THE APPLICATION OF INVERSE APPROACH TO THE EARLY STAGE OF PERFORMANCE-BASED BUILDING DESIGN

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ABSTRACT
The early stage of design is characterized by iteration of divergent phases in which design alternatives are generated and convergent phases in which alternatives are assessed and selected. It is during or at the end of these phases that decision-making occurs under considerable uncertainty. Therefore, the methods and tools applied during these phases should account for the iterative, complex, and uncertain characteristics of the design process. At present, the building industry lacks a consistent approach to decision making during the phases of the early stage of design. This study reports on an early attempt to develop a systematic method for generation and evaluation of design alternatives. Using linear inverse modelling, the method combines the divergent and convergent phases of design process in a way that generates a plausible range for the design parameters that will lead to a higher probability of better energy performance, which is represented here through a case study.

INTRODUCTION
A large portion of a country’s energy demand, global climate change and depletion of fossil fuel stock is associated with the built environment and buildings. The architecture, engineering and construction community has been seeking to take appropriate actions to reduce energy consumption while fulfilling the expectations relating to human comfort, health and environmental protection (J. L. M. Hensen & Lamberts, 2011). Fulfilling these requirements simultaneously is a difficult responsibility in building design process, particularly when these requirements should be accounted for from the earlier stages of design (Augenbroe, 1992), (Struck, de Wilde, Hopfe, & Hensen, 2009). The early stage of the design process is a vital phase of the development process due to its influence on all subsequent phases with regards to cost, quality and performance of the end product (Chong, Chen, & Leong, 2009). A poor selection of a design concept can rarely be compensated at later design stages and incurs a great redesign expense (Okudan & Tauhid, 2008).

Despite the importance, considering performance requirements at the building design stage embodies a complex decision-making task involving interdependences among variables which makes it difficult to elicit meaningful design guidance (Papamichael, LaPorta, & Chauvet, 1997). Different design strategies have been practiced and a large number of simulation tools have been developed to assist designer in their performance-based decision-making at the earlier stages. However, designers still request appropriate design decision support method and tool for the early stage of design, when many design parameters have not been decided upon. They look for a proper decision making framework that leads them toward reasonable performance, gives them enough confidence in their decisions, and integrates more aspects of performance into the design process.

In order to evaluate the current performance-based approach and design frameworks at the early stage of building design, we first investigate the nature of the design process as independent from the nature of the design output, by defining conceptual design and its components in the next sections, followed by an overview of the problems designers encounter in performance-based building design. Then a novel approach based on linear inverse modelling is proposed that can generate a plausible range for design parameters given the preferred thermal energy performance at the early stage of architectural design and the implementation of such method is represented through a case study.

Conceptual Design Phase
Horváth (Horváth, 2005) defines design process as "an iterative search process in which designers gather, generate, represent, transform, manipulate, and communicate information and knowledge related to various domains of design concepts". A principal aim of early design development, therefore, is the generation of promising concepts, to be further developed and revised in the embodiment and detailed design phase (Okudan & Tauhid, 2008). In this incremental practicing and learning process, it is impossible to develop a proper solution in one shot. Instead, according to Liu et al. (Liu, Chakrabarti, & Bligh, 2003) this phase of design consists of a series of divergent and convergent steps as:

• Divergent steps consist of generating concept alternatives.
• **Convergent steps** relate to evaluation and selection of the best concepts among the proposed alternatives.

**Divergence Phase in Conceptual Design Process**

The goal of divergent steps is to develop promising concepts in order to increase the possibility of producing better artifacts (Chakrabarti & Bligh, 1996). This requires generating a wide range of concepts to prevent disregarding valuable ones. Often designers implicitly discard infeasible solutions based on their experience, particularly at a more abstract level of solutions. However, many valuable alternatives might be discarded because of the subjective constraints intuitively implemented by designers.

**Convergence Phase of Conceptual Design**

The convergent process, which consists of concept design evaluation and concept selection, identifies the alternatives that best fulfill the decision-making criteria. The importance of this step is apparent, because a poor selection of a design concept can rarely be compensated at later design stages and incurs a great redesign expense (Okudan & Tauhid, 2008). The assessment strategies used by designers range from none to advanced. While some designers still rely on their experiences to evaluate various generated design alternatives, others tend to use goal-oriented strategies involving computer software simulation to assess and select the alternative that fulfills its performance objective.

There are common general frameworks for concept selection or concept ranking in order to identify the best alternatives. They range from simple decision matrices, analytical hierarchy process, methods incorporating uncertainties such as fuzzy clustering and utility theory, and also methods based on optimization concepts and heuristics. These decision-making frameworks are different based on the underlying principle used. Yeh (Yeh, 2002) demonstrates that different methods applied for design decision-making result in different final solutions. Thus, the choice of selecting a suitable decision-making method from the pool of methods available in itself is a critical decision (Okudan & Tauhid, 2008).

The two mentioned divergent and convergent phases of a design are repeated for different design parameters laterally, as well as they might be repeated along different levels of abstraction for each parameter, from vague to detailed design vertically, as Liu et al. (Liu et al., 2003) proposed. In this sequential design process of building, one might backtrack at any stage, change the previously decided parameters based on the new requirement.

**PROBLEMS IN ARCHITECTURE DESIGN CONCEPTUAL PHASE**

While there are a large number of well-established practice and methods in other design disciplines, in traditional architectural design processes, there is rarely an integrated and systematic method for design alternatives generation, analysis and selection processes in the early stages. This deficiency pertains to both the divergent and convergent steps of early design process. Regarding the divergent phase, the design option generation (for energy performance) in current practice mostly relies on the designers’ experience and the imprecise design information available (Wang, 2002), which is subject to interpretation based on the knowledge, expertise and insight of the designer alone. Therefore, most design processes are focused only on a relatively narrow range of possibilities, leaving a broad area of the design unexplored (Flager & Haymaker, 2007). The reason for this apparent to:

- Limited design alternative generation due to the restrictions of time and human cognitive; (Josephson et al., 1998), (Liu et al., 2003), (Woodbury & Burrow, 2006).
- Tendency of designers to design in a specific direction; (Darke, 1979), (Austin, Newton, Steele, & Waskett, 2002)

The problem is the same for the convergent phase, which involves the assessment and selection of the most promising alternatives. In order to analyse and select the best candidate option, most AEC practitioners often still use precedent-based design to help resolve design challenges. This traditional approach tends to incorporate measurable criteria only in relatively advanced phases of design instead of earlier phases, to validate a specific design option, rather than explore multiple alternatives. The reasons for the reluctance of designers to use performance-based tools at the earlier stage for energy analysis can be categorized as follow:

- The challenge of complex building design and difficulty of energy performance assessment (Darke, 1979). There are wide ranges and complicated parameters affecting the energy performance of buildings, many of which are out of the scope and expertise of architects.
- The large number of undecided parameters: Owing to the imprecise and incomplete design information available at the early design stage that arises from the large number of parameters that are not decided upon, it is difficult to assess and predict the performance.

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• The unreliable performance prediction related to other uncertainties: the unavoidable uncertainty in performance prediction due to uncertainty in decided-upon parameters such as material properties, scenario of use or other boundary conditions, as well as the inherent imperfection of any model as a representation of reality, lead to uncertainty in outputs and make the deterministic and over-confident prediction questionable (Rezaee, Brown, Augenbroe, & Kim, 2014).

• The multi-criteria nature of the design: Building design is inherently about fulfilling many performance requirements at the same time (Augenbroe, 2011). Multiple criteria often contradict each other; by participation of several decision makers with varying preferences, the analysis and decision-making would get more complicated.

Some researchers have addressed energy-related design procedures using optimization and heuristic algorithms. Welle et al. (Welle, Haymaker, & Rogers, 2011), for instance, developed a methodology for use of thermal simulation in an optimization environment in order to find the best solution for design implementing full design of experiment (DoE). Another line of research by Caldas has proposed a generative design system, using genetic algorithms (GA) combined with lighting and thermal analysis to generate performance-driven designs such as for patio houses (Caldas, 2011) or building façade elements. Turrin, Buelow and Stouffs (Turrin et al., 2011) have implemented the same technique combined with parametric modelling to achieve a performance-oriented process in design, with a specific focus on the building geometry. However, the majority of optimization techniques used such as GA are heuristic procedures that may find solutions for well-defined problems; in the complex, ill-defined nature of the building design process, particularly at the earlier stages of design where many of the parameters have not been determined, it’s questionable if their outcome remains valid after design proceed in un-predictable direction.

While optimization techniques are capable of rendering the best solution for some of the design parameters, there are some issues that make their application in early design stage arguable; (1) in the building design process, we do not seek to identify purely one “optimal solution”; we aim instead at supporting a more broadly feasible set of solutions that fulfils the performance requirements while allowing designers the freedom and creativity to move in different design directions. (2) A good approach in design is not the one that only leads to a better solution as a product, but also help designers in the process of design through understanding the problem itself, the importance of each design parameter, relationship between parameters, and the effect of one decision to the decisions about other undefined parameters simultaneously. The current application of optimization in building design lacks the ability to help designers in all dimension of the complex design process. (3) The building design practice in reality is an iterative process in which many backtracks might happen in each divergent-convergent phase as different requirements and constraints are evaluated and decisions are made. The large amount of time and high cost of running full design exploration and optimization in each stage while some might be refined as design proceed make their implication hard, if not impossible, for the architectural design stage.

Summary of the Problems

The early stage of design, as mentioned before, is characterized by its iterative nature of divergent and convergent phases that leads to decision-making under much uncertainty. The methods and tools applied to this stage, consequently, should account for the iterative, complex, and uncertain characteristics of design process. At present, the building industry lacks such consistent approach to early stage of design (Austin et al., 2002). These deficiencies pertain to both steps of early design process:

• The divergent phase, when concepts/alternatives are generated, there is no practical framework for designers to generate more promising alternatives regarding energy performance.

• The convergent phase, when concepts are evaluated and selected, there is no algorithm to validate the decisions and provide confidence in decision-making.

In this study, we propose a new methodology based on inverse modelling that combines the divergent and convergent phases of design process in a way that generates a plausible range for the (undecided) design parameters that will lead to a higher probability of the objective performance. In other words, we try to help designers find and choose the values of design parameters that are more likely to lead them to their preferred performance while allowing for design freedom. In this respect, the proposed process does not aim at identifying purely optimal solutions; it aims instead at supporting a more broadly intended design exploration, in which the designer can intervene to address the search process as well as extract knowledge from the generated solutions (Turrin et al., 2011). Based on the iterative nature of the design process, this method lets the designers iteratively make decisions about the design; as a new decision about any parameter is made, the information will be updated which will affect the estimation of the remaining undecided parameters and represent how a new decision will affect other interrelated parameters.
METHODS

An Overview of the Proposed Approach

The common procedure for performance assessment in design process is that the design parameters are fed into the physics-based model as inputs, and the (energy) performance prediction is computed as the output. Using the physical/mathematical theory for predicting the results of the analysis corresponds to solving the “forward” modelling procedure. The reciprocal situation, using the result or the performance output to infer the values of the parameters corresponds to the “inverse” modelling problem (Taranolta, 2006).

In the performance-based design approach, the performance requirement is defined and quantified from the beginning, and designers evaluate the performance output to see if “their design satisfies the objective performance”. Inverse modelling instead asks “what designs satisfy the objective performance”? In other words, the current evaluation of design -convergent phase- is performed in a forward mode. But what if we use the inverse approach to infer the design parameters that lead to the objective performance? What if the design parameters are not generated based on the subjective and intuitive nature of designers’ experience or a random generation, but based on the well-grounded objective performance? In the performance-based design process, such an inverse approach is proposed to estimate the design parameters based on the objective energy performance.

Linear Inverse Modeling (LIM)

This research uses the linear inverse approach to estimate the undecided design parameters given preferred performance objectives. In order to better understand the building energy performance model and the use of inverse modelling in performance analysis, we assume "y" to be the performance indicator, here building thermal load, which can be written as:

\[ y = f(x_1, x_2, x_3, \ldots x_n) = f(x) \]

where \( y \) is a function of different variables \( x \), which generally can be called \( x \). \( x \) represents design parameters such as orientation and wall U-value. Using the function \( f \), the forward problem finds \( y \) given \( x \), while the inverse problem finds \( x \) given \( y \).

\[ x : (x_1, x_2, x_3, \ldots x_n) \rightarrow y: (Forward \ problem) \]

\[ y \rightarrow x : (x_1, x_2, x_3, \ldots x_n): (Inverse \ problem) \]

So far, \( x \) and \( y \) are assumed to be deterministic, calculated with single values that show we know them with certainty. In reality, the design parameters have not been decided upon at some design stages, and boundary conditions are not known with certainty, which leads to uncertainty in \( y \). As described briefly in previous section, these uncertainties demand a probabilistic approach, which looks for the probabilities of \( x \) and \( y \), instead of point values for them. In probabilistic inverse modelling, rather than calculating a single “best” solution for parameters \( x \) according to some criterion, we can produce a large number of “likely” solutions: \( P(x) \) that both fit the data and any other information that is used (Schmidt, George, & Wood, 1998). The resulting inferences, shown as distributions, provide a means of estimating the likelihood of properties of parameters from preferred outcomes and explicitly emphasizes the multiple solutions that can lead to those outcomes. The range of the different likely parameter values fits well with the goal of providing a designer the freedom to choose among feasible options that have a high likelihood of meeting objectives.

Linear Inverse Modelling, LIM, consists of linear equality and/or linear inequality conditions, which is supplemented with approximate linear equations, or a target function. There are three sets of linear equations: equalities that have to be met as closely as possible (1), equalities that have to be met exactly (2) and inequalities (3):

\[
\begin{align*}
(1) \quad & A. x = b + \epsilon \\
(2) \quad & E. x = f \\
(3) \quad & G. x \geq h
\end{align*}
\]

1- The formulation of the model of \( E. x = f \)

The first step is to construct a model that relates the design parameters to the performance function probabilistically. This equality model is the result of the probabilistic model that depicts the performance indicator \( y \) as a function of design parameters \( x \). We develop a statistical model derived from a normative energy model as a surrogate of the physical relationship between the input and output, resulting in the computational time to be dramatically decreased. This claim was hypothesized and proved by Zhao (Zhao, 2012) as:

“Given feasible ranges of building design parameters, a set of inputs and the output (primary EUI) of the normative building energy model can be expressed as a linear regression model.”

The underlying assumption is that the normative energy model is a reliable representation of the relationship between building design, operational/scenario characteristics and building energy consumption (Zhao, 2012), (Kim, Augenbroe, & Suh, 2013), and is appropriate for early design decision-making. It is worth mentioning that the normative model is a reduced-order quasi-static building energy model based on the ISO 13970 standard (ISO, 2008). The statistical model of the normative energy model can be formulated as:

\[ y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \epsilon, \]

Where \( y \) is the performance indicator value (Total cooling and heating demand), \( x_1, x_2, \ldots, x_k \) are the corresponding values of the \( k \) design parameters or covariates (such as floor area, building orientation, wall material U-Value, etc.), \( \beta_0, \beta_1, \ldots, \beta_k \) the...
intercept and slope coefficients to be estimated, and \( e \) the random error. This study is only dealing with reducing the demand or thermal loads that affect the building design, and not addressing any mechanical systems and supply side. In order to develop this model, we first apply global sensitivity analysis using multiple linear regression analysis to identify the design parameters with the most significant impact; the Monte Carlo (MC) simulation is used to generate samples for the regression analysis in ModelCenter (PHX, 2013). Given the feasible ranges of parameters, the samples are created and fed into the model to compute their corresponding thermal demand; the original samples and their corresponding thermal loads are then used in a stepwise regression analysis for parameter sensitivity analysis.

2- The specification of constraints of parameters

Generally, the linear inverse model is a type of constrained linear regression problem in which parameters \( x \) are subject to the constraint \( E x = f \) and \( G x \geq h \). The model \( G x \geq h \) represent the constraints we define for design parameters, \( x \). The sources of constraints are defined based on literature study, the design requirements, regulations, limitations, the designers’ and stakeholders’ preferences etc. For instance, if we design an office building in a location in which the city policy obligates the building height in that region to be less than 50 feet, and the building requirements need spaces to be distributed in at least two stories, which is 20 feet, then we define our prior knowledge about the height of the building as a uniform distribution with the min value of 20 and max value of 50 feet. If any of the stakeholders has a preferred value of the number of stories or building height, e.g. the preference of architect to have 35 feet height due to an aesthetical objective, then this distribution might be changed to reflect that preference as a rectangular distribution, with the interval of 20 to 50 feet, and the mean value of 35 feet.

3- Elicitation of the performance objective:

In the \( A x \approx b \) equation, \( b \) represents the observation, data, or result of the performance model. At the early stage of building design, however, we lack any evidence/observed/known data regarding the performance. Here, we propose applying the ‘preferred model of performance’ instead of the ‘observed model of performance’ to be used in this model. For example, the objective energy performance can be expressed as a designer’s desire to have preference to have thermal demand below 60 W/m2/year.

4- Solving a linear inverse problem to replicate design parameters

Based on the preferred energy performance for a particular scenario of the building use in a city and associated linear regression model of building energy function, the next step is to drive design parameters estimation of building for that scenario. Our hypothesis can be rewritten as follows:

Given the preferred thermal energy performance of a particular type of the building in a city and a linear estimation of a building energy model, one can solve a linear inverse problem to generate distributions of the building energy model input variables, which lead to the preferred energy performance.

The calculation of the inverse inference uses Markov Chain Monte Carlo to randomly sample the underdetermined problem and select likely values given the approximate equation. The metropolis algorithm produces a series of samples –here one thousand samples- whose distribution approaches an underlying target distribution. The assignment of the inverse modelling process and analysis is implemented in R (Programming Language, version R-3.1.1), which probabilistically estimates design variables whose distribution will lead us to the preferred performance. The feasible region of the linear problem would be defined as the part of parameter space that contains all solutions of the reduced problem.

EXPERIMENTS AND DISCUSSION

The case we study here is Sprout Space, a reloadable classroom designed by the architectural design firm Perkins+Will. The project’s main objective is to develop a high-performance modular classroom for growing schools, and will be built in different locations with the priority for Chicago. It is a one-story rectangular building with an area equivalent to 96 square meters as depicted in figure 9.
The decided parameters of this project are gross floor area, massing, size, aspect ratio, and number of building story. The undecided parameters are windows to wall ratio (WWR) in each façade, material of the wall and glazing, and the roof angle. We have defined the energy performance objective in different scenarios as:

- S1: total cooling and heating demand to be less than 300 kWh/m²
- S2: Total cooling and heating demand to be less than 220 kWh/m²
- S3: Total cooling and heating demand to be less than 150 kWh/m²

The diagrams in figure 10 represent the probability distributions of the design parameters for low-rise educational buildings in Chicago, for different scenarios of objective from S1 to S3. The design parameters in these graphs represent the most significant ones computed out of the regression analysis we had come up with in the previous section. These graphs inform the designers of the possibilities they have for each parameter while being bounded to the associated energy performance objective. Moving from the more conservative target, S1, to the more aggressive one, S3, will place more restrictions on each design parameter based on their importance, the energy objective, and the dependencies between design parameters.

The probability distributions of design parameters in the first scenario, S1, are similar to uniform, which shows the lack of a strong design direction because of the very conservative energy target. However, the second and third diagrams suggest designers to design the south façade with the lower transparent area, or lower windows-to-wall ratio percentage to fulfill the more aggressive energy target. This is not the final design solution for designers to make their decision upon. As mentioned in the introduction, design is an iterative process of decision making for building parameters while there are interdependencies between those parameters. The main concept of this method is for it to be implemented iteratively as each parameter is decided upon. In other words, as a designer decides on a building parameter, they define that parameter deterministically as one single value and run the inverse approach once again to see how that decision affects decisions on other parameters. Following scenarios are the examples of the iterative decision-making process showing solution space after designers have chosen a few design parameters.

- S4: Total cooling and heating demand to be less than 180 kWh/m², and the height of the building is defined as 3 meters, and the windows to wall ratio of the south façade is decided to be 80% to fulfil a daylighting requirement.
- S5: Total cooling and heating demand to be less than 90 kWh/m², the building eight is 3 meters, and the U-value of roof, opaque wall and glazing are 0.3, 0.2, and 1.5 W/m²K respectively.

In these scenarios, after making decision regarding building height, aspect ratio, and the opening on the south façade, or material U-value, we run the analysis to see how these decisions would affect the rest of the parameters, as shown in figure 11.
CONCLUSION

In this study, we have made an initial investigation into decision support in early building design under uncertainty. A linear inverse modelling procedure was proposed and developed that can generate a plausible range of design parameters given the preferred thermal energy performance at the early stage of an architectural design. This method deals with the performance objective as input and inferences about the design parameters as output. It has been shown in the case study that such an approach also accounts for the iterative nature of an architectural design and promotes a step-by-step procedure for making a decision and updating information as each new decision is made. The results of the inverse modelling are probabilistic bracketing of each parameter that collectively will represent the feasible region of the design space. This gives a handle on the one-to-many problem that can support a broad range of architectural design solutions while bounded in the defined energy performance objective.

It should be noted that we only have considered what we call \textit{undecided parameter uncertainty} and ignored other types of uncertainty. Because the final form of the design and how it will evolve are unknown, undecided parameter uncertainty is of particular interest for early design decisions. This type of uncertainty will be high early on and thus poses a large challenge to making performance based design choices in comparison to other types.

The next step of this on-going project is to provide a comprehensive validation method in order to answer two questions: (1) are the solutions of the proposed inverse problem valid candidates to meet stakeholder preference? And (2) in comparison to the current approach, does this method give us more confidence and lead us to a higher probability of achieving the objective performance?

The first question is going to be answered by implementing forward modeling procedure in energy performance assessment. Individual design alternatives for each model (i.e. particular sets of value for x) will be compared using conventional forward modeling, and the results will be compared to the initial energy performance objective. For the case study we have provided in this manuscript, we have chosen the mean values of the posterior outputs,
which represent the estimation of the design parameters; then analyzed it in a conventional forward fashion through the normative energy model, and finally compared against the original stakeholder performance objectives. Although the results fulfilled the energy requirements in this simple case study, a more systematic method considering the iterative nature of the decision-making is going to be implemented in future. For the second validation question, the results of this method are going to be compared with some other decision making approaches to see if the proposed approach can lead designers to a higher probability of achieving energy performance compared to others.

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