 A	2 B	3 AxB	4 C	5	6	7 D	Performance Measure
1	1	1	1	1	1	1	1	y_1
2	1	1	1	2	2	2	2	y_2
3	1	2	2	1	1	2	2	y_3
4	1	2	2	2	2	1	1	y_4
5	2	1	2	1	2	1	2	y_5
6	2	1	2	2	1	2	1	y_6
7	2	2	1	1	2	2	1	y_7
8	2	2	1	2	1	1	2	y_8
I	I_1	I_2	I_3	I_4	I_5	I_6	I_7	Total
II	II_1	II_2	II_3	II_4	II_5	II_6	II_7	$T=\sum_{i=1}^{8} y_i$
I - II	I_1-II_1	I_2-II_2	I_3-II_3	I_4-II_4	I_5-II_5	I_6-II_6	I_7-II_7	
$(I - II)^2$	$(I_1 – II_1)^2$	$(I_2 – II_2)^2$	$(I_3 – II_3)^2$	$(I_4 – II_4)^2$	$(I_5 – II_5)^2$	$(I_6 – II_6)^2$	$(I_7 – II_7)^2$	
$\hat{w}$	$(I_1 – II_1)/8$	$(I_2 – II_2)/8$	$(I_3 – II_3)/8$	$(I_4 – II_4)/8$	$(I_5 – II_5)/8$	$(I_6 – II_6)/8$	$(I_7 – II_7)/8$	
S	$(I_1 –II_1)^2/8$	$(I_2 – II_2)^2/8$	$(I_3 – II_3)^2/8$	$(I_4 – II_4)^2/8$	$(I_5 – II_5)^2/8$	$(I_6 – II_6)^2/8$	$(I_7 – II_7)^2/8$	

3.1.2. Analysis

The rows 9-14 of Table 1 are used for analysis, where I_i and II_i are summation of level 1 and level 2 results in column *i*, respectively. Columns 5 and 6 represent uncertainties. Table 2 performs the analysis of variance (ANOV) to access the importance of each factor and the significance of interaction inspected.

Table 2 Analysis of variance

Factor	S	df	S/df	F	Significance
A	S_1	E_1-1	S_1/df_A	$\frac{S_1/df_A}{Se/dfe}$	Comparing with $F_\alpha(df_x,df_e)$: * at $\alpha = 0.05$ significance level ** at $\alpha = 0.01$ significance level Blank – Insignificant Note: e – reference of uncertainties; df – degree of freedom; E1 = E2 = E4 = E7 ≡ E; $ $S_e = S_5 + S_6$, when AxB is significant. Otherwise, $S_e = S_3 + S_5 + S_6$
B	S_2	E_2-1	S_2/df_B	$\frac{S_2/df_B}{Se/dfe}$	
C	S_4	E_4-1	S_4/df_C	$\frac{S_4/df_C}{Se/dfe}$	
D	S_7	E_7-1	S_7/df_D	$\frac{S_7/df_D}{Se/dfe}$	
AxB	S_3	$(E_1$-1$)(E_2$-1$)$	S_3/df_{AXB}	$\frac{S_3/df_{AxB}}{Se/dfe}$	
e	$ S_e	n-1-($df_A+df_B+df_C+df_D+df_{AxB}$)	S_e/df_e	*NA*	

3.1.3 Ensemble capability

It is highly preferable to embrace uncertainty analysis in the optimization process to yield more robust result. This is done by OAT via replication of experiment with perturbed initial conditions/boundary conditions/factor parameters. The analysis follows an expanded ANOV procedure described in text books (Roy 2010).

3.2 Flexible design and applications

The orthogonal array can be constructed to have as many schemes as possible with maximum number of factors with different levels for the smallest number of experimental runs, *e.g.* $L_8(2^7)$, $L_{16}(2^{15})$, $L_9(3^4)$, $L_{32}(4^9)$, $L_{25}(5^6)$ *etc.* (Bolboacă and Jäntschi 2007) The flexible design observes following principles:

a. Use an OAT array that has more rows than df required;
b. Different factors/interactions can't be assigned to a same column;
c. The interaction between two columns of $L_n(E^f)$ occupies E-1 columns described in the interaction table.

There are also many ways to meet various application needs, such as:

a. *Column merging* : Assign factors having different levels in an OA simultaneously;
b. *Dummy levels*: Assign factors having less levels to OA of more levels;
c. *Compounding factors*: Assign factors having more levels to OA of less levels;
d. *Fractional addition*: Make additional tests with a few new levels for a factor found having some kind of trend to influence the performance result;
e. *Dividing zones*: Repeat costly experiments less times than inexpensive ones.

4. Prospects

Orthogonal Array Test technique selects a set of test cases from a universe of tests and makes testing efficient and effective, having advantages of multiformity, parallelity and synthetic comparability. The optimum configuration resulted from OAT is the best combination among not only the test conditions but also all conditions of possible combinations in a given case.

Beside promoting model improvement, OAT has a lot of potential for meteorological applications, such as assessing the dependence of satellite retrieved atmospheric profiles on physical and statistical parameters of the data assimilation system, and transforming model output into sensible climate/weather parameters, for example. It could also help identify model structural errors when being used for model tuning as explained by Hourdin *et al.* (2016).

In practice, the performance measure criterion for system optimization is not unique. Keeping in mind the model approximate nature and observations uncertainties, it is important to make physical sense and not over-tune the factors. Professional knowledge of the fundamental processes inherent in the system also helps to make experiment design more efficient, *e.g.* knowing some interactions nonexistent could considerably decrease the level of effort.

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