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Design exploration of architectural geometries and structural performance for sports arenas based on SOM-clustering and structural performance simulation

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ABSTRACT: Indoor sports arenas are a kind of important public buildings, which require iconic architectural forms and well performing structures for the long-span roofs. Hence, during the early stage of an arena design, it is crucial for designers to define a proper building form based on integrated design exploration of both geometric typology and structural performance. To support such design exploration, this paper proposes a method based on SOM (self-organizing map)-clustering and structural performance simulation as well as SAG (Sports Arena Generator: a specific parametric model for arenas proposed by the authors). This method can support designers to explore designs according to both geometries and performance and also illustrate the relationships between geometric typology and specific performance values, which is crucial for both architectural design and the research about building performance. A hypothetic arena is used as an example to demonstrate and validate the method.

1 INTRODUCTION

Indoor sports arenas are a kind of important public buildings, which usually require iconic architectural forms (as landmark buildings) and also well performing structures for the long-span roofs. Moreover, the overall form and the structural performance of an arena are usually highly interrelated (Pan et al., 2016, 2018). For an indoor arena, the shape of the seating bowl mainly defines the boundary and span of the long-span roof structure. Correspondingly, the geometry of the roof also influences the overall building form and the structural performance. Therefore, during the early stage of an arena design, it is crucial for designers to define a proper building form based on both architectural geometry and structural performance.

The structural performance of a design can be evaluated based on structural performance simulation. However, some soft aspects of architectural geometry (e.g. aesthetics), so far, can be only evaluated based on the judgements and experience of designers, which is a characteristic of architectural design. Hence, during the early design stage, in order to define proper building forms for the following design stages, it is crucial for designers to explore diverse designs according to both architectural geometry and structural performance.

Nowadays, several methods have been used to support design explorations focusing on either performance or geometry. Alternatively, some methods are proposed to support integrated design exploration of both geometry and performance for only a small part of the possible designs. It still lacks a method to support such integrated explorations for numerous possible designs.

1.1 *Performative computational design based on optimization*

Performative computational design, which integrates parametric modelling, building performance simulations, and optimization based on heuristic searching algorithms, can be used to generate numerous designs and search for good ones according to specific performance criteria (Sariyildiz 2012, Gerber 2012, Turrin 2014). In this method, parametric modelling is used to formulate designs based on elements/components and their interrelationships controlled by design parameters, and to generate numerous designs by changing the parameter values (Hudson 2010). Building performance simulations are used to imitate real world conditions for designs to obtain related performance indicators of different aspects including structure, energy, daylighting, HVAC, acoustics, etc. Without doing simulations for all the generated designs (which is usually time-consuming), optimization is used to search for good designs iteratively by a searching algorithm (e.g. genetic algorithm) according to specific criteria about performance.

By using this method, the optimization selects designs only based on the requirements of some hard performance (which can be quantitatively evaluated by simulations), while the soft aspects of the designs have no chance to be evaluated during the optimization. Most of the designs are weeded out during the optimization since they are not good enough in specific performance, which means they usually have no chance to be investigated by designers.

1.2 *Interactive design optimization*

To overcome this problem, interactive optimization is proposed, which allows designers to explore and select a part of designs during the iteration and to control the searching direction of the optimization by changing some operations (von Buelow 2012, Mueller et al. 2015, Harding et al. 2018). Some typical interactive optimization methods are based on genetic algorithm. In these methods, among the designs provided by the current iteration, designers are allowed to explore and select designs to survive or to breed new designs for the next iteration (von Buelow 2012, Harding et al. 2018). Moreover, designers can adjust the operations of breeding (crossover) and mutation (Mueller et al. 2015) to drive the optimization, therefore, to retain their preferred designs or to explore more different design. However, these methods can only explore a part of the generated designs.

1.3 *SOM-based clustering and its application in design explorations*

Clustering or cluster analysis, as an unsupervised learning method, can automatically group objects according to their similarities of specific features (Murphy, 2012). By clustering, the objects within the same clusters (groups) are homogeneous or similar in specific features, while those in different clusters are heterogeneous. The similarities between objects are evaluated by specific similarity function (e.g. Euclidean distance) according to the input data of the objects. Various algorithms, e.g. K-means, hierarchical clustering, SOM (Self-Organizing Map), can be used to fulfill clustering and have been used in architectural design exploration to group designs according to their geometric features (Harding, 2016; Pan et.al, 2018).

Specifically, SOM (Self-Organizing Map), is considered in this paper, since its ability in data visualization. SOM clusters objects by a one-layer artificial neural network. The nodes (neurons) on the network can move to and capture the nearest objects in the data space iteratively, according to specific distance function and regulations. The objects captured by the same nodes belong to the same clusters. Such process is fulfilled based on a series of steps (Kohnen, 1982, 2014): (1) The objects are placed in a p-dimensions data space related to their input parameters (p is the number of parameters for each object). (2) Before the iteration, a neural network is formulated by the users to define the number of nodes and the topology of the net (quadrangle or triangle), and is also placed in the p-dimensions data space. (3) For each iteration, every object is investigated one by one, to find the nearest node of the net based on a distance function (e.g. Euclidean distance). Such a node, which is called the Best Matching Unit (BMU), moves to the related object in a step; (4) The neighbor nodes near the BMU, which are defined by a neighborhood function, also move with the BMU. (5) The above two steps repeat for each iteration. Simultaneously, the step, in which the BMUs and their neighbor nodes move to the related objects, reduces gradually as the iteration times increasing. Such reduction of moving step makes the net transforming largely at the beginning of the process and becoming stable at the end.

After the clustering process, by unfolding the net, the objects/designs are captured by nodes of different clusters. On the net, similar clusters of designs are located closely while the different ones are far away to each other. Therefore, designers can have a quick glimpse of all designs and explore them according to geometric types.

1.4 *Further requirements*

As mentioned above, performative computational design based on optimization can support the design explorations mainly focusing on quantitative performance, while clustering-based exploration can group designs according to their geometric features. Interactive design optimization can support the exploration of both geometry and quantitative performance only for a small part of designs provided by the iterations of optimization. To further meet the requirements of arena designs, this paper proposes a method based on SOM- clustering and structural performance simulations, aims at supporting the design exploration of both architectural geometries and structural performance for numerous proposed designs.

2 PROPOSED METHOD

The proposed method is composed of three parts: a specific parametric model for arenas (SAG) and related structural performance simulation, SOM-clustering, and data visualization (Fig. 1). A specific parametric model for indoor sports arenas, SAG (Sports Arena Generator), has proposed by the authors (Pan et al., 2016, 2018) based on Rhino and Grasshopper and is used in this paper to generate arenas with diverse geometries. The structural simulation fulfilled by Karamba 3D (Preisinger et al., 2014), is used to evaluate the roof structures of the generated designs. SOM- clustering fulfilled by MATLAB, is used to cluster the designs according to geometric features. To support integrated design exploration, the generated designs and the related data (provided by the first two parts) are visualized in a specific approach. The proposed method is applied and verified in a case study in the next section.

2.1 *Parametric model and structural simulation of arena designs*

SAG (Sports Arena Generator), a versatile and flexible parametric model of indoor arenas, has been proposed by the authors (Pan et al., 2016, 2018). This model integrates the multi-functional spaces and long-span roof structures of arenas and is flexible to generate diverse geometries for arenas. This model is composed of three main elements (pitch, seating bowl, and roof structure) according to the spatial composition of arenas. The pitch is defined as a box space enclosed by a seating bowl. The

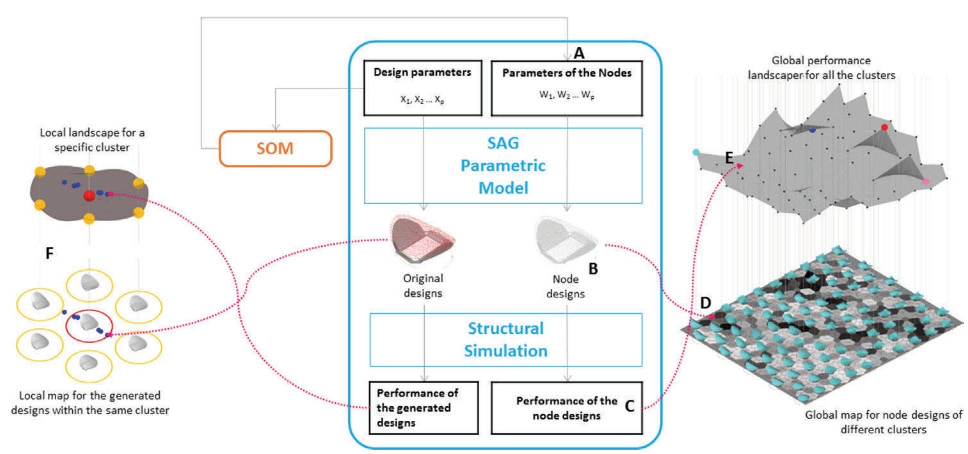


Figure 1. Scheme of the proposed method.

boundary of the seating bowl is a variable curve defined by parameters. Based on the boundary of the seating bowl, a roof structure is defined by other parameters. By changing the values of the parameters, diverse geometries can be generated which include most of the possible forms of arenas. However, geometries with special design concepts (e.g. discreet roof, hybrid structures) are not included.

In this paper, two frequently use indicators, structural weight (SW) and strain energy (SE), are used to evaluate the structures (von Buelow 2012, Chui et al. 2012, Brown et al. 2016). The values of the indicators can be obtained by the structural performance simulation fulfilled by Karamba 3D. A two-layer steel space-frame structure is used for the roof. The topology of the space-frame is fixed in quadrangle (4m×4m). The axes of the structural elements are directly generated by the parametric model. The material can be assigned by designers, and the sectional sizes are optimized by Karamba 3D for each design, according to the constraints of displacements and elemental stresses provided by designers.

2.2 *SOM-clustering for geometric features*

To using SOM-clustering to group all the generated design according to their geometric features, the design parameters of each design are used as the input data for clustering. To eliminate the influences of the parameter ranges, the input parameters are processed by feature scaling according to:

$$x_{ik}' = \frac{x_{ik} - x_{k\ min}}{x_{k\ max} - x_{k\ min}} \quad i = 1,2\ldots n \quad k = 1,2\ldots p \tag{1}$$

where x_{ik} is the k[th] parameter of the i[th] object, n is the total number of the objects, p is the number of the parameters for each object.

During the clustering, the BMU for a specific object is evaluated by the Euclidean distance between them, which is calculated by:

$$D_{j,\ i} = \sqrt{\sum_{k=1}^{p}\left(w_{jk} - x_{ik}\right)} \quad j = 1,2\ldots \mathrm{m} \tag{2}$$

where $D_{j,k}$ is the Euclidean distance between the j[th] node and the i[th] object, w_{jk} is the k[th] parameter of the j[th] node, m is the total number of the nodes.

In this paper, the neighborhood function for clustering is initialized in the value of 3, which means the 3 layers of nodes (neurons) around the BMU in the network will move with the BMU during the early iterations. The values will gradually reduce to 0 within N/2 iterations (N is the total number of the iterations).

After the iterations, the parameters of the nodes, the Euclidean distances between nodes, and the designs/objects grouped to different clusters can be obtained. The nodes usually dose not overlap with certain design/object in the input data space. However, it is also possible to use the parameters of a node (Fig. 1 A) to generate a node design (Fig. 1 B) by the same parametric model and to obtain its performance data (Fig. 1 C) by the simulation. A node design can be considered as the typical design for the cluster to represent other designs.

2.3 *Data visualization for integrated design exploration*

The designs and related data obtained by the first two components are visualized according to the following processes.

First, the node designs, which are typical designs in the clusters, are placed on the node of the network (Fig. 1 D) to generate a ‘global map’. On the map, similar node designs are located closely while different ones are far away to each other, and the colors between the node designs indicate the distances between them (the darker the color is, the longer the distance is).

Designers can explore designs between clusters, which is called 'global exploration'. Based on the performance of the node designs, a performance landscape (Fig. 1 E) can be generated above the global map. Therefore, designers can explore the node designs with related performance. Furthermore, based on the global map and the lasndscape, designers can observe the change of the performance value for different types of geometries. This approach can clearly illustrate the overall relationships between the forms and performance, which is crucial for the design exploration of the early design stage as well as the research of building performance.

Designers can also explore designs within a specific cluster (Fig. 1 F), which is called 'local exploration'. For a specific cluster, the designs of the node (the red ring and dot in Fig. 1 F) and the neighbor nodes (the yellow rings and dots in Fig. 1 F) as well as the original designs in this cluster (represented by the blue dots in Fig. 1 F) are presented by a specific range of the global map (which is called a local map). Correspondingly, a local performance landscape can be generated based on the performance values of these related designs. Therefore, designers can do a local exploration for a group of similar designs, to study the changes of performance led by small changes of geometry

3 CASE STUDY

The design of a hypothetic arena (20,000 fixed-seats) is used as a simple example in this paper. Four design parameters are selected to generate 695 designs. The parameters are written as L (the length of the building), W (the width of the building), E (the edge position of the building outline), and H (the central height of the roof). These parameters are also the inputs for clustering. For the SOM, a triangle lattice network with 10*10 neurons/nodes is used. After the clustering with10,000 iterations, the 695 designs are grouped into 88 clusters. The data of the 88 nodes are used to generated related node designs which are placed in the center of the clusters (Fig. 2 A).

It is worth noting that if each object/design has more than two input parameters (the dimensions of the input data space are more than two) and the topology of the network is triangle, the SOM network is usually a 3D network (Fig. 2 B) when it is fully unfolded (no any twist or torsion). The distances between two nodes are different. One frequently-used method to illustrate the network is still using a 2D map with different colors between nodes to indicate the real distance between

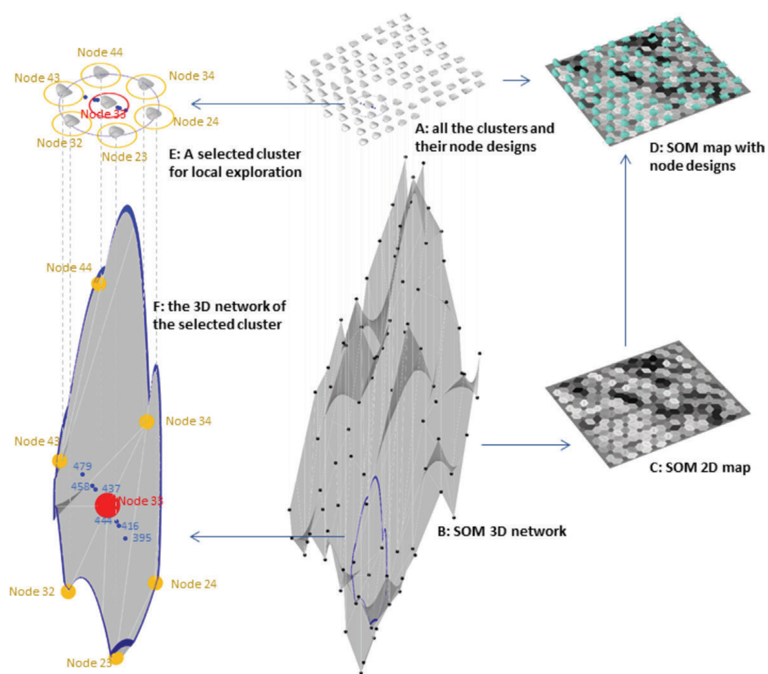


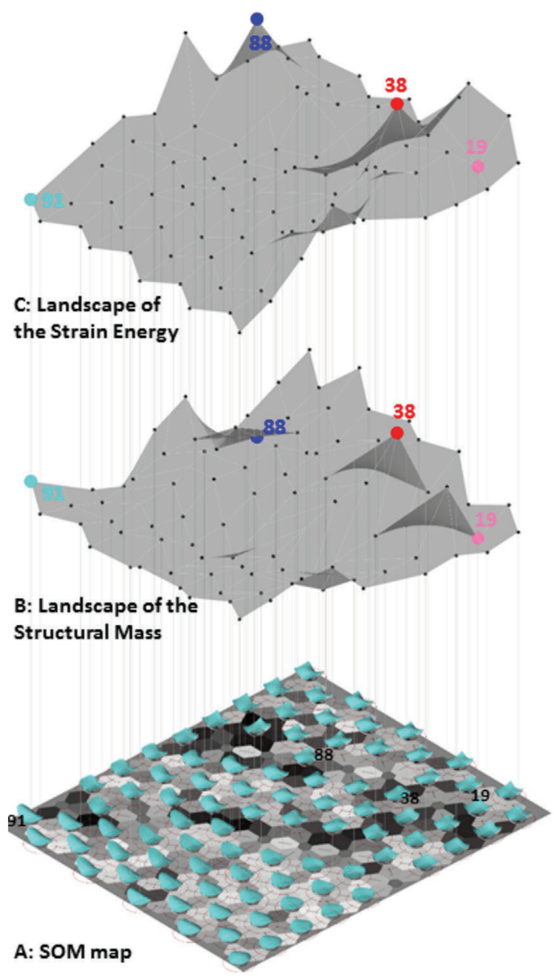
Figure 2. The generation of SOM global and local maps with related designs.

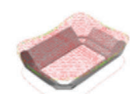
them (Fig. 2 C, D). The darker the color is, the longer the distance is. This method is also used to arrange the objects/designs in each cluster (Fig. 2 E, F)

Based on the 2D map with 88 node designs (Fig. 3 A) and the two performance landscapes (Fig. 3 B, C) generated by the related performance values (SW and SE) of the node designs, the relationships between the geometric types and the performance values are demonstrated. Designers can explore the designs based on both geometric types and relate performance. Four node designs which obtain the extreme values for the two performance indicators are highlighted and presented with the geometries, design parameters, and performance (Fig. 3). Designers can also select other nodes to investigate and compare.

Moreover, designers can also explore designs based on constrains of performance values. An example is demonstrated in Figure 4. The node designs having a structural weight less than 17.5 kg/m^2 and strain energy less than 12.11 kN·m are highlighted. Designers can select specific clusters to investigate.

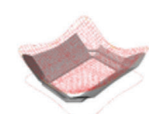
Take the 33rd cluster as an example, which satisfies the constraints mentions above, the designs grouped into the cluster (the blue dots in Fig. 5) and the node design of the cluster (the red ring and dots in Fig. 5) and the neighbor clusters (the yellow ring and dots in Fig. 5) are presented on a local map. The related local landscapes for the performance are also presented above the map. Designers can study each original design according to the geometry and performance.





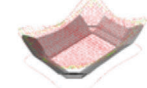
Node 38

L:	87.20	E:	2		SW (kg/m²)	18.93 (max.)
W:	42.40	H:	27.6		SE (KN.m)	116.1



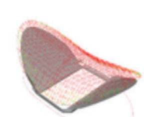
Node 19

L:	98	E:	3		SW (kg/m²)	16.32 (min.)
W:	28	H:	15		SE (KN.m)	45.96



Node 88

L:	82.70	E:	3		SW (kg/m²)	16.92
W:	40.96	H:	22.5		SE (KN.m)	142.4 (max.)



Node 91

L:	163.7	E:	1		SW (kg/m²)	18.19
W:	12.88	H:	45		SE (KN.m)	11.50 (min.)

Figure 3. Global exploration based on the map and performance landscapes.

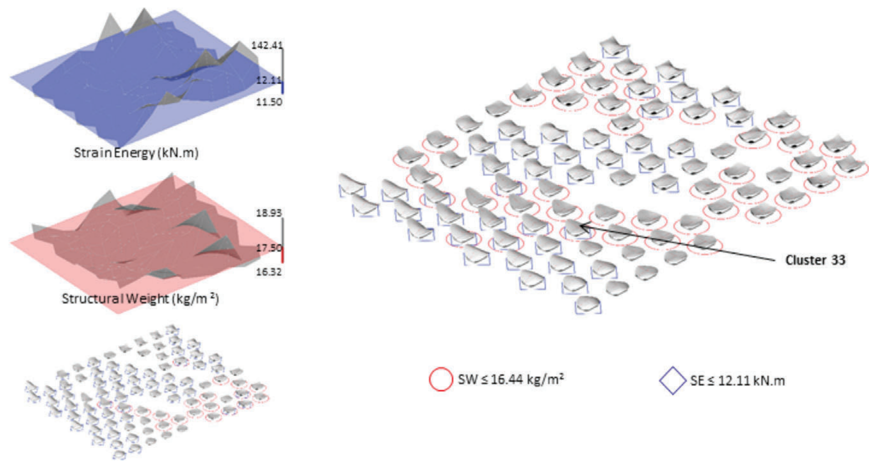


Figure 4. Global exploration based on constraints of performance.

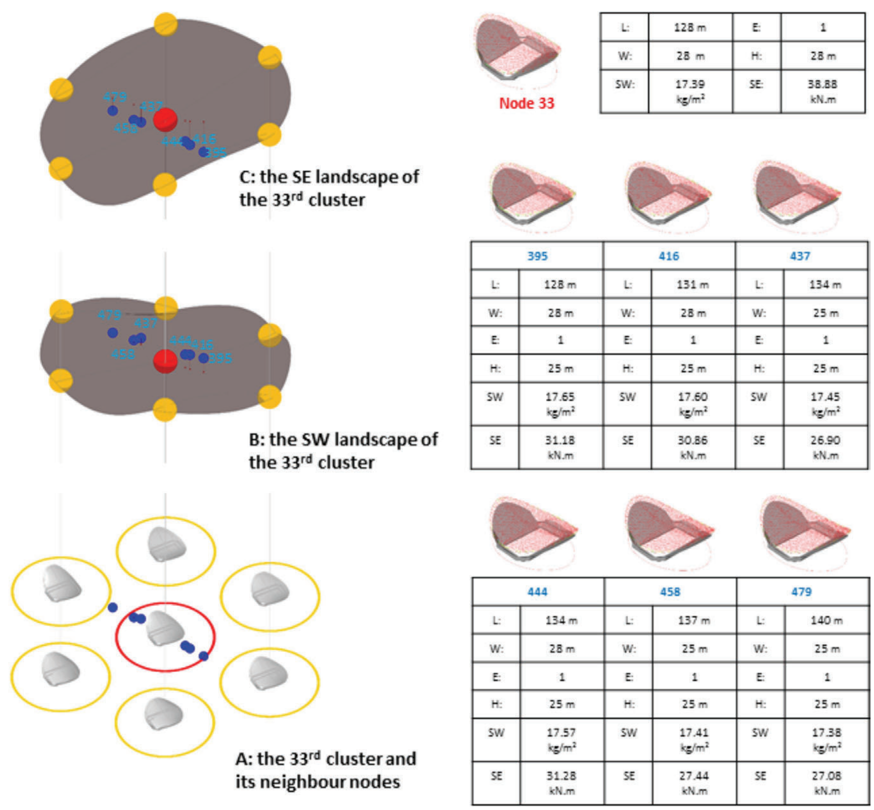


Figure 5. Local exploration.

4 DISCUSSION AND CONCLUSION

This paper proposes a method to support integrated design exploration of both architectural geometries and structural performance, which is crucial for the early design stage of indoor arenas. In the method, based on self-organizing map (SOM), various designs generated by a parametric model can be clustered into different groups according to their geometric features. Moreover, based on the map/network which presents different types of designs, the related performance values are also provided as landscape, which illustrates not only the performance information of different types of designs but also how the performance values change among different geometries. The relationships between geometries and structural performance, which are visualized by the proposed method, is crucial for architectural design as well as the studies of building performance.

To improve the method, the future work will focus on overcoming some limitations of it. Besides the simple example in the case study, some complex and real designs will be used to validate the method. In this paper, the number of generated designs is limited. For some complex designs, more design alternatives need to be investigated. Hence, for these cases, some techniques (like supervised learning) should be used. Furthermore, besides structural performance, more aspects need to be considered for this method. The future work will focus on these points, to improve the proposed method.

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