Metamodel-based Dynamic Daylighting Simulation

Dan Hou[1,2], Gang Liu[1], Qi Zhang[1], Lan Wang[1,3]
[1] School of Architecture, Tianjin University, Tianjin, China
[2] Department of Architecture, School of Design and Environment, National University of Singapore, Singapore
[3] Institute of MPS, Tianjin Fire Research, Tianjin, China

Abstract

Currently, building performance optimization approach attracts more and more architects' attentions and is expected to become the future trend to substitute the conventional manual comparison in sustainable building practices. However, the time-consuming simulations such as daylighting simulation, brings a large obstacle for its application. To mitigate this issue, this study proposes an advanced approach combining adaptive metamodel with Daysim (AMDS), to improve the efficiency of simulation for dynamic daylighting metrics with spatial feature (AP_{UDI}). Several groups of tests are conducted for debugging and validating its performance. The results show the time cost can be reduced to only 7%~17% of the general simulation while the accuracy keeps on the acceptable level. This study shows the potential of metamodel in predicting building performance, and is expected to inspire its application in other grid-based simulation, like CFD.

Introduction

As many attempts to combine the intelligent computing algorithms (Genetic Algorithms (GAs), Multi-Objective Evolutionary Algorithms (MOEAs), etc.) with building simulation techniques emerge, such optimization approaches attract more and more architects' attentions and are expected to become the future trend to substitute the conventional manual comparison in sustainable building practices.

During the optimization process, the exploration of the solution space usually requires hundreds or thousands of simulation evaluations. Due to the complexity of real building, the detailed simulation may take several hours. Such computationally expensive simulations may lead to the benefit of the optimization schemes insufficient to offset the high cost of time and thus make them impractical for the real projects.

To mitigate this issue, some researchers take various measures to reduce the single simulation time or the simulation calls during the whole optimization process, which have been reviewed by Nguyen et al. (2014). It can be seen that more current focus concentrates on the later, and the metamodel (surrogate model or response surface approximations) seems to be a promising solution to this problem. Those studies adopt it to generate the general mathematical approximations of the optimization model within the design space by completing few simulations, and then the objective value of any solution can derive from that approximation directly.

Although above methods can extremely save the time cost of the whole optimization, their adaptation has more or less limitations. They are obviously not suitable to solve the problems with long single simulation time, for instance, the daylighting or CFD simulation of large-scale space. Additionally, compared with the single simulation result which is used to assess a certain performance of the whole building like energy simulation, such results have a feature reflecting spatial distribution, and thus make the evaluation criteria flexible.

This paper selects the annual daylighting simulation as the study object due to its wide application and flexible grid-base metrics. After realizing the limitations of the conventional static metrics, some researchers turn their attentions to the dynamic daylight performance metrics such as *Daylight Autonomy* (*DA*) and *Useful Daylight Illuminances* (*UDI*). The key advantage of them is that they consider the time series of illuminance, which means they are calculated based on the daily and seasonal variations of daylighting in the whole year (Reinhart et al., 2006). Nevertheless, the spatial distribution that is also reflected in the simulation results and meaningful for space design, is often overlooked. In the indoor environment section in the LEED certification system (2009), it utilizes the area percentage of the illuminance above certain threshold to assess the daylighting performance, but the illuminance is only simulated for the specified date and time. Therefore, the metrics in this study is based on both spatial and time consideration.

In terms of the approach to improve the simulation efficiency, some studies focus on the development of daylighting algorithms like the hybrid global rendering method proposed by Cutler et al. (2008) which combines forward ray tracing with radiosity and shadow volumes rendering. Although this method is extremely efficient in saving the computation time within the allowed precision, it requires the architects or engineers to master the new simulation tool, Lightsolve Viewer (LSV), which brings extra burden to them and thus delay the whole design process. In another study, Yi (2016) first adopted the Kriging modelling to improve the efficiency of illuminance simulation by Radiance and coupled the results with energy simulation to improve its accuracy. The effectiveness of such approach was illustrated, while its improvement which cut the simulation time in half

https://doi.org/10.26868/25222708.2017.706

(20.43 h) is still insufficient for optimization and this approach is limited by the complexity of building.

Taking above issues into consideration, the adaptive metamodelling technique is adopted in this study to combine with DAYSIM to achieve single simulation instead of optimization. The primary idea to reduce the simulation time is to narrow the computation domain instead of to adjust the grid density. This approach can be used in complex case with unevenly distributed glazing and irregular space. Another innovation is to take advantage of the interpolation method carrying by the daylighting calculation algorithm to control the precision of results according to the requirements. However, it should be noticeable that this study only takes DAYSIM as the calculation tools rather than modifying the daylighting calculation method in it. Actually, it dose not matter which calculation method is used.

There are different types of metamodel with their own adaptations to solve different problems. And some important parameters significantly affect the accuracy of metamodel and time cost of whole approach. Therefore, a series of tests adopting Adaptive Metamodel-based Daylighting Simulation (AMDS) are compared with the general simulation, which illustrates how efficient they are to derive the relatively precise results within very little time. Finally, the further investigation of the proposed approaches and the possibilities of metamodeling technique to solve other problems are discussed in the conclusion section.

Methodology

Adaptive sampling metamodel

In order to address the complex problems with time-consuming simulation, many researchers and engineers use metamodels to replace the actual expensive computer analyses, facilitating multidisciplinary, multi-objective optimization and concept exploration (Simpson et al., 2001). The goal of metalmodel is to construct an approximation that closely resembles the original system while can be computed much cheaper to evaluate. So it is actually "the model of the model" (Meckesheimer et al., 2001).

Metamodeling technique is the approaches to construct the metamodels. There are three primary procedures of metamodelling, including:

- Adopting the experimental design which selects the sample points in the design space and then performs multiple simulations at these points.
- Choosing the metamodel type and fitting the model that approximates the simulator behaviour on the required domain.
- Validating the model to determine whether it can be used in the computation-intensive processes.

Among them, the experimental design (the sampling methods) has great influence on the precision and efficiency performance of the metamodels since it determines the content and size of the sample set. However, most engineering problems are the grey- or black-box problems whose behaviour is partially or entirely unknown to engineers. It is difficult to identify in advance how large the experimental design must be to reach a given accuracy. So the sequential design (adaptive sampling) which has the flexible sampling methods has gained popularity in recent years (Wang and Shan, 2007).

Figure 1 shows the iterative process of sequential design. Sequential design intelligently selects new samples in the interesting areas that are difficult to approximate, depending on the analysis of the data (models and samples) from previous iterations. Compared to the one-shot approach (fixed sampling), it has obvious advantage in generating a more efficient distribution of samples. The requirements of sequential design are not only space-filled which means the points need to be spread out evenly over the design space, but also can capture as many local characteristics as possible. This is the trade-off between exploration and exploitation (Crombecq et al., 2011), which is one focus in this paper.

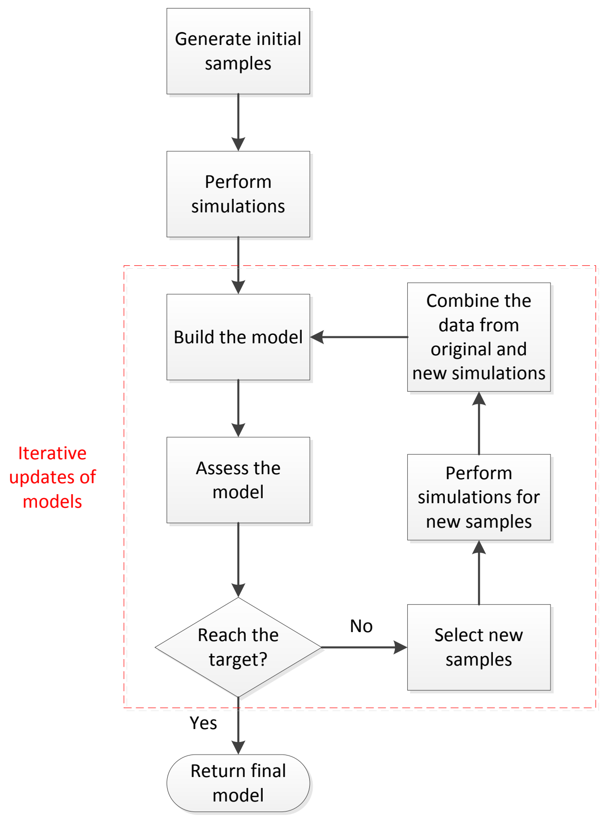

Figure 1: The flowchart of the adaptive sampling metamodel.

The assessment of models is another critical procedure in the metamodelling with sequential design. In addition to be seen as the terminal condition, it also provides the valuable information to guide the sampling process, especially for the exploitation which zooms in the interesting regions. Since even one more simulation may bring great burden for the computation efficiency, it would be better to minimize the total number of samples while maximize the accuracy of the models at the same time. This is also an essential consideration in the sequential metamodelling.

However, it is noteworthy that the general validation process can be also time-consuming since it often needs additional simulations for sample points to predict the difference between the real and metamodel-based values such as *RMSE* and R^2 (Wang and Shan, 2007). It means that users will pay for extra time every iteration just for assessing the model instead of improving it. This will discount the benefits from the application of metamodels.

In architecture-related field, the application of metamodel is still on its exploring period. Most studies directly select one kind of sampling method or metamodelling technique or validation criteria without exploring other adaptations. So it is difficult to identify whether that combination is (the most) appropriate for certain problem. The inappropriate metamodelling technique could not improve the computation efficiency, but leads to an inaccurate or even false metamodel and thus increase the computation time cost. Therefore, on the basis of AMDS, this study also analyses the adaptation of four types of metamodel to daylighting simulation by comparing their performance: Radial Basis Functions (RBF), Kriging, Gaussian Process (GPML) and Least Squares (SVM).

Dynamic daylighting metrics with spatial features

Generally, one daylighting simulation will generate the illuminance map including all the values in the defined grid, but whether all of them are required to reach the high precision or density to calculate the final metric is overlooked by users. For instance, in terms of the metric proposed in LEED, the real key point is to judge whether the illuminance is within the range instead of the detailed value since its demand is just to obtain the area percentage which is almost equal to the number of grid points that reach the goal. It is obvious that much computation cost is useless if the users set the parameter as usual to run the relatively very precise simulation. So it is necessary to make research on the metrics-oriented daylighting simulation methods, which are better to be consistent with the objectives in the general optimization problems.

Due to its wide application in building optimization problems, this paper considers the dynamic daylighting metrics, *Useful Daylight Illuminance* (*UDI*). However, instead of directly using it, a modification similar to the metrics in LEED is applied to reveal the spatial feature of the daylighting requirement. The new metrics is defined as the following:

$$AP_{UDI} = \frac{A_{UDI>acceptable\ value}}{A_{total}} \qquad (1)$$

AP_{UDI} represents the percentage of area with *UDI* equaling or exceeding the acceptable value. Such area can be an indicator of workplace allocation for architects. And AP_{UDI} can be an optimized objective to find a design with best continuous daylighting performance. The thresholds of *UDI* are from 450 lux (not too dark for certain kind of building) (Standard for daylighting design of buildings in China, 2013) to 2000 lux (not too bright) (Nabil and Mardaljevic, 2005). And the acceptable value depends on architect's expectation which has no influence on the approach, so it is defined as 60% in this study.

Adaptive metamodel-based daylighting simulation (AMDS)

In terms of the AP_{UDI}, the final goal is actually to identify the boundary of area meeting the requirements. So the precise values of the sample points inside or outside the boundary could not affect the metrics calculation, but greatly extending the simulation time. Taking it into consideration, this study proposes a dynamic simulation approach that employs the metamodelling technique to filter the less important region initially and focus the computation resource on grasping the key information for metrics.

If the calculation of every point can be seen as a separate simulation, the formulation of *UDI* in any point is as below:

$$Z = f_{UDI_{450-2000}}(x, y) \qquad (2)$$

x and y means the coordinates of a point. The metamodel is constructed to replace the time-consuming simulator to calculate Z. This work is implemented on the Matlab platform, and uses the metamodel construction tool developed by the group from University Gent, SUMO Toolbox.

Actually, the unique priority is the interesting area which is determined by contour lines indicating *UDI* larger than 60%, instead of the whole design space in other engineering problems. So the general adaptive sampling methods which pursue space-fillingness are not appropriate for this study. Therefore, the new adaptive sampling methods are adopted in this approach, as well as the new evaluation criteria.

Figure 2 presents the complete workflow of this approach. It should be noticed that except for metamodel, an important parameter in DAYSIM, *Ambient Accuracy* (*-aa*), also plays an important role in reducing the computation time. Actually, the illuminance of grid points is calculated by interpolation. The number of real simulated points is significantly affected by grid domain, density and *–aa* (Larson and Shakespeare, 2006). The larger *–aa* is, the less the number of points is, meanwhile the lower the accuracy is. Considering that the initial goal is to locate the interesting regions and define their general shapes, a coarse grid and large *–aa* are adopted at the first iteration (Figure 3 (a)). Then the simulation results are used to build the first metamodel, which can be used to generate the *UDI* of a refined grid in the whole space. A series of contour lines that compass the area meeting *UDI* requirement, can also be obtained based on them. At the second iteration, a local refined grid will be generated based on each contours (Figure 3 (b)). Due to the irregular shape of regions, a tolerance is given to them to contain more edge sample points (outside the contours) for improving the accuracy. After simulating these new grids, the results of them will be combined with the previous simulation results to reconstruct the metamodel.

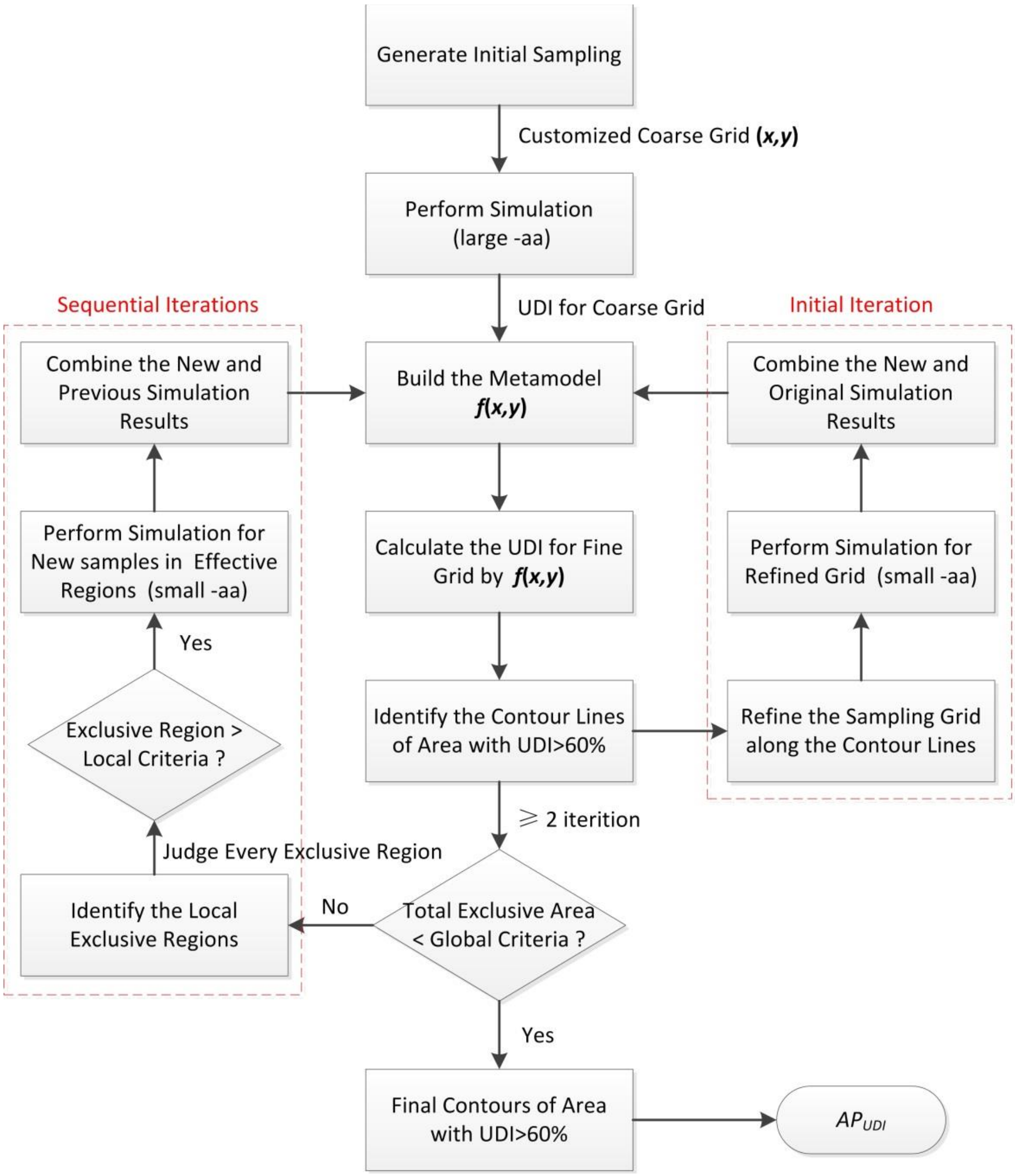

Figure 2 The framework of metamodel-based simulation using adaptive sampling method along contour lines.

The goal of this approach is actually to build a relatively precise metamodel. During the iteration process, the quality of metamodel determines the termination of the whole process. Instead of using the common method like cross-validation, a new measurement which is defined as the total exclusive area between the previous and current contours, is adopted, without extra simulation for validation. When this measurement is lower than the pre-defined criteria, it indicates that the contour lines have been stable and thus precise enough in the global region. In this way, every sample is taken full advantages to improve the precision of model.

The sequential iterations have the different steps. It can be seen from Figure 3 (c) that the exclusive area between two sets of contour lines is actually composed of several small regions. The larger the region is, the poorer the stability of this local area is. Therefore, it is necessary to add new samples nearby to improve the accuracy of contour lines. However, not all the exclusive areas can be taken as the effective regions since some small ones have little influence but may cost much time to be calculated. So there is a local criteria to filter out the truly meaningful regions. Then for every such region, the centroids of it and current contour lines are linked. This straight line is cut by both current and last contour lines, and the midpoint of this line segment is selected as the new sample point.

Actually, the metamodel has two functions in the whole process. On one hand, it plays a role as finding approximate position of interesting area with little computation cost. On the other hand, it accordingly re-positions the contour lines by constructing the new models until meeting the accuracy requirements. In summary, this approach presents the potential to implement an efficient and precise daylighting simulation. The next sections show a series of tests to demonstrate its merits and limitations.

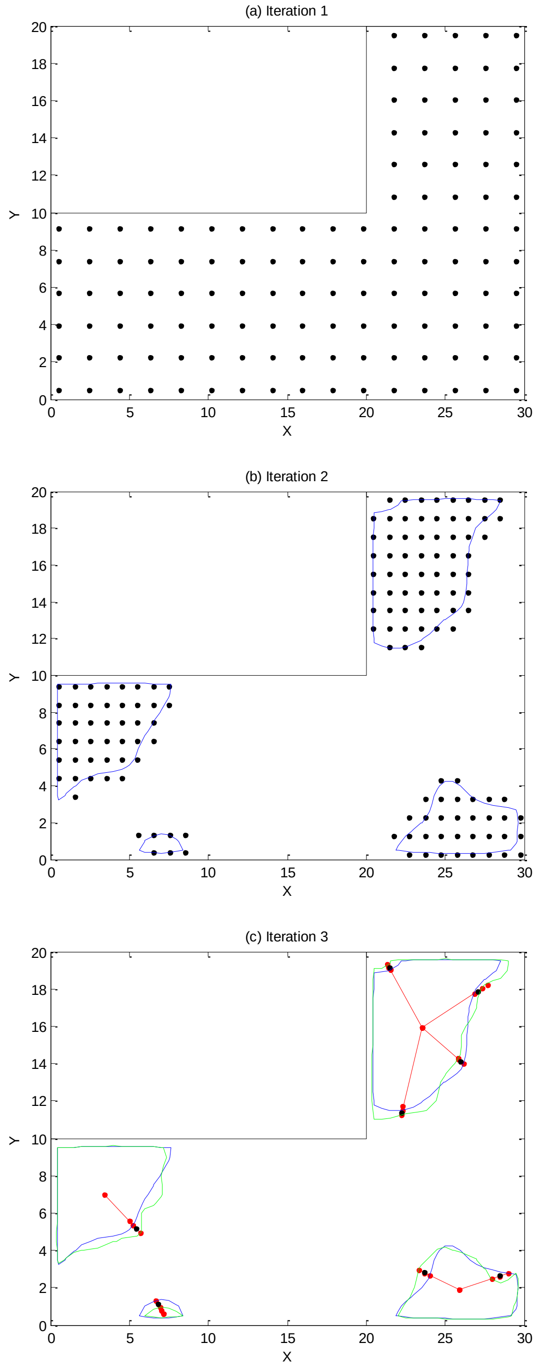

Figure 3: Samples and exclusive domians at different iterations.

Selection of key factor values in AMDS

Since AMDS is composed of successive steps, the latter always depends on the results of the former. So it is necessary to make sure the information captured at those important steps adequate, especially the early ones. As the performance of them is closely related to key factors such as grid density and *–aa*, the influence of single key factor is shown in this section to assist the selection of its value.

As one goal of this study is to reveal the adaptation of different types of metamodel in daylighting simulation, every group of tests include the four selected metamodels: RBF, Kriging, GPML and LSSVM.

Case description

The test building model is actually a virtual room with irregular plan, which is added windows facing south and east and a skylight to construct the complex daylighting system (Figure 4). Besides, the positions of glazing are not set as usual since they may be arbitrary during the optimization process. In a word, these unusual features are created to test whether the following approaches are universally applicable to any conditions.

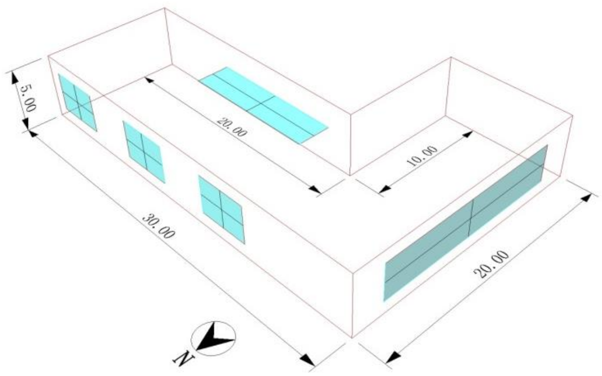

Figure 4: The schematic view of the test modeling (unit m).

The simulation parameters are set as Table 1 to guarantee the results as accuracy as possible. They are kept constant in all the tests. As for *–aa*, the group of tests in the next section and base case are set as 0.1.

Table 1: Main Daylighting Simulation Parameters

Parameter	*Ambient bounces (-ab)*	*Ambient divisions (-ad)*	*Ambient super-samples (-as)*
Value	7	2000	100
Parameter	*Ambient resolution (-ar)*	*Direct sampling (-ds)*	*Maximum ray reflection (-lr)*
Value	300	0.2	6

Initial grid density

The selection of initial samples, as the starting point, is very important, because there is no way later to discover what is missing at the beginning. In terms of this study, the initial grid means the initial sample set. Compared with the random selection, the uniform grid is more appropriate for this study since it ensures that the possibility of capturing information is equal to each point in the grid. Since the aim of this group of tests is to specify the initial grid density, the attention is only paid to the initial iteration, so they are actually the one-shot metamodel-based tests.

However, only AP_{UDI} is not enough to confirm the accuracy since the spatial distribution (location) of the area with *UDI* larger than 60% may also have a certain deviation. In order to describe this condition, another metrics, *Overlapping Ratio*, is specified as the percentage of the overlapping area between the oriented area respectively found by the metamodel-based strategy and base case:

$$OR = \frac{A_{overlap\ area}}{A_{basecase,UDI>60\%}} \quad (3)$$

This metrics is used in the evaluation of all the following tests.

Table 2 shows the performance of different types of metamodel under different grid density. 8×6, for example, represents the number of grid points on the x and y direction.

In terms of AP_{UDI}, except Kriging, their deviation from base case are not significant in spite of grid density. This actually reflects an illusion phenomenon since not all the included area really meets the *UDI* requirement, which can be seen from the trend of *OR*. It is obvious that *OR* value is increasing with grid refined, indicating more and

Table 2 (a): The AP_{UDI} calculated by metamodels under different grid density

Grid Density	Simulation Time	RBF	Kriging	GPML	LSSVM
8×6	19min	25.11	8.1	25.51	25.51
16×12	24min	25.51	25.33	25.37	25.38
32×24	35min	25.41	25.41	25.41	25.31
60×40 (Base case, only simulation)	26.14				

Table 2 (b): The OR calculated by metamodels under different grid density

Grid Density	RBF	Kriging	GPML	LSSVM
8×6	78.43	28.41	79.35	79.06
16×12	95.55	94.95	95.12	95.47
32×24	97.5	97.51	97.49	97.08

more area are found in the right positions. Furthermore, for *OR*, more significant improvements appear in the comparison between low and medium density. The high density actually cannot contribute much for improving the accuracy of results. In other words, the sensitivity of metamodel to grid density decreases gradually.

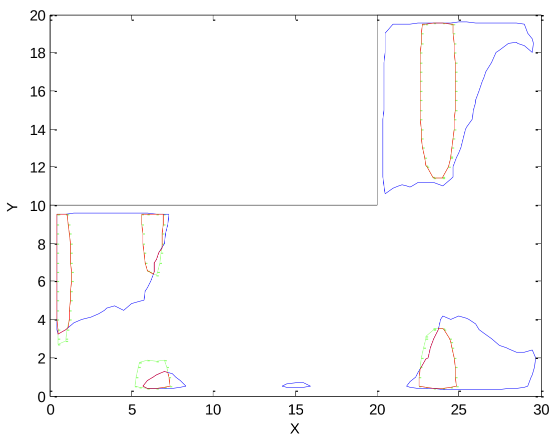

Figure 5: The overlapping area of Kriging-based results under the density of 8×6. (Blue: AP_{UDI} contour lines of simulation; Green: AP_{UDI} contour lines of metamodel-based approach; Red: intersection area between them)

As for the comparsion between metamodels, except Kriging under the low grid density, for both metrics, the differences between them are also not significant, especially with the high density. It is because the results are not sensitive to the type of metamodel when there is adequate information for prediction.

For that exception condition, Kriging performs worst and leads to a large gap compared with other metamodels and base case. A series of contour lines with very different shape and distribution can be seen from Figure 5. As there are several windows introducing daylighting and the shape of room is irregular, the illuminance is distributed extremely unevenly in this case, which brings greater difficulty in making predication. Due to the deficiency of data, Kriging model may perform unsteadily. Therefore, for the complex cases, the initial grid density should not be too low.

In summary, too low grid density can leave out much information while too high grid density cannot make obvious improvement of accurary but cost much time. So the medium one is a compromise solution to mitigate both negative effects.

Global ambient accuracy

As AMDS shows, an initial coarse simulation is need at the outset, and then the simulation accuracy should increase gradually. But as seen from above tests, it is obvious that even the grid points grow exponentially, the differences of accuracy and simulation time between the tests are not significant. Based on the theoretical analysis (Larson and Shakespeare, 2006), the value of -aa is able to make significant influence. So it is essential to discover how much the influence can be, to make informed decision depending on the requirements at the early iteration.

The tests in this sections adopt the 16×12 grid. The results and their trends are shown in Figure 6. All the metamodels have similar performance from the beginning to 0.3. After that, except LSSVM, the other metamodel-based results still keep the similar variation. Until 0.5, their deviations of AP_{UDI} from base case are not exceed 2%, and the largest derivation of *OR* keeps at around 12%. For the initial global prediction, such error

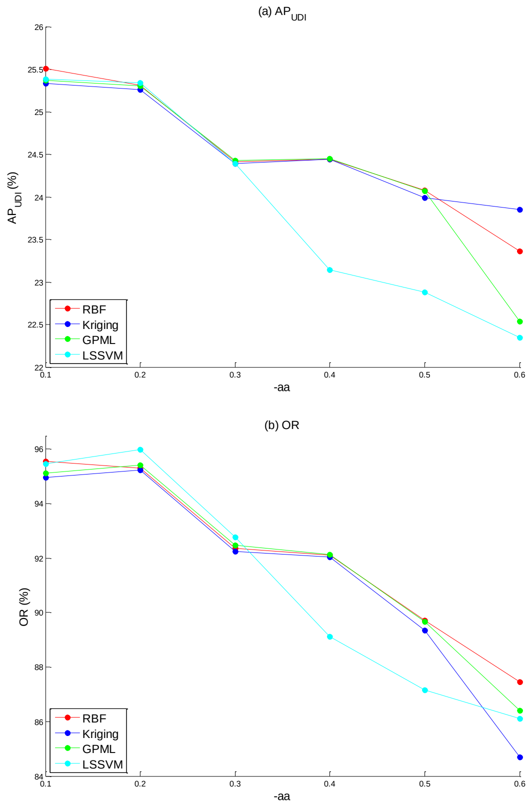

Figure 6: The variation of AP_{UDI} and OR with the increasing –aa.

rate is allowable and acceptable. However, when -aa is equal to 0.6, there appears obvious gaps between different metamodels, which particularly can seen from *OR*, the low values imply that the data is not as reliable as other situations.

In contrast, LSSVM performs worst at 0.4 and 0.5, which indicates its ability of prediction based on low accuracy data is inferior to others so that it is not appropriate to be adopted at initial iteration.

In addition, it should be also noticed that in spite of AP_{UDI} or *OR*, each presents a step-down trend with *-aa* decreasing. The value at 0.1 and 0.2 are almost on the same level, so are those at 0.3 and 0.4. But there is an obvious gap between 0.2 and 0.3. This reveals that the selection of -aa can be tactful, in detail, the larger -aa on the same level is more preferable since it can obtain the same accuracy with less time cost.

Based on the accuracy performance of metamodels, the values of *–aa* ranging from 0.1 to 0.5 are appropriate. However, in order to reduce the time cost, 0.4 and 0.5 are finally selected in the following tests since the simulation time of 0.2 is many times than that of 0.4 and 0.5.

Complete simulation results and Discussion

This section makes a series of experiments adopting the complete AMDS approach to get an insight of its performance. Instead of exhausting the combination of all parameters, this group mainly aims to focus on the influence of global and local *–aa* since the grid density weakens when the calculation domains concentrate on the small area. The options of local *–aa* exclude 0.1 due to its high time cost even though with few sample points. And based on the results of previous section, the performance of LSSVM at early stage makes it uncompetitive compared to other types of metamodel, so it is discarded in this group.

Table 3 shows the parameters and results of 12 tests. Among the common parameters, the selection of global and local criteria is critical to iterations and thus affects the accuracy and time of those tests. It mainly depends on the user's requirement and space scale, while it does not mean the smaller the criteria is, the better the results are. This is because the daylighting simulation time is not proportional to the number of points. It is not worth spending more time on simulation only for one or two points.

Compared to the base case, on one hand, the time cost of all tests has significant reduction from 83% (460s) to 93% (197s). On the other hand, the deviations of AP_{UDI} or *OR* also maintains on a low level which can be acceptable in most cases and optimization, respectively from 0.6% to 1.2% and from 95.19% to 96.52%.

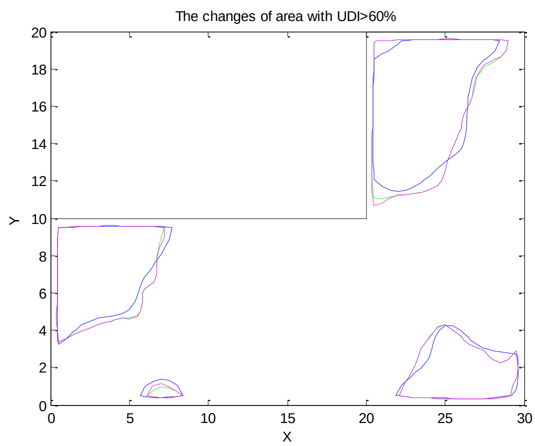

Figure 7:The changes of contour lines in the whole process (Test 6; Blue: iteration 1; Green: iteration 2; Red: iteration 3).

As for the comparison between 12 tests, it can be seen that except simulation time (and total time), there exists only small differences in terms of the rest indicators. It is obvious metamodelling time is marginal compared with simulation time. Among them, the subgroup of Kriging needs slightly less time to build metamodel. For simulation time, tests with local *–aa* of 0.3 need less than half time of tests with 0.2, while the differences between tests with global *–aa* of 0.5 and those of 0.4 are only around tens of seconds. So local *–aa* actually plays a decisive role in the efficiency improvement by AMDS. Meanwhile, although there is no clear trend in terms of AP_{UDI}, the tests with high local *–aa* find slightly more real demanding area, which can be seen from *OR*. Taking above analysis into account comprehensively, the selection of *–aa* is dependent upon whether an user values efficiency more than accuracy, and vice versa.

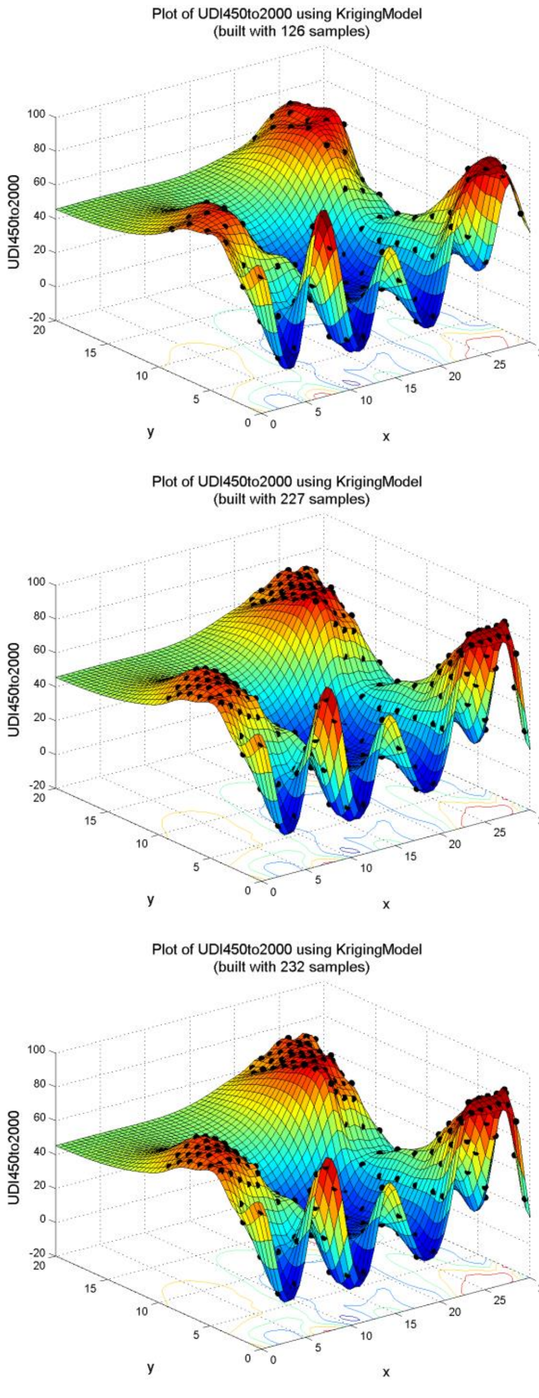

Figure 8: Metamodel of different iterations (Test 6) (The X<20 and Y>10 region is actually not in the plan and thus can be overlooked).

Figure 7 and 8 show an example of the whole changing process of demanding area and metamodel respectively. The three metamodels are constructed based on the increasing adaptive sample points. Actually, when a new sample point is very closed to an existing one, the latter would be substituted by the former so as not to make metamodel over-fitting.

However, Figure 7 shows an unusual and unexpected phenomenon that the contour lines of iteration 2 and 3 are highly coincident, and *OR* of iteration 3 is even slightly lower than that of iteration 2. In other words, the accuracy of metamodel decreases even with more samples. This can be seen from test 11, the only one with 4 iterations, performs worst among all. A possible explanation for this is that the simulation results of the last iteration lack fidelity, which is caused by the calculation method inside Daysim may be not so appropriate to simulate the *UDI* of very scattered points. From another perspective, it illustrates that the adaptive sampling method in AMDS still needs to be improved.

Conclusion

This paper proposes an advanced daylighting simulation method (AMDS) specified for the metrics based on the spatial and time consideration. It takes full advantage of the prediction ability of metamodel to locate the interesting area that meets the *UDI* requirement. The new adaptive sampling methods and an evaluation method of metamodel are developed depending on the features of daylighting simulation. The results of tests illustrate AMDS can significantly improve the computation efficiency meanwhile maintain a high accuracy. In addition, the result indicates the commonly used types of metamodel including RBF, Kriging and GPML are suitable to be used in daylighting simulation while LSSVM is not stable enough to make prediction by using data with relatively low precision.

However, the AMDS approach still needs the further investigation since the adaptive sampling method after second iteration sometimes causes the regression of accuracy. It should be combined with the calculation modelling in Daysim. Furthermore, more cases with different level of complexity and scale will be used to test the AMDS approach. Actually, this approach is just a starting point. The inspiration of it can be applied in the study of other grid-based simulation like CFD in future.

Acknowledgement

This study is supported by the National Natural Science Foundation of China (51338006), Programmer of Introducing Talents of Discipline to Universities

(B13011), and National Science and Technology Major Project of China (2016YFC0700201). We are also thankful for the support from China Scholarship Council (CSC).

References

Larson G W, Shakespeare R (2004). Rendering with Radiance: the art and science of lighting visualization. Booksurge Llc.

LEED 2009 for New Construction.

Meckesheimer M, Barton R R, Simpson T, et al (2001). Metamodeling of combined discrete/continuous responses. *AIAA journal*, 1950-1959.

Nabil A, Mardaljevic J. (2005). Useful Daylight Illuminance: A New Paradigm to Access Daylight in Buildings. *Lighting Res Tech*, 41–59.

Nguyen A T, Reiter S, Rigo P (2014). A review on simulation-based optimization methods applied to building performance analysis. *Applied Energy*, 1043-1058.

Reinhart C F, Mardaljevic J, Rogers Z (2006). Dynamic daylight performance metrics for sustainable building design. *Leukos*, 7-31.

Standard for daylighting design of buildings in China (GB 50033-2013).

Simpson T W, Poplinski J D, Koch P N, et al (2001). Metamodels for computer-based engineering design: survey and recommendations. *Engineering with computers*, 129-150.

Wang G G, Shan S (2007). Review of metamodeling techniques in support of engineering design optimization. *Journal of Mechanical design*, 129(4): 370-380.

Yi Y K (2016). Adaptation of Kriging in daylight modeling for energy simulation. *Energy and Buildings*, 479-496.

Table 3: The parameters and results of tests based on AMDS approach.

Type	**Common parameters**	**Test no.**	**Global –aa**	**Local –aa**	**Iteration**	**Number of adaptive sample points**	**Total time (s)**	**Simulation time (s)**	**Metamodelling time (s)**	**AP_{UDI} (%)**	**OR (%)**
Base case	Grid: 60×40	0	0.1	-	-	-	2653		-	26.14	-
RBF	1. Initial grid (number of points): 16×12 2. Refined grid (distance of points): 1m×1m 3. Global criteria: 0.5% ×plan_area 4. Local criteria: 0.1% ×plan_area	1	0.5	0.3	3	153	197	178	19	25.55	95.51
		2	0.5	0.2	3	152	417	396	21	25.19	95.75
		3	0.4	0.3	3	154	251	232	19	25.38	96.46
		4	0.4	0.2	3	154	460	441	19	25.36	96.52
Kriging		5	0.5	0.3	3	152	201	189	12	25.14	95.23
		6	0.5	0.2	3	151	411	400	11	25.37	96.52
		7	0.4	0.3	3	153	217	205	12	25.08	95.78
		8	0.4	0.2	3	153	454	438	16	25.35	96.34
GPML		9	0.5	0.3	3	152	204	191	13	25.30	95.25
		10	0.5	0.2	3	152	421	407	14	25.26	95.56
		11	0.4	0.3	4	157	287	269	18	24.95	95.19
		12	0.4	0.2	3	153	448	435	13	25.22	96.29