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Application of Surrogate Models for Building Envelope Design Exploration and Optimization

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ABSTRACT

Building performance simulations are usually time-consuming. They may account for the major portion of time spent in Computational Design Optimization (CDO), for instance, annual hourly daylight and energy simulations. In this case, the optimization may become less efficient or even infeasible within a limited time frame of real-world projects, due to the computationally expensive simulations. To handle the problem, this research aims to investigate the potentials of surrogate models (i.e. Response Surface Methodology - RSM) to be used in the building envelope design exploration and optimization that consider visual and energy performance. Specifically, the work investigates how, and to what extent, 1) problem scales may affect the application of RSM, and 2) different ways of using RSM may affect the quality of Pareto Front approximations. Thus, a series of multi-objective optimization tests are carried out; preliminary discussion is made based on the current results.

Author Keywords

Multi-objective optimization; building envelope; surrogate models; design of experiments (DoE); response surface methodology (RSM).

ACM Classification Keywords

I.6.3 Application; I.6.4 Model Validation and Analysis

1 INTRODUCTION

Computational Design Optimization (CDO) is a rising field of research in sustainable building design. It has been applied to many aspects including building envelope design, building service system, and renewable energy generation, etc. [4]. Thus, simulation-based optimization is frequently employed by architects and engineers to assist the early design decisions. However, simulations are usually time-consuming, for instance, annual hourly daylight and energy simulation or computational fluid dynamics (CFD) simulation; this poses substantial obstacles to the application of CDO within a feasible time frame of projects.

Surrogate models (or meta-models) are promising solutions to this problem. They are actually approximation methods that mimic the behavior of original simulation model at a reduced computational cost [9]. Among various surrogate models, Response Surface Methodology (RSM) [7] is commonly used, along with Design of Experiments (DoE) [3]. RSM contains a group of mathematical and statistical techniques used to explore the functional relationship between input variables and output variables; while DoE is used to create a well-distributed sampling of design points, allowing to extract as much information as possible from a limited number of simulation runs.

In the sustainable building design, surrogate models, developed based on RSM, are used for the prediction of energy performance [10] and indoor environmental quality, including thermal, daylighting [6] and ventilation performance [11]. Within these applications, validated surrogate models are used to replace computationally expensive simulations (like dynamic energy and daylight simulation or CFD simulation). Although the potentials of RSM are observed in above-mentioned literature, there are still concerns regarding the advantage of RSM, as reported in [2], because, in some cases, the number of simulations necessary to get a reasonably accurate RSM may be approaching the number of simulations needed for the simulation-based optimization.

This work aims at evaluating the applicability of RSM to the building envelope design exploration and optimization (mainly considering visual and energy performance). Specifically, the work investigates how, and to what extent, 1) problem scales may affect the use of RSM, and 2) different ways of using RSM may affect the quality of Pareto Front approximations. As a research-in-progress, the second part of the investigation is not included in this paper, but only providing a framework for future research.

2 METHODOLOGY

To achieve the research goal, a series of multi-objective optimization tests are arranged based on two different problem scales (i.e. two cases with a different number of design variables) and three different workflows (not included in this paper, but in future research).

(1) By comparing the accuracy of surrogate models in the two proposed cases, possible effects of problem scales on RSM are investigated.

(2) By comparing the quality of (Predicted) Pareto Front approximations of the three proposed workflows within the same time frame, potentials of using RSM (or different ways of using it) will be discussed in future research.

2.1 Problem Scales

To investigate possible effects of problem scales on RSM, two test cases are shaped based on a similar building envelope design optimization problem (Section 3). The first test case is based on a parametric model including two design variables, while the second one includes forty-one.

2.2 Workflows

To investigate potentials of using RSM (or different ways of using it), three workflows will be used based on related literature (Figure 1). Two of the workflows use RSM in different ways, but the remaining one does not.

According to Cavazzuti [1], RSM can be utilized in two ways during the design exploration and optimization: (1) replacing the simulations by surrogate models that will be used with an optimization algorithm, i.e. RSM-based or "virtual" optimization, in contrary to simulation-based or "real" optimization; and (2) locating the area in which the optimum is expected to be based on the response surface, it facilitates narrowing down the design space in the neighborhood of the optimum for the further optimization. Therefore, the complete workflows of the two options to utilize RSM are illustrated in Figure 1, and denoted by Workflow2 and Workflow3, respectively. In addition, the typical way for simulation-based optimization that does not use RSM is also illustrated, and denoted by Workflow1.

It is worth noting that running a certain number of simulations is required no matter whether RSM is used or not. It is needed either for training the response surfaces, or for running the simulation-based optimization. The difference between these two scenarios lies in whether "shifting" (instead of eliminating) the computational effort for simulation from within an optimization loop to a prior time, or not. Specifically, in Workflow1, simulations are required within an optimization loop, while in Workflow2 and Workflow3 they are shifted to a prior time (i.e. before the optimization loop, for training response surfaces). Furthermore, the simulations required by Workflow3 are not all in once (as Workflow2), because simulations are needed as well after narrowing down the constraints of design variables, for updating the response surfaces

2.3 Comparative Study

Comparative studies are/will be carried out according to the schema shown in Figure 2. In order to investigate possible effects of problem scales, the left schema is used; while in order to investigate the potentials of using RSM, the right schema will be followed in future. Moreover, the same timeframe of implementing these tests should be ensured for the sake of comparison. Considering that simulations account for a major portion of time spent in all tests, the number of simulations to be run in a specific test is an important monitoring factor. For the same purpose, the selection of algorithms for DoE, RSM and optimization will be kept the same, as well as the corresponding settings.

3 CASE STUDY DESCRIPTION

For the application of RSM, a simple building envelope design optimization was formulated in Grasshopper [5] – a parametric modelling tool frequently used by architects for exploring varied building configurations. Generally, the aim of the problem is to figure out the optimal roof configuration for visual and energy performance, based on which two similar test cases are created (Figure 3).

3.1 Geometry Generation

The two buildings are assumed to be one-story sports halls with a fixed rectangular plan (40m*70m) and a changeable spherical roof, located in Guangzhou, South China. The skylights are allocated to each cell (40 cells in total) of the roof, respectively. Basically, these two test cases are the same, except for the principle of allocating skylights (i.e. the number of design variables regarding skylights). Specifically, in Case 1, there are only two design variables, i.e. the height of roof and the window-to-roof ratio (each cell shares the same ratio). While in Case 2, there are 41 design variables in total, because each of the cells has an independent window-to-roof ratio. The design variables are shown in Table 1, as well as their ranges.

In addition, considering that the focus of this paper is the applicability of RSM, other design variables regarding shading devices and/or constructions are not discussed here for the sake of simplicity.

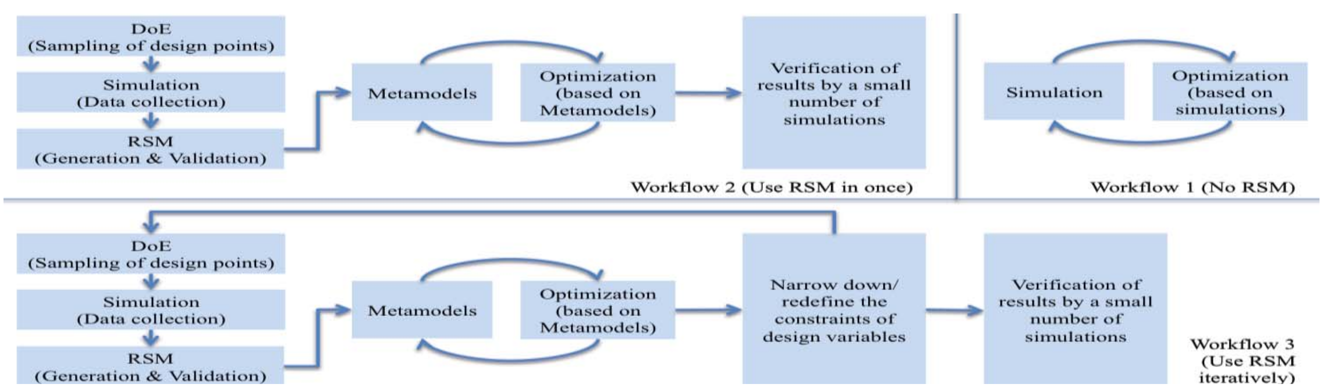

Figure 1. Workflow1: Simulation-based optimization (top-right); Workflow2: RSM-based optimization in once (top-left) - Cavazzuti [1]; Workflow3: RSM-based optimization iteratively (bottom) - Cavazzuti [1].

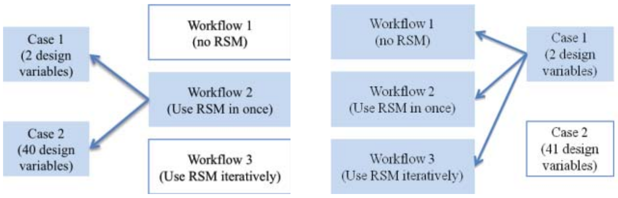

Figure 2. Schema to investigate possible effects of problem scales (left); Schema to investigate the potentials of using RSM (right)

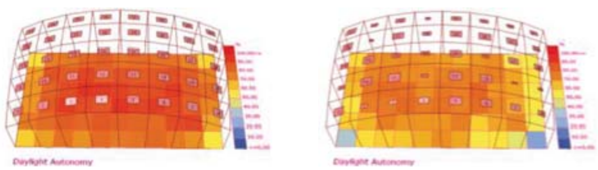

Figure 3. Case 1: Two design variables (left); Case 2: Forty-one design variables (right)

Design variables	Roof_height	16m - 30m
	Glazing_ratio(s)*	0.01 – 0.15
Performance criteria	EUI	--
	IU	--
Performance Constraints	sDA	--
	AI	--

Table 1. Design variables, Performance criteria and constraints

3.2 Simulation Setup

Energy Use Intensity (EUI) and Illuminance Uniformity (IU) are selected as performance criteria, while Spatial Daylight Autonomy (sDA) and Average Illuminance (AI) are chosen as performance constrains (Table 1). They will be used as optimization objectives and constraints in future research.

Therefore, annual hourly daylight and energy simulations are performed by Daysim and Energyplus sequentially, based on the platform described in [12]. The platform couples Grasshopper with modeFRONTIER [8].

4 DESIGN OF EXPERIMENTS (DOE) & RESPONSE SURFACE METHODOLOGY (RSM)

In order to develop the surrogate model, the following steps are followed: 1) Sampling of Design Points by DoE; 2) Data Collection by Running Simulations; 3) Surrogate Model Generation by RSM.

In the first stage, the number of design points (i.e. design variable vectors) and their locations within the design space are defined. A well-distributed sampling is helpful for obtaining a reliable surrogate model. Among all the available DoE algorithms, Uniform Latin Hypercube Sampling is chosen in order to ensure a random and uniform distribution in each dimension.

Numerical simulations are performed based on the selected design points in the previous stage. The simulation time needed for each design point is around 5 minutes, and the affordable number of simulations for each test is assumed to be 300 times (i.e. around 25 hours in total). Among all the simulation data, 270 are collected for training the response surfaces and 30 are used for the RSM validation.

In the last stage, a set of RSM algorithms is used to train multiple response surfaces for each performance indicator (i.e. EUI, IU, sDA and AI respectively). By comparing the fit or quality of obtained response surfaces (i.e. RSM Validation), a final surrogate model is selected for each performance indicator. In this research, this set of RSM algorithms includes “Classical meta-models” (i.e. Polynomial Singular Value Decomposition, Stepwise Regression) and “Statistical meta-models” (i.e. Shepard K-Nearest, Kriging).

5 OBSERVATION OF THE CURRENT RESULTS

In order to investigate possible effects of problem scales, the accuracy of surrogate models in the two proposed cases are compared.

As shown in Table 2, in general, the accuracy of surrogate models in Case 1 appears to be better than that in Case 2. The RSM Distance Charts show the distance between real designs (30 simulation data sets for the RSM validation lying on the blue 45° slope) and virtual designs (computed with the RSM algorithm). By observing these charts, current results suggest that the IU and sDA estimation in Case 1 is much better than that in Case 2. This is also indicated by the R-squared values (i.e. coefficient of determination), which provide information on the goodness of fit of a model. An R^2 value of 1 indicates a perfect fit. The Max and Mean Absolute Errors give us information that the errors in the IU and sDA prediction are relatively high compared to the real simulation values in both cases. Moreover, an error message was observed when using Stepwise Regression algorithm to train response surfaces in Case 2, because of the relatively small training set size. It indicates that a larger sample size is needed. Therefore, as the increase of the problem scale, the accuracy of RSM can be lower due to the limited or insufficient sample size.

6 FUTURE RESEARCH

In order to investigate potential pros and cons of utilizing RSM, the quality of (Predicted) Pareto Front approximations of the three proposed workflows will be compared in future research. Besides, further study on the RSM selection and parameter tuning will be carried out in order to ensure the predictive capabilities of the RSM.

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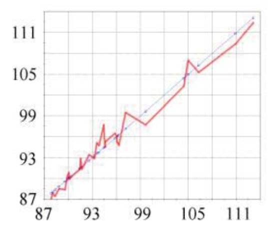
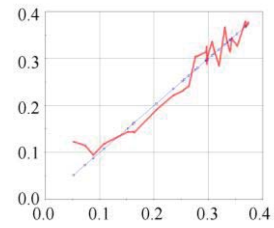
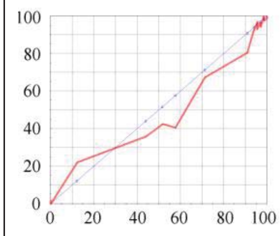
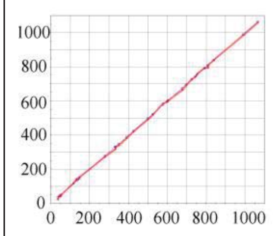
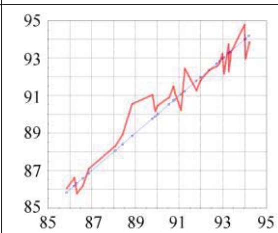
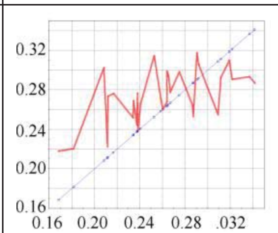
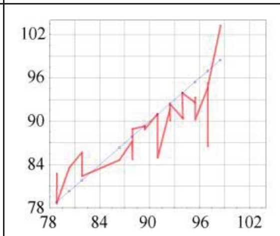
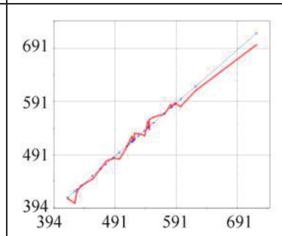
	EUI	IU	sDA	AI
Case1 RSM Distance Charts				
Max Abs. Error	3.31 kWh/m^2	0.07	16.97%	13.93 lux
Mean Abs. Error	0.91 kWh/m^2	0.02	2.42%	4.85 lux
R^2	0.967	0.932	0.988	0.999
Case2 RSM Distance Charts				
Max Abs. Error	1.71 kWh/m^2	0.09	10.38%	21.61 lux
Mean Abs. Error	0.53 kWh/m^2	0.03	2.29%	7.10 lux
R^2	0.934	0.233	0.671	0.980

Table 2. RSM validation (270 simulation data sets for training the response surfaces; 30 simulation data sets for the RSM validation)

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