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COMPUTATIONAL SUPPORT FOR THE GENERATION AND EXPLORATION OF THE DESIGN-PERFORMANCE SPACE

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ABSTRACT

While recent advances in computational building performance modeling have been remarkable, their impact on building design community has been limited. In this paper we focus on one possible contributing factor, i.e., insufficient support for navigation in design-performance space. To address this shortcoming, we concentrate on a process that involves: *i)* generation of alternative building designs, *ii)* performing parametric performance simulations, and *iii)* exploration of the resulting design-performance information space.

MOTIVATION AND BACKGROUND

It is generally believed that the utilization of computational building performance simulation tools can contribute to the improvement of building designs. Accordingly, many such tools have been developed. Yet, their application in (and thus their impact on) the building delivery process has been rather limited. In this paper we focus on one possible contributing factor, i.e., insufficient support for navigation in design-performance space. While many efforts have been invested in algorithms and models that help generate building performance data, much less has been done to support the process of organizing, exploring, and evaluating such data. Some of the past approaches to augment the capabilities of simulation for effective design decision support include optimization, statistical analysis, bi-directional design support, and visualization.

Optimization

Optimization techniques have been proposed to support design decision making. Arguing that "evaluative information" produced by simulation does not help much to produce better-performing designs, optimization techniques offer prescriptive information to the designer. Optimization models work with predefined performance objectives (Radford and Gero 1988). They can, in principle, consider the entire solution field. However, this typically requires that the performance measures are expressed in single criterion form. Since they are prescriptive rather than evaluative, their role is related to synthesizing a design solution rather than evaluating a given solution. It is arguable that a one-time optimization may not be what the designer really desires.

The bi-directional approach

Bi-directional computational design support is another technology toward provision of "active" design support environments. It uses an iterative approach (investigative projection technique) that converges towards a preferable design using a "quasi-greedy" procedure (Mahdavi 1993, Mahdavi and Berberidou-Kallivoka 1993, 1994, Mahdavi et al. 1997). It aims at design refinement using optimization techniques "locally" to proceed from one design state to another based on objective functions, preferences, and constraints relevant to the current design state. Bi-directional computational support enables the users to make desired changes in performance variables and observe the corresponding changes in design variables. A preference-based approach is used to overcome the ambiguity problem of performance-to-design mapping. In this approach, various internal and external constraints such as building codes, contextual parameters, technological limitations, and user's preferences are formalized. The main shortcoming of the bi-directional approach is its limited scalability, particularly in view of complex configurational aspects of buildings (Mahdavi et al. 1997).

Regression analysis

Another approach for design decision support is the development of regression analysis models. In these techniques the relationships between different variables are established mathematically using, for example, a least squares approach (Sullivan et al. 1985). By defining these relationships a better understanding of the effects of design input parameters on the resulting performance attribute is realized (Lam and Hui 1996). Although statistical analysis techniques are useful in identifying the significance of each design variable, they do not necessarily offer an environment that allows for the effective comparison of the performance implications of various design decisions.

Visualization

The vast amount of performance data produced by simulation tools can reduce the effectiveness of building performance analysis in the context of the design process. Post-processing this data into expressive (e.g. graphical) formats needs a sort of expertise most designers lack. Integration of visualization tools into simulation environments allows for the representation of performance data in the form of charts and graphs automatically after the simulation. However, visualization is as such insufficient for effective decision making. There have been some efforts to integrate multiple performance simulation tools with a visualization environment for the graphic representation and comparison of performance data. However, such environments are often grounded on simplistic views of both buildings and their performance. Moreover, they do not effectively support the understanding of the performance implications of multiple changes in design.

In summary, while methods and tools are available for "generic" visualization and statistical analysis of engineering data, there is a glaring lack of an effective and exciting computational environment to generate, view, and evaluate building performance information. Current simulation environments do not support rapid generation of alternative designs for simulation. They are not equipped with mechanisms to allow parametric simulation of a design. Furthermore, even if a user would generate alternatives and simulate them parametrically, the environments still fail to support comparative and explorative navigation through the generated result space. These deficiencies in simulation environments are believed to hinder their wide usage for design improvement. Overall, the efforts to augment the simulation to improve design decision making support have not been very successful. The few attempts toward the provision of such support are mostly limited and hardly scalable.

OVERVIEW OF THE PROPOSED GSN-SUPPORT SYSTEM

To address the previously discussed shortcomings of the current simulation environments, we concentrate on the "GSN" process (generate-simulate-navigate) involving: *i)* generation of alternative building designs, *ii)* performing parametric performance simulations, and *iii)* exploration of the resulting design-performance information space. The nature of our current GSN support system proposal can be best described following a typical system operation sequence:

a) The initial design is entered into the system by the user.

b) Design alternatives are generated, either by the user, or by the system. In the latter case, two approaches have been considered. The first approach uses a rule-based system to geometrically modify the initial design. The second approach relies only on scalarization of the design variables. The scalarization leads to the representation of a building as point in an *n*-dimensional design space. Each coordinate of such a space accommodates a salient (either semantic or geometric) design variable. Examples of such variables are relative compactness, relative aperture area, volume-related thermal mass, and area-weighted thermal transmittance.

c) The entire corpus of design alternatives is subjected to (possibly multi-disciplinary) performance modeling. Such modeling may either rely on detailed numerical simulation (in case alternatives are geometrically specified) or use alternative methods that are based on heuristic knowledge, statistical analysis, or neural network copies of simulation programs (in case design alternatives are specified in terms of scalarized indicators of the geometric properties of the building).

d) Based on the modeling results, an *n*-dimensional design-performance space is constructed.

e) User can navigate through the design-performance space using computational visualization tools.

f) Preferred designs in the design-performance space are mapped back to geometrically specified designs. This reverse-mapping may be performed by the user, or via a rule-based system.

THE GENERATION OF ALTERNATIVE DESIGNS

Once the initial design is communicated to the system, it is exposed to a systematic alternative design generation by manipulating its various components which have impact on the resulting performance measures. This alternative design generation can be done either by the user or by the system. In the case of a design generation by the system, two approaches are possible. The first approach is a rule-based system to geometrically modify the initial design. The second approach utilizes the scalarization of the design variables.

The "geometric" approach to design generation

In this approach, there can be two ways of manipulating a building design to generate alternatives. The first one is a detailed (geometric) manipulation, whereby the initial building design can be used as the base case for geometric derivations. In order to achieve the direct manipulation of design geometry, rules are needed.

A recent work done in this area is the development of a representation that allows rapid manipulation of geometric and semantic building information (Suter 1999). In this representation partitioning and refinement rules are applied to geometric entities (structured in entity hierarchies) in order to manipulate the geometric information. Furthermore, dimension and offset constraints are defined which allow the user to control the manipulation. The attachment of semantic information to geometric entities are realized via attribute manipulation rules. It is envisioned that the modifications to the design can be achieved rapidly and consistently with the utilization of this representation.

The second way of manipulation is based on a volume-equivalent representation of the building. In this case, the building geometry can be simplified into a volume-equivalent mass (Figure 1) similar to a representation used in Balcomb 1997.

The parametric geometric changes are then made in the latter (simplified) representation. These manipulations of the simplified representation can also be realized via rules and constraints similar to those developed by Suter 1999.

The "scalarized" approach to design generation

The "scalarized" approach to alternative design generation is based on the scalarization of the design variables. This results in the representation of the design as a point in an n-dimensional space. From the performance simulation point of view, each aspect of a building forms a variable that affects the resulting performance attributes (Figure 2).

A parametric simulation of a building will produce the data to form an n-dimensional design-performance information space. In order to create this space, the design variables must be defined in terms of scalar values. The selection of the essential design variables and their definition in numeric terms is a critical part of this research. Various candidate design variables are tested for their "expressive" potential and the most expressive ones are used during the alternative design generation.

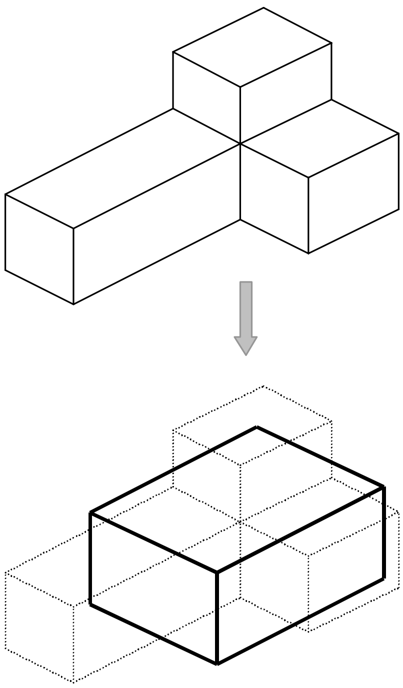
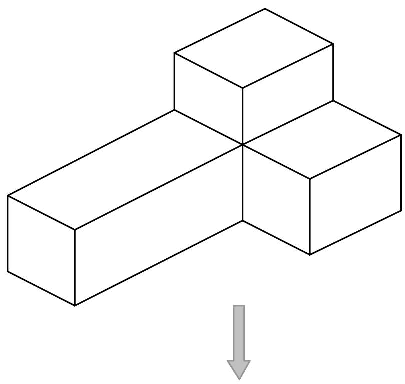


Figure 1. Abstraction of the building geometry into a volume-equivalent mass



Variable	Value
Variable1	V_1
Variable2	V_2
Variable3	V_3

Figure 2. Scalarization of building design

DESIGN VARIABLES

Building design variables capture either geometric or non-geometric (semantic) information on the building. Table 1 lists a few examples of common semantic design variables.

While most semantic design variables are scalar in nature, geometric design information is more difficult to express in terms of scalar values. Some familiar scalar indicators of building geometry are: The ratio of a building's length to its width (plan aspect ratio), the floor-to-floor height, the ratio of a space's height to its depth, the ratio of glazing area to the facade area, and the ratio of the glazing area to floor area (for rooms).

Table 1: Commonly used non-geometric design variables

Non-geometric design variables	**Unit**
U	$W \cdot m^{-2} \cdot K^{-1}$
Thermal Mass	$kg \cdot m^{-2}$
Shading Coefficient	-
Visible Transmittance	-
Internal Loads	$W \cdot m^{-2}$

One important ongoing effort within the framework of the present research is to develop improved aggregate descriptors of building geometry. The design variable "relative compactness" is one of the preliminary results of this effort. It utilizes the relation between a building's volume and total surface (enclosure) area. A similar relationship has been established as the characteristic length ($l_c = V \cdot A^{-1}$ [m]) which is simply the ratio of a building's volume (V) to its envelope area (A). The characteristic length was used, for example, in LEK-diagram (Line of European K-values) which established a relationship between the mean heat transfer coefficient of the building envelope and building geometry (Mahdavi et al. 1996).

In another effort toward numeric characterization of building shapes, the relation between volume and area is explored as related to building's fabric heat loss (Markus and Morris 1980). Utilizing the standard formula for steady-state building heat loss calculations, this research established the following relationship between (transmission and ventilation) heat loss (Q in $W \cdot m^{-3} \cdot K^{-1}$) and building geometry:

$$Q = \sum(A \cdot U) \cdot V^{-1} + n \cdot 3^{-1} \qquad \textit{(Eq. 1)}$$

where,

n = number of air changes per hour

For rectangular buildings, the ratio of surface area to volume is established by using the height (H), length (L) and width (W) variables of the building. The ratio of surface area to volume is given by:

$$A \cdot V^{-1} = 2 \cdot H^{-1} \cdot \gamma \qquad \textit{(Eq. 2)}$$

where,

$\gamma = ((1 + \beta) \cdot \alpha^{-1} \cdot \beta^{-1}) + 1$

$\alpha = W \cdot H^{-1}$

$\beta = L \cdot W^{-1}$.

In order to compare the surface area to volume ratios of buildings with different shapes, the volumes must be equal. It has been stated that cube has the least surface area to volume ratio as compared to other shapes with the same volume (Markus and Morris 1980). Therefore, the ratio of change (ROC) for the comparison of different building shapes has been derived by using cube as the reference. The ratio of change has been calculated by comparing the surface area to volume ratio of a building to that of a cube with the same volume:

$$ROC = \gamma \cdot 3^{-1} \cdot (\alpha^2 \cdot \beta)^{1/3} \qquad \textit{(Eq. 3)}$$

This ratio is independent of the actual size of the building and allows thus for the comparison of different building shapes.

In an effort to develop better aggregate descriptors of building geometry, we used the concepts of characteristic length and the ratio of change to derive the geometric variable "relative compactness". The measure of relative compactness of a shape is derived by comparing the volume to surface area ratio of a shape to that of the most compact shape with the same volume. The most compact shape in geometry is sphere, therefore, when the volume to surface area ratio of another shape is compared with the sphere's, the following relationship can be established:

$$RC_{sphere} \cong 4.84 \times V^{2/3} \cdot A^{-1} \qquad \textit{(Eq. 4)}$$

Even though the sphere is the most compact shape, it is perhaps not the ideal reference, as most buildings have orthogonal polyhedronal shapes. Cube is the most compact polyhedron. Using cube as the reference shape, we obtain:

$$RC_{cube} = 6 \times V^{2/3} \cdot A^{-1} \qquad \textit{(Eq. 5)}$$

Relational and contextual variables

The relational and contextual variables of a design also affect the way it performs. The contextual variables are the ones related with the surrounding environment's properties. The relational variables specify the connection between the design and its context. The orientation of a building within a site is perhaps the most common relational variable. It defines how the building is exposed to outside environment. The relative height of the ground floor of a building is another example of a relational variable. The relational variables can be integrated into design variables.

Climate is the major contextual variable affecting the behavior of a building. Even though it is not a design variable in control of the designer, defining it in single numbers and using it during the alternative design generation could be of interest.

Traditionally, the most common single-number descriptors of thermally relevant climatic conditions are heating and cooling degree days. A step towards aggregating these is the ratio of heating to cooling degree days. More elaborate yet compact numeric methods for characterizations of the climatic context typically involve the application of fourier analysis to measured outdoor environmental parameters. The elevation and density of the surrounding buildings and vegetation, and the topographical properties of the site constitute further contextual variables.

SIMULATION OF DESIGN ALTERNATIVES

The generated design alternatives are subjected to performance modeling. For the "geometric" approach, the performance modeling is a detailed numerical simulation of the generated design alternatives. Whereas the "scalarized" approach requires the use of alternative methods that are based on heuristic knowledge, statistical analysis, or neural network copies of simulation programs. Among these alternative methods to numerical simulation an artificial neural network model is considered for further evaluation.

Artificial neural networks belong to the same general category of statistical tools as generalized nonlinear regression models. They are used primarily for function estimation, complex curve fitting, and pattern recognition. One advantage of neural networks is that the framework that they provide makes no assumption about the underlying data. In neural network modeling, a mathematical model that represents the relationship between design variables and the performance attributes is constructed. Sample data is needed to generate this model. In order to obtain the sample data, parametric performance analysis should be applied to a design. A number of simulations are needed to represent a broad solution field.

The first prototype of the proposed system focuses on typical residential building designs. Thus, a sample of such buildings are selected. These base case buildings are used for extensive parametric analysis. The obtained data is then used to generate a mathematical building performance model. In neural network modeling, a portion of the data can be used to train the neural network while the rest is used to test the accuracy of the model.

It is envisioned that a series of these mathematical models would be constructed in order to cover a reasonably wide range of possible designs. These models can be categorized according to one or more parameters. Climate is one possible contextual parameter that the mathematical model categorization can be based on. Another contextual parameter is the site and the surrounding environment. Building size may also provide a basis for model grouping.

The multi-aspect building performance simulation system SEMPER (Mahdavi 1999) is used as the simulation environment. NODEM (Mahdavi and Mathew 1995), the energy analysis module of SEMPER, is the simulation application selected for the first prototype.

CONSTRUCTION AND EXPLORATION OF THE DESIGN-PERFORMANCE SPACE

To generate the design-performance space, the performance attributes must also be expressed as single values. In case aggregate performance indicators are not generated automatically by the simulation program, data must be aggregated via appropriate post-processing. Examples of thermal performance indicators are shown in Table 2.

The design-performance space can be constructed based on discretized design variables and performance indicators. This is an n-dimensional virtual space, where n = d + p (d = the number of discrete design variables, p = the number of discrete performance indicators). It can be visualized and explored using advanced data visualization tools. Thus, the designer can visualize various views of the solution space and is able to understand the relationship between design variables and corresponding performance attributes. By visually marking the initial design's performance value in the design-performance "landscape", the designer can easily understand where the initial design stands within the overall space. Besides, he/she can explore possible design alternatives to improve the performance of the initial design. Advanced representation techniques can help to visualize certain tendencies within and relations amongst data.

As the final step, the preferred design(s) (as localized in the n-dimensional design-performance space) could be mapped back to topologically specified designs. This reverse mapping can be achieved by the user. In this case, the values of the design variables of preferable designs would provide the informational basis for the modification of the design's configuration and properties.

Table 2: Examples of thermal performance indicators and their units

Performance indicator	Unit
Annual loads (heating, cooling, electricity)	*kWh*
Peak loads	*kW*
Peak temperature	^oC
Temperature Deviation Factor (TDF)	-
Thermal comfort indices (PMV and PPD)	-, %

An alternative to this manual mapping is an automated reverse mapping mechanism. Here, the selected result is mapped back to design via a rule-based system. Rules and constraints which have been envisioned to generate alternative designs (Suter 1999), may provide a basis for this approach.

AN ILLUSTRATIVE EXAMPLE

For the purpose of a simple demonstration, the following case explores the neural network model generation option using sample data obtained from several parametric simulations of a base building (cp. Figure 3).

This base building has a 54 m^2 floor area and its height is 3 meters. It consists of 3 spaces. The windows are located on north and south sides of the building. The glazing is distributed evenly on both facades with three windows located symmetrically on each. The total facade area is 90 m^2 and the total percentage of glazing on the facade is 10%. (In this specific case study, the glazing type is fixed and thus, not subject to parametric variations). The U-value of the external wall construction is 0.5 $W \cdot m^{-2} \cdot K^{-1}$. The ground slab is 6 cm thick. The air exchange rate is assumed to be 0.7.

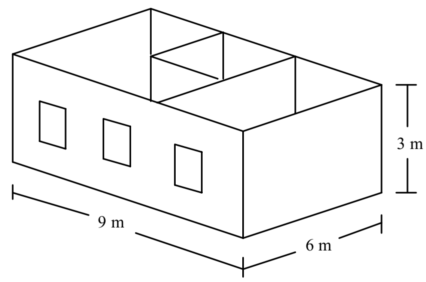


Figure 3. The base building

The design variables used to generate design alternatives are percentage glazing, U-value of the walls, and slab thickness. The values assigned for these design variables are listed in Table 3. Each design variable has been altered individually while keeping the other variables constant.

Table 3: The design variables and their values used in parametric simulations

Design variable	Value		
Glazing %	10	25	40
U-value ($W \cdot m^{-2} \cdot K^{-1}$)	0.2	0.5	1
Slab thickness (*cm*)	6	15	30

Two performance indicators were used for performance analysis. These are the annual heating load in $kWh \cdot m^{-2}$ and temperature deviation factor TDF (cp. Mahdavi et al. 1997):

$$TDF = \left[\sum_{i=1}^{n} (t_i - t_{sp})^2 \cdot n^{-1} \right]^{1/2} \qquad \text{(Eq. 6)}$$

where,

t_i = average indoor temperature at time step i.

t_{sp} = target indoor temperature.

The energy simulation program (NODEM) was used for the parametric simulation of the building. The generated design alternatives were simulated for Pittsburgh's climate. The annual heating load was calculated by the simulation program. The individual cell temperature data were aggregated to obtain the temperature deviation factor (TDF).

For the neural network modeling a commercially available computer simulated neural network (Braincel™) was used. The neural net was trained with the sample data until an acceptable error range was reached. The trained neural net was also tested on data which it wasn't trained. The results obtained from the neural net were compared with the simulation results and were found to be close. After obtaining the weights for the nodes of the neural net, the mathematical model was constructed by utilizing the scaling and activation functions in Braincel™. The whole design-performance space was constructed using this mathematical model.

This enriched design-performance data was visualized in a three dimensional surface graph where the two design variables, U-value of walls and slab thickness, are plotted against the performance attributes, annual heating load and TDF. The third variable, percentage glazing, can be used for active manipulation by the user. The user can change this variable's value and observe changes in the surface plot. Thus, all the design variables are actively explored by the user. Two instances (for 10% glazing and 30% glazing) of the surface plot for annual heating load are visualized in Figure 4. Another instance (surface plot for TDF) is illustrated in Figure 5.

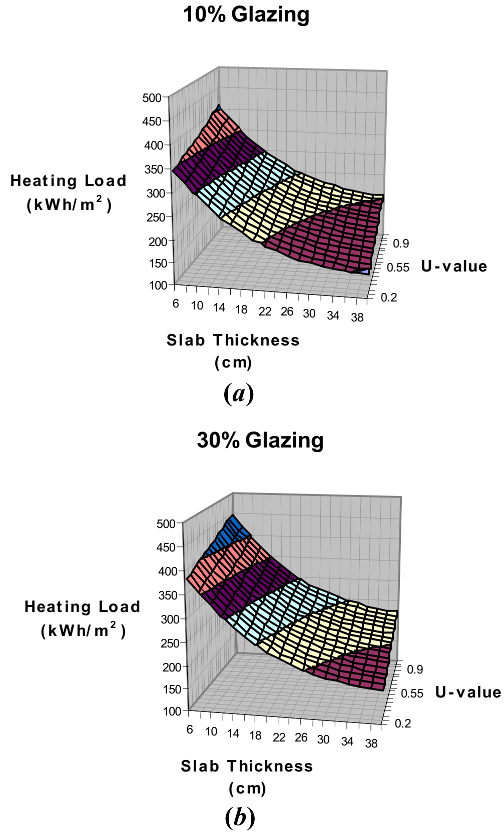


Figure 4. Surface plots for slab thickness and U-value, versus heating load (a) 10% glazing, (b) 30% glazing

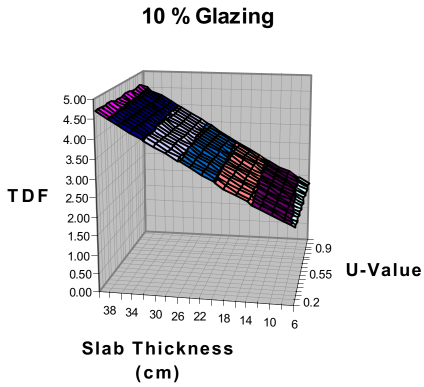


Figure 5. Surface plot for slab thickness and U-value, versus TDF (10% glazing)

CONCLUSION

The prototypical realization of a GSN support system was presented. The system allows for the rapid generation of alternative designs, parametric simulations, and navigation through the resulting design-performance information space. The research provides novel methods to capture geometric building information in terms of dimensions of a virtual design-performance space. Moreover, it demonstrates that it is possible to enrich building performance analysis by integration of parametric analysis and alternative design generation in computational building performance simulation environments.

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