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Integrating the Multi-Functional Space and Long-Span Structure for Sports Arena Design:

A design exploration process based on design optimization and self-organizing map

Wang PAN*, Yimin SUN[a], Michela TURRIN[b], Christian LOUTER[b], Sevil SARIYILDIZ[b]

*South China University of Technology & Delft University of Technology
Building 8, Julianalaan 134, 2628 BL, Delft, the Netherlands
W.Pan-1@tudelft.nl

[a] South China University of Technology,
[b] Delft University of Technology

Abstract

The multi-functional space of sports arena is highly related to the long-span structure. To support the integration of these two aspects, design optimization combining parametric modeling, performance simulations, and searching algorithm can be used. However, optimization is powerful in dealing with quantitative performance, but for some soft requirements on buildings, design exploration of geometries based on the judgments of architects is still necessary. Self-organizing map (SOM), as a model-based clustering algorithm, can be used to support this kind of explorations on geometric typology. Nevertheless, it is difficult to ensure the accuracy of clustering, especially for complex parametric models. To support the design exploration on geometry (besides the exploration on quantitative performance supported by optimization) during the conceptual design of sports arenas, this paper proposed a process based on a versatile and flexible parametric model for sports arenas and self-organizing map (SOM). Within this process, to increase the accuracy of SOM clustering, a pre-processing step for the parameters of design alternatives is also proposed. A design of a hypothetic sports arena is used as a case to demonstrate and verify the process.

Keywords: design exploration, self-organizing map (SOM), clustering, parametric modeling, multi-objective optimization (MOO), multi-functional space of sports arenas, long-span structure

1. Introduction

The multi-functional space of sports arena is highly related to the long-span structure. The integration of these two aspects mainly defines the overall geometry of the building and influences some important performances (viewing quality of spectators, acoustics, structural self-weight, etc.) of the building.

To support integrated designs, design optimization, as a design process consisting of parametric modeling, building simulations, and searching algorithm, is used to combine different aspects into the conceptual design phase. Within this process, parametric model associates different aspects into a variable model and generate various design alternatives by changing the values of parameters. Building simulation imitates real condition for the alternatives to obtain the indicating values of related performances. Searching algorithm iteratively selected well-performing solutions according to assessment criteria.

Nevertheless, optimization selects well-performing solutions based on quantitative performances but not soft requirements (e.g. aesthetics). It can lead to a result that the well-performing solutions selected by optimization may not be appreciated by architects, since the geometries of such solutions do not meet some soft requirements. So far, such soft requirements cannot be effectively evaluated by numbers and have to be assessed based on the judgment of human designers (architects). Although some interactive optimizations allow designers to select solutions during optimization process according to their preference [1, 2], the range of selections is still limited, since some design solutions may be outside the searching path and have no chance to be investigated during optimization.

Hence, for conceptual design, besides optimization, it is crucial to explore diverse design alternatives based on geometry. To achieve this, parametric modeling can be used to provide diverse design alternatives for selection, and self-organizing map, as a clustering algorithm, can be used to facilitate designers to explore these alternatives and select preferred solutions according to geometric types.

1.1 Parametric Modelling and Optimization for Sports Arena Design

As mentioned, design optimization combining parametric modeling, building simulations, and searching algorithm is widely used. For sports arena design, a series of works have been done to generate variable seating bowl for stadiums by parametric modeling [3, 4, 5]. Some other works associated the seating bowl with specific roof structures based on parametric modeling [6, 7, 8]. Furthermore, some works do optimization focusing on the performances of structure, energy, daylighting, or ventilation, based on the parametric model with fixed types of geometry [8, 9, 10].

These productive works can be used to support the integrated design of sports arenas efficiently, but there are still some limitations. The geometric types of the design alternatives included in these parametric models are limited and lack of diversity, which constrains the range of design exploration. Furthermore, the optimization based on this kind of parametric models can only select solutions that are similar in geometry, which possibly impedes the finding of well-performing solutions. These processes are suitable for the case that architects have strong ideas for one or several types of geometries in their minds, but for most of the time, architects would like to study diverse geometries at the beginning of design [11]. Hense, it is crucial to provide a flexible and versatile parametric model including design alternatives with diverse geometries.

It worth noting that, even though diverse design alternatives can be provided by a flexible parametric model, optimization may select limited types of them which are well-performing for some quantitative performances. However, architectural design is not a process that only selects the well-performing solutions, but a process that also needs to consider geometry/form and related soft requirements. So far, these aspects cannot be effectively assessed by computers, but have to be judged by human designers. Hence, it is also crucial to provide designers a chance to explore diverse design alternatives (generated by flexible parametric model) based on geometric typology. This requires a tool which can group numerous design alternatives according to their geometries.

1.2 Self-Organizing Map as a Clustering algorithm

To satisfy the proposed requirement, clustering (cluster analysis), as an unsupervised learning process dealing with data partition according to their features, can be used. Generally, clustering can be considered as a process to arrange objects into various groups (clusters) according to the calculation of their data related to specific features, so that the objects within the same cluster should be as similar as possible in the features, while the objects in different cluster should be as different as possible [12, 13]. The similarity/dissimilarity for quantitative objects is defined by distances related to the input data [13]. Various algorithms can be used to achieve clustering in different ways, the classifications and the details of these algorithms can be found in [13].

Among various algorithms for clustering, self-organizing map (SOM), an artificial neural network (ANN) model proposed by Teuvo Kohonen [14], is considered as a model-based algorithm [13]. To cluster the objects, the nodes of the artificial neural net move to and capture different objects iteratively, according to specific functions and regulations, and the objects captured by the same nodes belong to the same clusters. Such process is fulfilled based on a series of steps [15]: (1) Before the iteration, a net is formulated by users to define the number of nodes and the topology of the net; (2) For each iteration, every object is investigated one by one, to find the nearest node based on a distance function. Such node, which is called the Best Matching Unit (BMU), then move to the related object in a distance; (3) The neighbor nodes near the BMU also move with it to the related object. The neighbor nodes are defined by a neighborhood function. (4) The above two steps repeat for each iteration. Simultaneously, the distance, with which the BMUs and their neighbor nodes move to the related objects, reduces gradually as the iteration times increasing. Such reduction of moving distance makes the net transforming largely at the beginning of the process and becoming stable at the end. (5) The process will stop when the iteration time meets the terminal condition.

Comparing to other frequently used clustering algorithms (e.g. k-means, hierarchical clustering), one of the advantages of SOM is that it not only groups similar objects in the same cluster but also gather similar clusters closely and make different clusters being far away on the network (map) [15]. This characteristic of SOM illustrates the distribution of the objects (design alternatives), based on which designers can have a quick glimpse of the data space and select preferred clusters.

Based on this characteristic, SOM has been used for design exploration for architectural conceptual design. For the design exploration based on performance, the input data for SOM clustering are the indicating values of performances, alternatives with similar performances are grouped together [16]. For the design exploration based on geometry, Harding use the parameters related to geometry as the input for clustering, and based on which, diverse design alternatives are well-arranged on a 2D map according to the features of the geometries and colors [17].

For these applications of SOM clustering in design exploration, it worth noting that there is no any pre-process for the input data of the objects (design alternatives). For the design exploration based on performances, since the input data are the values of performance indicators which are considered be independent to each other, there is no problem for the lack of pre-process of input data. For the design exploration based on geometries, the input data are the parameters which define the geometry. If the parametric model is simple and the parameters are not highly interrelated, it is no problem without pre-process of the input data. However, for most of the design practices, parametric models are usually complex. In these models, the parameters are highly interrelated and hierarchical, and some parameters largely impact the geometry than others. Furthermore, for clustering, different scales of the ranges for different parameters also influence the results. Hence, it is not reasonable to treat all the parameters equally in these cases, therefore, effective pre-process for these parameters are necessary to ensure the accuracy of the clustering results.

1.3 Further Requirements

Based on the analyses above, for the current design optimization process and SOM clustering applied to the conceptual design of sports arenas, some further requirements should be satisfied. First, diverse design alternatives are essential for the formulation of good design. Second, explorations for design alternatives based on both quantitative performance and geometry are crucial. Third, for the application of SOM clustering to support the exploration based on geometry, the pre-process of the input parameters is necessary to ensure the accuracy of clustering. To satisfy these requirements, a design exploration process is proposed for sports arena design.

2 Proposed Process

The workflow of the proposed process begins with a proposed versatile and flexible parametric model and the design space formulated by it. Based on the design space, the process divided into two paths (Fig.1). The first path (the upper one in Fig.1), which is based on a conventional multi-objective optimization (MOO), focuses on searching well-performing solutions (according to quantitative requirements) in the whole design space, without consideration of the preference of architects on geometry. The second path focuses on the solutions with preferred geometries, based on the clusters of design alternatives selected by architects in design exploration. Both the two resulting solutions will be finally presented for architects to make the final decision.

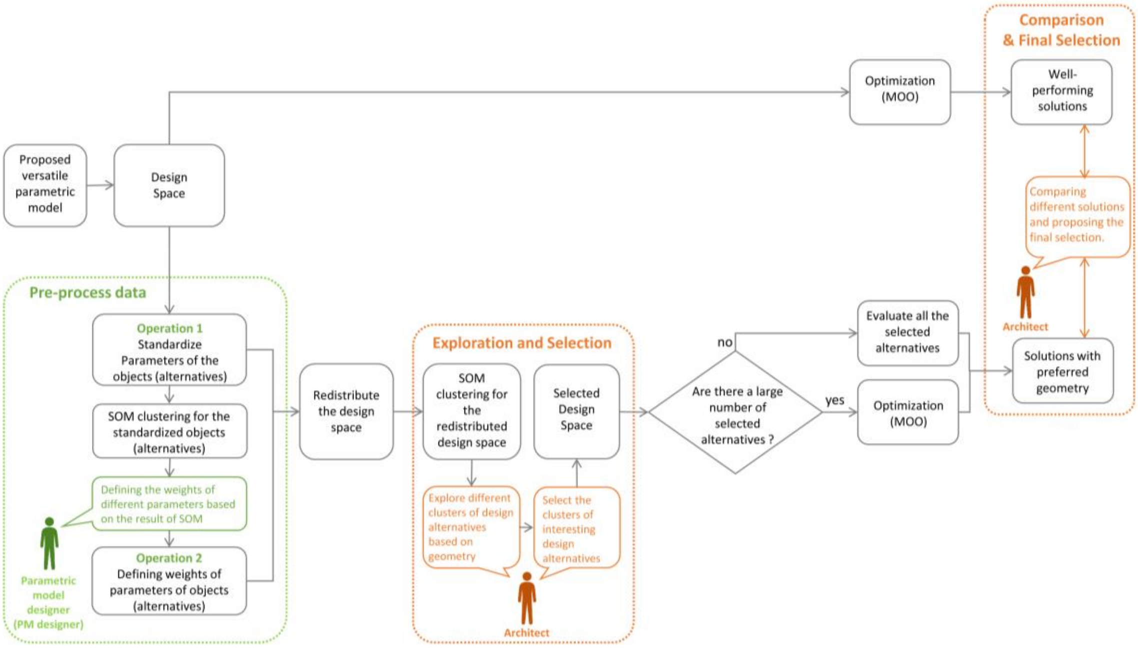


Figure 1: Workflow of the proposed process

For the second path, the exploration of clusters of design alternatives is supported by SOM. To increase the accuracy of clustering, the parameters (which are also the variables for the MOOs) are pre-processed by two operations: standardization and assigning of weights. Then, the pre-processed parameters of all the design alternatives are set as input for SOM clustering. Based on the clustering result, architects can explore various clusters of design alternatives and selected the preferred ones to formulate a 'selected design space'. After that, another MOO is applied to searching for well-performing solutions among the selected alternatives. If the number of selected design alternatives is small, it is also possible to evaluate all of them without MOO.

It both of the paths, the criteria for the MOOs (or MOO and evaluation) should be the same and can be related to various aspects according to design requirements. Specifically, for this paper, the viewing quality of spectators, acoustics, and structural performance are emphasized, to support the integrated design of the multi-functional space and long-span structure in sports arenas.

2.1 A versatile and flexible parametric model for sports arenas

A versatile and flexible parametric model for sports arenas, which combines the multi-functional space and long-span roof structure, has been proposed by the authors and is used as the foundation of this proposed process. This model is composed of three main elements: pitch, seating bowl, and roof structure. The pitch is defined as a box space and its planar outline is used as the inner boundary of the seating bowl, while the outer outline of the seating bowl is a variable curve defined by six parameters. Based on the boundary of the seating bowl, a roof structure with one of the three frequently-used structure types (grid-shell, space-frame, truss-beam) is defined by other six parameters. Based on these parameters, various types of sports arenas can be generated which include most of the possible geometries, but geometries with special design concept (e.g. discreet roof, hybrid structure) are not included.

2.2 Pre-process of data for SOM

2.2.1 Standardization

To eliminate the influence of different scales of variables, standardization is widely used for hierarchical clustering, k-means clustering, etc. in the calculation of the distance between objects in data space. However, for SOM, the clustering of objects is not directly related to the distances between them but related to the distance between neuro nodes and the objects. Hence, the original distribution of the objects in the data space will influence the results. Therefore, the standardization here is used to redistribute the objects in data space, to eliminate the impacts of different scales. For the i^{th} parameters v_i of an object (design alternative), the upper boundary and the lower boundary of the range are v_{i-max} and v_{i-min}, respectively, and the standardized parameters v_i' equals to:

$$v_i' = \frac{v_i - v_{i-min}}{v_{i-max} - v_{i-min}} \quad (1)$$

2.2.2 Defining weights of variables

To adjust the magnitude of the parameters according to their impacts on the geometries, different weights (w_i) are set for the standardized parameters (v_i'), and the weighted parameters (v_i'') equals to:

$$v_i'' = w_i \cdot v_i' \quad (2)$$

However, it is difficult to define the precise impacts of parameters on geometries. One of the possible ways is inviting the parametric model designer (PM designer) who formulated the parametric model to define the weights, since he/she is considered being more familiar with such impacts. Nevertheless, for complex parametric models, this way cannot guarantee accurate weights for parameters.

To overcome this problem, in this paper, a trial-and-error method based on SOM is used to support the PM designer to define the weights. First, the parameters of all the objects (design alternatives) are standardized according to equation (1) and then set as the input for SOM clustering.

To support the designers to define the weights, the results of the clustering are presented in an efficient way (see Fig.2). First, the presentation supports designers to exam the similarity of design alternatives within the clusters. For each cluster on the map, the nearest and the furthest objects (design alternatives) to the node are presented, respectively (see the blue boxes at the bottom of Fig.2). Based on these objects (as references), designers can predict other design alternatives within the cluster (as other alternatives are something between the referenced ones). Additionally, the parallel coordinate charts of all the objects (design alternatives) are also presented to illustrate the similarity within clusters (see the right part of Fig.2).

Furthermore, the presentation of the clustering results also supports designers to exam the similarity for nearby clusters (see the three maps in Fig.2). On the map, the nearest object to each node is placed on the node, since this object is considered as the most representative one of the cluster. The colors of the connections between the nodes indicate the related distances (darker color indicates longer distance). Then designers can exam whether similar clusters are close and different ones are far away.

If there are errors for the similarities (of the design alternatives within clusters and between nearby clusters), the PM designer can adjust the weights of related parameters according to their judgments, and then clustering the weighted objects again to see whether there is any improvement. This trial-and-error step is repeated until the PM designer and architect are satisfied, then the weights of parameters are defined.

2.3 Exploration and selection based on geometric types

Based on the defined weights, the parameters of all the design alternatives of the original design space can be pre-processed according to equations (1) and (2). Then, these pre-processed parameters are used as the input for SOM to cluster all the design alternatives. Based on the investigation for every cluster, architects can explore different geometries and select the preferred clusters. Then the related design alternatives of the preferred clusters are automatically selected to formulate a 'Selected Design Space' (see the bottom part of Fig.2).

If the number of the selected alternatives is too much larger than the total number of alternatives called by optimization, then MOO is used to search well-performing solutions among the preferred alternatives. During the MOO, some clusters of alternatives may totally be eliminated, because of their bad performance. If the number of the selected alternatives are smaller or not too much larger than the total number of alternatives called by optimization, all the alternatives can be evaluated according to the same criteria of the MOO. In this case, all the selected types of geometry can be retained for the final comparison.

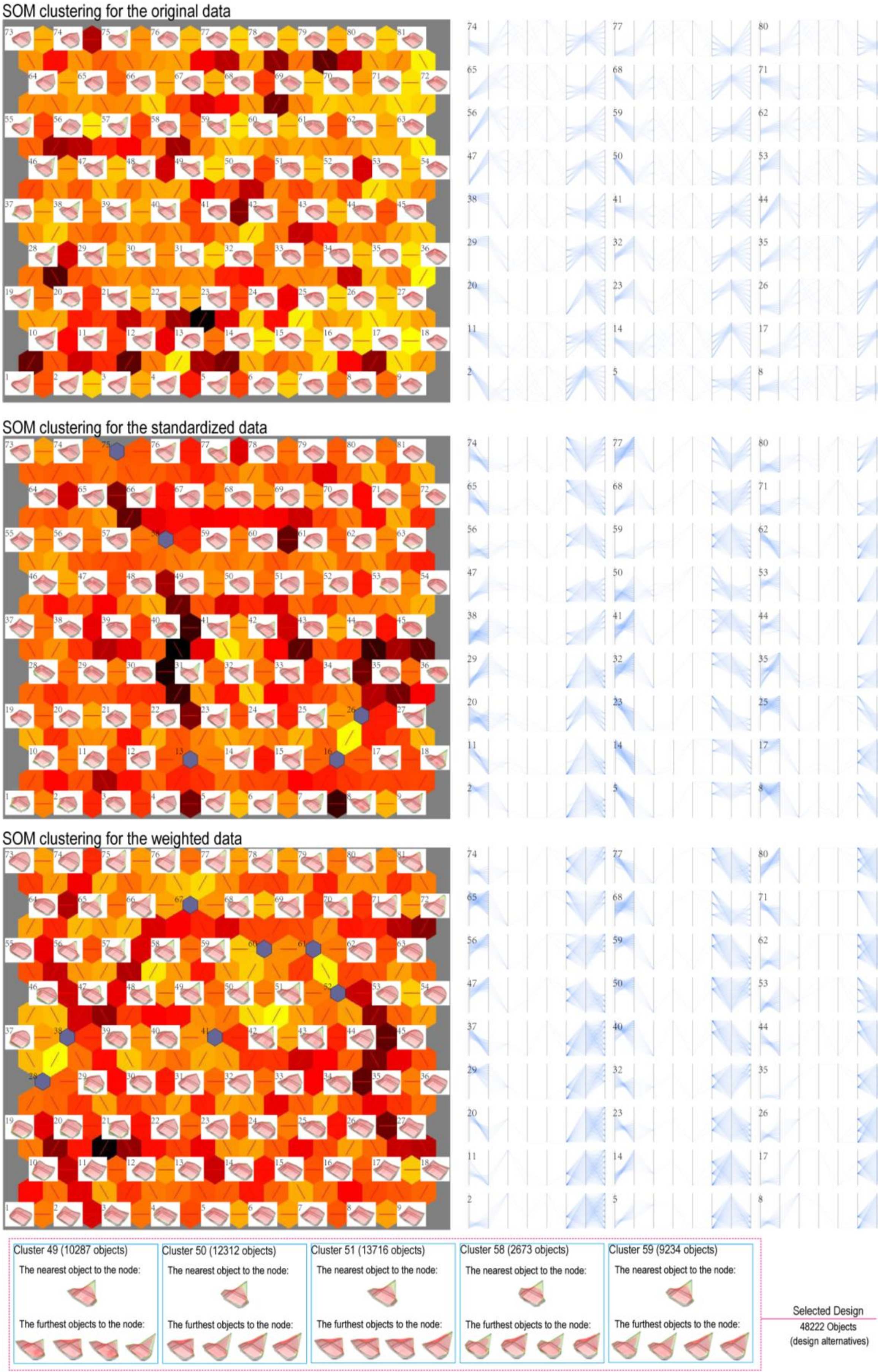
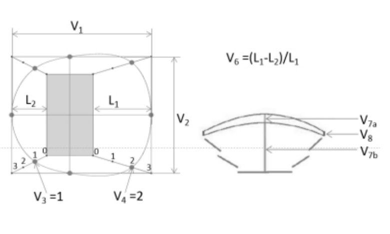


Figure 2: The pre-process of the parameters and the formulation of the selected design space

3 Case study

To demonstrate the proposed process, a design of a hypothetical sports arena is used as a case. The arena is required to able to sever the competitions of ice-hockey, gymnastics, basketball, etc. and stage performance with a side stage and the pitch are set in 40m×70m. The amount of the fixed seats should be around 10,000 (9,500 to 10,500), and 60% - 75% of them should be used for performance stage (should not be behind the stage). Eight parameters related to the overall geometry are selected as the input for SOM and as the variables for MOOs (see table 1). To simplify, only space-frame is selected as the structural type, and its topology is fixed in rectangle grid with the size of 4m × 4m. According to the emphasized aspects mentioned in Section 2, the minimizations of average viewing distance of spectators (Obj.1), reverberation times (Obj.2), and structural self-weight (Obj.3) are set as the objectives of quantitative performance for the MOOs, and the requirements on elemental stress and vertical deflection are set as constraint according to EU codes. NSGAII is selected as the searching algorithm for MOO.

Table 1: Parameters as the input for the SOM clustering and as the variables for the MOOs

	Description		Range	Diagram
V_1	Length of the building		80m - 120m, step 1m	
V_2	Width of the building		15m - 20m, step 1m	
V_3	Corner position of the building outline		0, 1, 2, 3	
V_4	Corner position of the building outline		0, 1, 2, 3	
V_5	Degree of the building outline		1: polyline 2: curve	
V_6	Ratio of Asymmetry		0, 0.2, 0.4, 0.6, 0.8, 1	
V_7	Height of the roof V_7=V_{7a} +V_{7b}	V_{7a}: Clear height for the pitch	18m – 40 m, step 2m	
		V_{7b}: Structure depth in the roof center	2m – 6 m, step 0.5m	
V_8	Structure depth on the roof Boundary		0.8m- 2m, step 0.2m	

The pre-process step for original data is illustrated in Fig 2. In the clustering results of the original design space, it can be found that the clustering is mainly impacted by V_1, V_2, and V_7, since their large scales, which reduces the similarities of objects within clusters. After the standardization of parameters, such similarities are improved but are still not accepted by the PM designer (acted by the first author in this case) and the architect (acted by a colleague of the first author). The similarities between the nearby clusters are not accepted either. Based on the clustering results and the judgment of the PM designer, the weights of V_3, V_4 and V_5 are increased. After a series of trials and errors, the weights of V_3, V_4, and V_5 are set in 2, 1.5, 1.2, respectively, the related clustering results are present in the third row in Fig.2. Although there are still some errors for the similarities, the results are accepted by the architects. Based on the exploration of the clusters of design alternatives, the clusters of 49, 50, 51, 58 and 59 are selected by the architect to formulate the selected design space. Fig 3. illustrates the Pareto solutions and related performance data of the MOOs based on both the original design space and the selected design space, which support the architect to do the final selection.

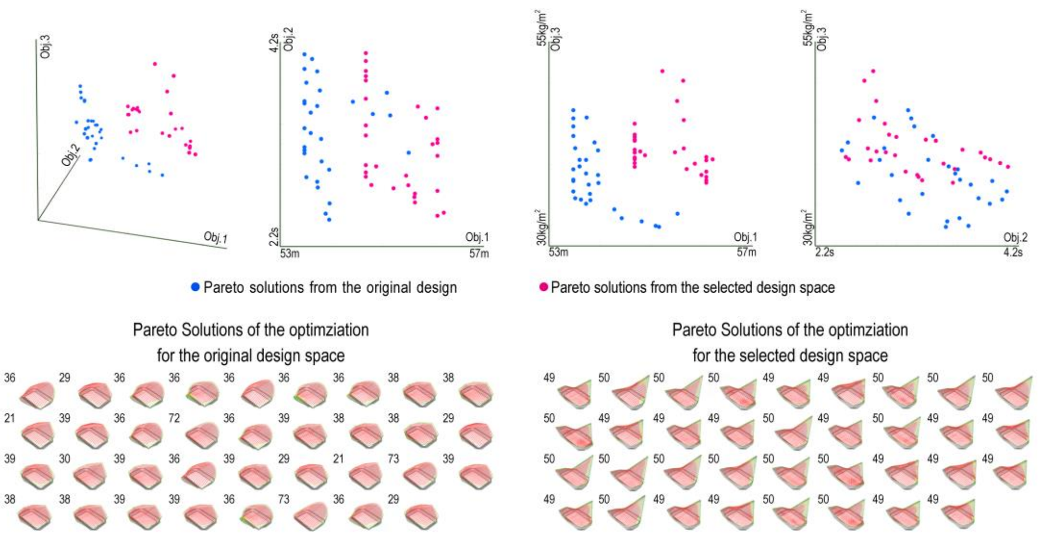


Figure 3: Results of the MOOs for the original design space and the selected design space
(the cluster index of each solution is labeled beside it)

4 Discussion and conclusions

This paper proposed and illustrated a design exploration process based on both design optimization and SOM-clustering, to provide the architects both well-performing solutions and preferred solutions. The pre-process of the original data is emphasized to increase the accuracy of the clustering. Based on the results illustrated in Fig.2, it can be found that the similarity within the clusters and between the nearby clusters are improved by the pre-process. In Fig.3 it can be found all the geometries appreciated by the architect (cluster 49, 50, 51, 58, and 59) are not selected as the well-performing solutions by the MOO based on the original design space, which demonstrates the necessity of this proposed process.

However, for the step of weight defining for parameters, the trial-and-error method is time-consuming and can not guarantee the accuracy of the weights. A smart and automatic method should is necessary, which is one of the future works of our research.

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