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Suggestions for solution space exploration in the early stage of architectural design based on a literature review

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Suggestions for solution space exploration in the early stage of architectural design based on a literature review

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Abstract. Early design decisions have higher potential to influence building performance compared with the decisions made at later design stages. Performance simulation and optimization algorithms have been integrated to assist early design in reducing carbon emissions, improving indoor thermal comfort, etc. However, early decision making within a limited time frame is still challenging due to the large number of design options, the lack of decision-making guidance, and the trade-offs among various requirements. Selecting appropriate methods to explore design space is the key to find an ideal solution. This paper reviewed the challenges and identified the key questions to access the ability of existing decision-making methods to cope with different challenges. It is concluded that the interactive exploration of design space could be more effective and efficient by (1) combining the surrogate models and the automated optimization algorithms to improve the efficiency of the building performance calculation and the optimal design space position; and by (2) extending the optimal design space to increase the solution diversity, and (3) filtering the near optimal design space with consideration of the stakeholders' preferences and values. Further integration of tools for building performance simulation, diversity description and decision-making guidance is needed to support the decision -making process.

Keywords: buildings, early design, design space, decision support, interactive exploration

1. Introduction

1.1. Needs for design space exploration in the early building design stage

A 'design space' or 'solution space' is a dataset of all possible design options [1]. Respectively, the dataset of all performance indicators is the 'performance space' [2]. Design Space Exploration (DSE) is the process of finding the final design solution. Exploring architectural solution based on building performances has been recognized as an effort to reduce energy consumption and environmental impacts. In practice, design variables, including but not limited to geometry [3], thermal conductivity [4,5], energy efficiency of HVAC and renewable energy systems [6], constitute the design space. Corresponding performance space consists of quantitative requirements and qualitative requirements depending on the targets and preference of stakeholders, such as Green House Gas emission [7], life cycle cost [8], aesthetics [9] and spatial experience. Based on the consensus that the earlier a decision is made, the higher potential of influence a decision has on the final building performance and costs [10], DSE for the early building design is a key step to achieve the final targets.

However, as shown in Figure 1, the final solution might never be the ideal one because of the complexity of design space and the capacity of the DSE methods. Identifying the challenges in early architectural design stages and developing proper DSE methods is of significant importance.

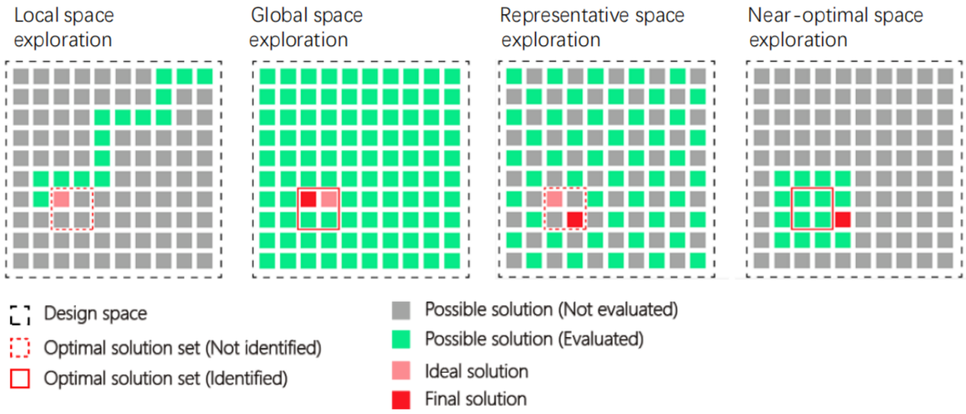

Figure 1. The design spaces explored in the design process under different approaches. (The form of the figures had been inspired by literature [41], yet the ideas are different from it.)

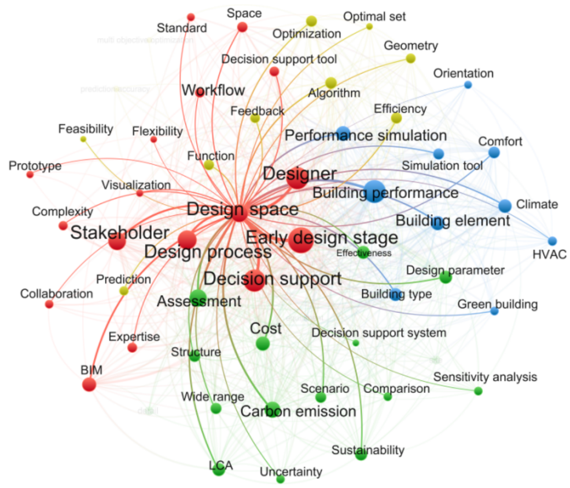

Figure 2. Keywords and their relationships of the literature on design space exploration in the early stage of architectural design. (drawn by the authors)

1.2. Previous review and gaps

Prior to this study, methods [15-19] and tools [13,14] for building performance simulation and optimization have been reviewed comprehensively. The integration of energy simulation and optimization engines improve the interoperability of tools; the application of surrogate models, such as Artificial Neural Networks and Regressions, in building energy analysis accelerate the calculation speed; the integrated parametric 3D modeling platforms, like Grasshopper, provides optimization and visual decision-making guidance. However, the integration of building performance simulation and optimization is not enough for DSE because of the multiple challenges in early design stages. Although existing methods and tools had been summarized in literature [20-22], they have not been fully reviewed from the perspective of early design challenges. This review aims to (1) identify the challenges for design space exploration, (2) assess the ability of existing DSE methods in response to the challenges, and to (3) propose potential improvements for the DSE methods.

The paper is organized as follows： Section 2 presents the methodology of literature review. Section 3 analyzes the challenges for DSE in performance-oriented building design and concludes the questions to assess the ability of DSE methods. Existing DSE methods assessment and potential improvements are proposed in Section 4.

Table 1. Representative articles focusing on DSE

Ref.	DSE method	Space Explored	Quantitative Objectives	Performance simulations	Automated optimization or not?	Diversity Control	Design-performance space informed by	Decision guided by	Integrated with design tools?
[41]	MF	Global (4032 alternatives)	Heating and cooling	Cloud simulation	No	No	PCP	PCP	
[32]	UE	Representative (90% orthogonal array and 10% LHS)	Life cycle carbon emissions and cost	eQuest; SimaPro, Athena, excel	No	Keep the wide ranges of objectives	PDF	No	No
[13]	MF	Representative (Design of Experiments)	Heating, cooling,peak of heating and cooling	metamodels	No	Geometry diversity	PCP, Response Surface, Bar Chart	PCP, SA	BIM (Dynamo)
[34]	SE	Global (4032 alternatives)	Life cycle carbon emissions and cost	Pre-computed	No	No	Scatterplot of Objectives	Scatterplot	No
	SE	Global (4032 alternatives)		Pre-computed	No	No	Histogram of Objectives	Histogram	No
	SE	Global (4032 alternatives)		Pre-computed	No	No	SA tornado diagram	SA tornado diagram.	No
[1]	MF	Representative (MCS)	Energy demand and thermal comfort, daylight	Be10;metamodels	No	No	Histograms of inputs	SA	No
	MF	Representative (MCS)		metamodels	No	Increase the number of solutions remained	PCP	SA pie chart, PCP	No
	MF	Representative (MCS)		metamodels	No		PCP, Histograms of inputs	Regional SA, PCP, Histograms,	No
[21]	UE	Local	Energy consumption	metamodels	No	AIS	Point performance	No	No
	SE	Local	Energy consumption	metamodels	No		SA, false signal rate	SA, false signal rate	No
[20]	UE	Local	energy demand and indoor climate	metamodels	No	No	Point performance	No	No
	SE	Local		metamodels	No	Histogram of inputs	Point performance	Performance changes	No
	SE	Local		metamodels	No		Point performance	Performance changes	No
	MF	Representative (random MCS)		metamodels	No		PCP	PCP	No
	MF	Representative(quasi-randomMCS)		metamodels	No		PCP	PCP	No
[50]	UE	Local	Life-cycle GWP	metamodels	No	Information entropy	Point performance	No	No
	SE	Local		metamodels	No		Point performance	SA	No
	ASPE	Near-optimal	Life-cycle GWP; life-cycle cost	metamodels	GA		near-optimal performance space	No	No
[22]	UE	Local	Structural and energy performance	Grasshopper	No	3D model, sparseness and outlier	Point performance	No	Yes
	UE	Local		Grasshopper	No		Point performance	No	Yes
	SE	Local		Grasshopper	No		unknown	Gradient estimation	Yes
	ASPE	Optimal		metamodels	Multi-objective optimization		unknown	No	Yes
[36]	SE	Representative (LHS)	energy performance and thermal comfort	metamodels	No	PDF	PDF,Histogram of Objectivesetc.	SA,PDF,etc	No
[37]	UE	Global	Structural and energy performance	Grasshopper	No	3D model	Point performance	No	No
	UE	Representative (LHS)		Grasshopper	No		Point performance	No	No
	ASPE	Optimal		Grasshopper	NSGA-II	No	No	No	No
	ASPE	Near-optimal		Grasshopper	NSGA-II	3D model, sparseness and outlier	performance space	Diversity filter	No
	SE	Privous data		Grasshopper	No		Gradient estimation	Gradient estimation	No
	MF	Privous data		Grasshopper	No		performance space	Gradient estimation	No
	MF	Representative (LHS)		Grasshopper	No		performance space	Clustering	No
	MF	Representative (LHS)		metamodels	No		performance space	PCP, Gradient estimation	No
[8]	ASPE	Near-optimal	Embodied carbon; Energy Use Intensity; construction cost;	EnergyPlus; Radiance;	Multi-objective	Increase the number of solutions	performance space, PCP	PCP	No
[52]	SE	Representative space (LHS)	Structural and energy performance, embodied carbon	Grasshopper	No	3D model, sparseness and outlier	Gradient estimation	Gradient estimation	No

2. **Methodology**

To find out the research focus in recognized literature, the search was conducted in the Web of Science. The search syntax was formulated using "building", "early design", "design space exploration" and its synonyms. The results were limited to English language. 822 articles remained after excluding gray literature and research in other areas. After sorting these articles by relevance, the titles and abstracts of the top 500 articles were downloaded and analyzed through VOSviewer [23]. The keywords and their relationships were shown in Figure 2. "Design space" has strong correlations with "early design", "decision support", "building performance", "assessment", and "stakeholders" while the occurrence frequency of "design space" is lower, which indicates that further study in design space exploration is required to some extent. Then the articles were filtered based on the title and abstract. After reading the full papers, 13 most related articles in Table 1 were reviewed.

3. Challenges for DSE in the early building design

3.1. Challenges at early design stages

Previous reviews [11] have highlighted challenges[1] of building design at the early stages, which results in difficulty in exploring design space.

Time limitation. Having a good understanding of the "design-performance space" is the key to identify the most potential solution. However, only simulation that runs within a second or two enable truly immersive, interactive design space exploration [9], which means that simulation with sophisticated engines, such as EnergyPlus and Radiance, takes 20 s and 5 min for a simulation on a standard PC is [24] too long for iterations at early design stages.

Huge design space to be explored. The curse of dimensionality arises when the number of variables and the number of levels of each variable within a defined range are large. For example, in [25], there are 5 design variables and the numbers of levels per variable are 5, 11, 9, 10, and 20. The size of the global design space is $5 \times 11 \times 9 \times 10 \times 20 = 100{,}000$. It is impossible to evaluate each option and obtain a complete performance space. In this case, reducing the global design space to local space, representative space, optimal or near-optimal space is critical (Figure 1).

Stricter requirements in quantitative performance. Energy and environment crisis are pushing buildings to achieve (nearly) zero energy/carbon emission cost-effectively [26,27]. Moreover, building users also require more comfortable and healthier living environment. In combination with the intelligent service equipment, the requirements with regard to indoor climate [28] and air quality [29,30] are becoming higher. Fortunately, automated optimization is capable of identifying an "optimal" solution [2] set for quantitative performance.

Diverse requirements in qualitative performance. The original difference between the terms "building" and "architecture" implies that architectural creativity, preference and values in qualitative aspects, such as aesthetic and layout [9], should be encouraged. Designers should reflect on and avoid the optimization-centered building design approach.

Conflict of the requirements. Architectural design is complicated due to both quantitative and qualitative requirements and the conflict between multiple objectives[12]. For example, achieving fewer GHG emissions might require vast initial cost [31]. While multi-objective optimization algorithms can balance different quantitative performance through the Pareto-Fronts, human involvement is necessary when it comes to objectives that cannot be mathematically defined [9].

Lack of knowledge for decision making. Stakeholders, like the owners and designers, might have no expertise in HVAC, Life Cycle Assessment, etc.. Rules of thumb are too restrictive to deal with a huge design space [20]. Designers require straightforward decision-making tools and instructions that are integrated into their design environment [13]. Decision making methods and tools have been developed to assist decision making, such as Probability Density Function (PDF) [32], Parallel Coordinate Chart (PCP) [38]. More explanations are presented in Section *4.3.5*.

3.2. Questions to assess DSE methods

Nine questions are tailored to assess the ability of DSE methods because the challenges described above raise high requirements simultaneously on DSE methods in terms of computational speed and cost (Q1-Q3), navigation to the ideal solution (Q4-Q5, Q8), option diversity for each decision (Q6-Q7) and tools (Q9).

Q1. Is the performance simulation fast enough for brainstorming?

[1] The uncertainty of parameters and future scenarios can also affect decision making. But it is a wider field of decision making, and should be discussed separately. It is not contained in the review.

[2] From a mathematical point of view, the "optimal" solutions have the "best" quantitative performance.

Q2. Is it fast to position the optimal or near-optimal design space for quantitative performance?
Q3. Is the workload and duration tolerable for human and computer?
Q4. Is the ideal solutions covered in the space explored?
Q5. Is the optimal or near-optimal design space covered in the space explored?
Q6. Dose the space explored preserve enough room for creativity and individual preference?
Q7. Is human-computer interaction allowed?
Q8. Is the final solution influenced by the initial option?
Q9. Are design guides and tools available or accessible for designers?

4. Assessment and potential improvements of existing DSE methods

In this section, existing DSE methods are identified and assessed. What's more, potential improvements in DSE are proposed.

4.1. Existing design space exploration methods

After summarizing and adapting the prior typologies defined by [20-22], this paper classified them into 5 categories, Unguided Exploration (UE), Sequential Exploration (SE), Manual Filtering (MF), Automated Search and Post Exploration (ASPE), Human-Computer Interactive Exploration (HCIE).

A series of heuristic decisions made without guidance enable designers to explore the options flexibly based on designers' knowledge, preferences and even fortune, which also implies that UE method may lead to uncertain, occasional and inefficient outcomes. This method can't suit the huge design space.

With SE method, building performance change after one decision and guidance for next decision are informed so that designers are navigated to a better direction sequentially. Generally, the most influential variables are identified and specified sequentially. Decision-makers are allowed to express subjective values during the process. However, the final solutions identified may be different due to the selection of SA method [33], nonlinearity [1] and individual preference [21]. What's more, this method, requiring more than 20 steps to determine the final solution [20,21], is inefficient within the limited time framework.

MF provides decision-makers with a design space in the form of an option dataset. The space maybe representative space sampled by LHS(Latin hypercube sampling) [32] or MCS (Monte-Carlo simulation) [20,32], or global space [34,35] when the whole space is small, or (near)-optimal design space [8], The variables and corresponding performance of each option are transparent. The key is to display the "design-performance space" more statically and explicitly so that it is easier to identify the potential solution. Decision makers filter the preferred options according to the requirements of all stakeholders. However, the size of spaces for MF may be so small after several filtering that additional options are required to remedy this, which means fast calculation for the additional options is required to ensure the continuous exploration [1,20,36].

ASPE is the most widely used method. As mentioned above, automated optimization algorithms can create a set of optimal solutions rather than a single design. Researches and tools have been developed by researchers [37] to explore the optimal space through MF. Specifically, presenting 3D models [38] clustering analysis [39] or filtering with the assistance of PCP. However, the post processing is not explained by most of research of building performance optimization. The diversity of options available for the final selection could not fulfill qualitative design requirements.

Interactive Genetic Algorithms ensure that architectural preferences are expressed progressively during cooperation with an algorithm [9]. Humans perform all prioritization and design synthesis while computers are taking the advantage of automated optimization. However, the tools are still not widely used even by researchers due to the computing cost and accessibility to people without knowledge of profession computer science.

4.2. Results of the assessment of existing DSE methods

UE and SE is too inefficient to suit the huge design space while HCIE require professional knowledge and techniques of computer science. MF and ASPE are most potential methods to deal with the challenges in early architectural design. Based on the review in Table 1, each DSE method is assessed and the results are shown in Table 2. It is worth noting that "○" mean that there are opportunities to improve the DSE methodology. The results show that MF and ASPE have the most potential to be improved or integrated. Surrogate models might be used to generate enough potential solutions instantly and automated optimization algorithms are potential measures to speed up the process of decision making in early design stages. Automated optimization algorithms can help arrow down the design space to optimal space while near-optimal design space could be useful to increase solution diversity for post manual exploration. Human intervention based on easy-to-use decision support tools are needed.

Table 2. The characteristics and the ability of DSE methods to cope with the challenges ("×" refers to "No", while "√" indicates "Yes". "○" means the answer depends on the different scenarios. For example, if meta-model is used for energy simulation, it is fast enough to enable truly immersive brainstorming, but the answer is "No" if EnergyPlus is used)

Challenges	Capable of DSE?	UE	SE	MF	ASPE	HCIE	Potential Measures
Time limitation	Is the performance simulation fast enough for brainstorming?	×	○	○	○	○	Surrogate models
	Is it fast to position the optimal or near-optimal design space?	×	×	√	√	√	Automated optimization
	Is the workload and duration tolerable for computer and computer?	×	×	○	√	√	
Huge design space	Is the ideal solutions covered in the space explored?	○*	○*	○	○	√	Focus on optimal or near-optimal design space
Stricter quantitative requirements	Is the optimal or near-optimal design space covered in the space explored?	○*	○*	√	√	√	Automated optimization
Diversity requirements in qualitative performance	Dose the space explored preserve enough room for creativity and individual preference?	√	√	×	×	√	Human intervention
Conflict of the requirements	Is human-computer interaction allowed?	×	×	√	○	√	
Lack of knowledge	Is the final solution influenced by the initial option?	√	√	×	×	×	Choose MF, ASPE, or HCIE
	Are design guides and tools available or accessible for designers?	√	√	√	○	×	Develop easy-to-use tools

* The solutions are covered in the explored space only if the designers have enough experience or good fortune. But the probability is very small.

4.3. Potential improvements of DSE methods in applications

Potential measures to address the issues are proposed in Table 2, among which, meta-models can calculate building performance instantly; automated optimization can position the optimal space fast; near-optimal design space not only ensure the achievement of quantitative performance but also provide more room for individual preference. Decision support tools based on the combination of meta-models, automated optimization, and near-optimal design space, can facilitate quality design space exploration.

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4.3.1. Speed up building performance simulation with surrogate models. Researchers have made efforts to look for potential substitutions of dynamic simulation engines. For example, quasi-steady energy demand calculation method based on DIN V 18599 , "idealized model" be10, PHPP (Passive House Planning Package) excel spreadsheets were used to obtain real-time outcomes [1,24,40]. However, standard static formulations are not always available for other performance, like daylighting and ventilation. Although advances in computer science have facilitated cloud simulations [41] and parallel simulations [42] which break through the limitations of the PC, additional cost is caused to buy enough computing power [43]. The most potential measure seems to be meta-models [44]. They are surrogate models developed by Regressions [45], Artificial Neutral Networks [46], etc..They are able to evaluate instantly (< 0.1 s [47]), provide distribution estimates [21] of the performance space. Meta-models have been developed to reproduce samples instantly to remedy the problem that the number of remaining options is small after steps of filtering [1,20,21,46].

4.3.2. Use proper optimization algorithms to position the optimal design space fast. With the quantitative requirements, like energy consumption and GHG emissions, getting more stricter, it is critical to first focus on optimal or at least near-optimal space. For multi-objective optimization, Si et al. have tested the ability of several automated optimization algorithms and concluded that NSGA Ⅱ performs the best and are capable of heuristically searching the global design space and generate "optimal" space - Pareto Frontiers. On the other hand, the speed of performance simulation determines largely the efficiency of optimization. In this case, the combination of surrogate models and automated optimization algorithms are preferred. Compared with exploring the global design space manually, post exploration in the optimal space is more efficient [9].

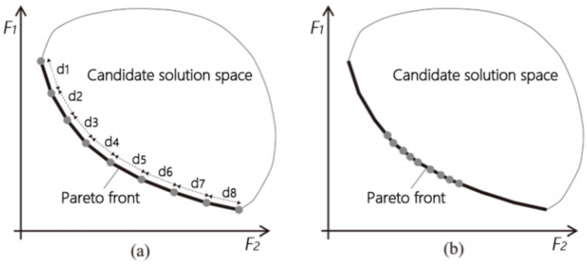

Figure 3. Distributions of Pareto-optimal solutions [50]

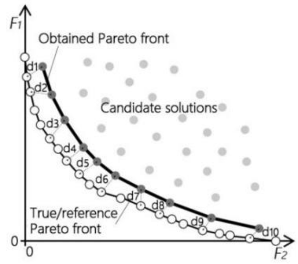

Figure 4. The difference between true and reference Pareto-Fronts [50]

4.3.3. Expand the optimal design space to near-optimal space for solution diversity. Comparison on optimization algorithms conducted by Si et al. [49] showed that the size and distribution of the optimal solution set solved by automated optimization algorithms are always affected by the parameter settings and the inherent ability of the algorithms themselves. Figure 3 [50] shows the possible distributions of Pareto-Fronts and Figure 4 [50] shows that it is the reference instead of true Pareto-Fronts can be solved due to the ability and efficiency of the algorithms themselves. Hence, one should not expect too much from so-called automated and intelligent algorithms.

To avoid numerical centered optimization and the shortage of solution diversity for post exploration, expanding the optimal design space to near-optimal space can preserve more room for qualitative diversity [8,9,50]. For example, Brown et al. have illustrated that 2.5% penalty for the quantitative objective increases 86% of geometric diversity [50]. Hester et al. [21] concluded that 40% design specification is enough to make an excellent decision if influential design variables are specified as early as possible, which indicates that 60% design diversity for qualitative decision-making is possible. That is to say, exercising individual creativity, preference, and values within a near-optimal space can ensure a final solution which is excellent in both quantitative and qualitative performance.

4.3.4. Increase human intervention while taking the advantages of computer. UE and SE methods are inefficient because it takes more than 20 steps generally [20,21]. At the other extreme computer-aided design technologies has directed design space exploration to an numerically optimization-centered process. In this case, human should perform all prioritization and design synthesis while taking advantage of the fast computing and visual feedback [9]. Integrating the advantages of ASPE in optimization, HCIE in interaction and MF in human intervention provides more opportunities to fully explore the global design space.

4.3.5. Visual decision support tools. Three types of visual tools for decision making have been developed. Firstly, tools for performance description, data points [56] or distribution, after every decision. It is self-evident that showing the change of performance distribution with PDF [32], CPD [33] or Scatters Chart [34] is more helpful in understanding the overall change of performance space, compared with performance data points. Secondly, tools for decision making guidance. SA [1,34] helps decision makers focus on the influential variables firstly while Clustering Analysis (CA) [39] and 3D models [38] are so straightforward that can help decision makers filter out unfavorable clusters/options. Thirdly, tools for diversity description of the rest options [9] with the clusters, ranges or frequency [1] of design variables. These tools are characterized by statistical charts as listed in Figure 5. In order to help decision makers understand the high-dimensional "design-performance space", three types of tools are required, whereas they are not fully integrated. In this case, decision makers cannot fully understand the "design-performance space" and make proper decisions. On the other hand, the tools are mainly developed by researchers who participated in concrete construction project. Some of them, like clustering (in Wallacei) [39] and DesignExplorer [38] have been integrated into Grasshopper, while others are not fully integrated into design tools.

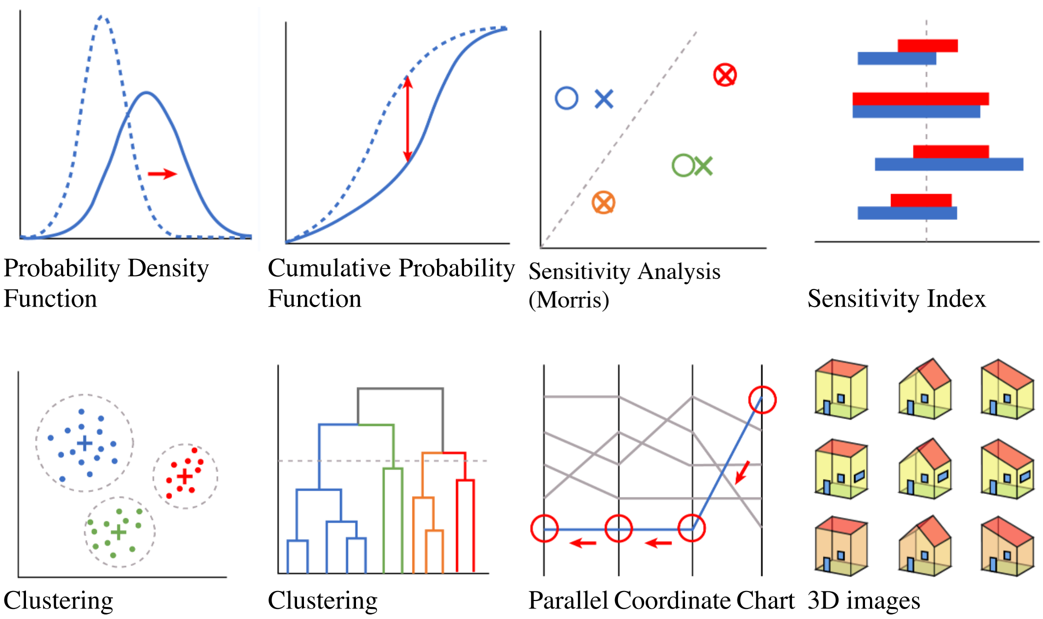

Figure 5. Decision support tools/charts.(drawn by the authors)

5. Discussion and Conclusion

DSE is a complicated design-oriented process aiming to search the final solution which is as close as to the "ideal" solution, within a finite time frame and an "infinite" design space, where both specialists and non-specialists are encouraged to participate. UE and SE is inefficient to suit the huge design space while HCIE require professional knowledge and techniques of computer science. MF and ASPE are most potential methods to deal with the challenges in early architectural design.

To ensure a final solution which fulfills both quantitative and qualitative requirements, (1) surrogate models are recommended to speed up performance simulation because of the advantage of fast calculation; (2) the combination of surrogate models and automated optimization algorithms is needed to position the optimal design space fast; (3) expanding the optimal design space to near optimal space for manual filtering is the best interactive way to integrate stakeholders' preference and values; (4) three types of decision support tools should be integrated to provide better design guidance for designers.

Currently, stakeholders' involvement in design space definition have not been highlighted although research articles pay much attention to create decision making opportunities for all stakeholders. In addition, tools for building performance description, diversity description and decision-making guidance need to be further integrated to assist the process of "ideal" solution exploration.

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