ABSTRACT

Despite recent developments, early-design phase urban-scale performance assessment remains limited, notably due to computational complexity. In this paper, we introduce a new predictive model (or metamodel) approach for assessing the performance of early-design phase neighborhood projects from simple geometry- and irradiation-based parameters. A multiple linear regression model is fitted using a dataset acquired through parametric modeling and simulation of neighborhood design variants. Various trials are made by training the metamodel over subsets of the data to verify its robustness and improve its prediction performance. Results highlight the potential for this approach to become the underlying engine in an early-design phase exploration and decision-support framework.

INTRODUCTION

Energy performance in the built environment is strongly conditioned by the morphological features of the buildings, such as shape and spacing, and their interaction with climate and the surrounding context, notably affecting the solar exposure of building surfaces. As such, the need and benefit of assessing building performance at the early-design phase and macro-scale has well been acknowledged, as these respectively represent the moment and scale at which decisions are made on design parameters of influence (Lechner, 2009; Zeiler et al., 2007). Despite recent efforts to provide support to designers, practical use of design-support tools is still limited, particularly due to excessive computational complexity of urban-scale simulations, limited integration into the exploratory early-design phase and insufficient interactivity with the designer (Beckers and Rodriguez, 2009; Hensen and Lamberts, 2011). Most existing building performance assessment methods are based on the resolution of equations that simulate the thermal behavior of a building. Such methods lead to high accuracy, so long as the required significant amount of details is available to the user, which is typically not the case at the early-design phase (Zhao and Magoulès, 2012). To overcome this limitation, statistical methods based on mathematical expressions can be used to bypass the need for full simulations. The use of statistical methods and machine learning techniques in the field of building performance is fairly recent. These techniques are used for building energy forecasting (Asadi et al., 2014; Ekici and Aksoy, 2009; Fouqueur et al., 2013; Hygh et al., 2012; Tsanas and Xifara, 2012), performance optimization (Caldas, 2008; Evins, 2013; Evins et al., 2012; Magnier and Haghighat, 2010; Nguyen et al., 2014; Wang et al., 2005; Yi and Makkawi, 2009), and sensitivity analyses (Eisenhower et al., 2012; Hemsath and Alagheband Bandhosseini, 2015; Martins et al., 2014). While most studies focus on the building-scale, only a few target the urban-scale, of which Kümpf and Robinson, 2010; Martins et al., 2014, who employ genetic algorithms to optimize building and urban form for exploiting solar irradiation.

This paper proposes a neighborhood performance assessment approach based on a predictive model (or metamodel). Our goal is to predict the value of a metric quantifying a performance criterion, when given very little information of the neighborhood design being assessed. According to our knowledge, this approach has not yet been developed at the neighborhood-scale.

METHODOLOGY

Overview

Metamodels “are used to replace the actual expensive computer analyses, facilitating multidisciplinary, multi-objective optimization and concept exploration” (Simpson et al., 2001, p. 129). At the early design phase, such models are thus useful for facilitating design space exploration. Metamodeling consists in (Simpson et al., 2001): selecting an experimental design to generate data in an efficient way, e.g. using the design of experiment (DoE) approach; selecting a model to represent the data, e.g. polynomial model, decision tree; and fitting the model to the data using a specific technique, e.g. least-square regression. An overview of our approach, which includes these steps, is illustrated in Fig. 1. The data is generated through parametric modeling and simulation of neighborhood design variants, and then analyzed and fitted using multiple linear regression. These phases are detailed in the following sections.

Parametric modeling, design variables and inputs

We first need to define and select the experimental design that will allow the acquisition of data. In our case,
designs. To define the set of design parameters to use as variables, the following requirements were considered. The variables should:

1. represent parameters with which designers normally play at the early-design phase of neighborhood-scale projects
2. have a significant impact on the solar access / energy performance of buildings
3. be reasonably easy to vary parametrically and to compute for a neighborhood design

this experiment consists in the parametric variation of design parameters to generate a diversity of neighborhood Relevant design parameters which did not conform to these criteria were considered either as fixed or as constraints to respect. Parameters related to point 1 were extracted from masterplan documents (Gauthier, R., Atelier Poisson and SDOL, 2012; PDL Gare-Lac, 2010), and through the collaboration with a local urban design firm (Urbaplan). To identify the parameters most likely to affect the performance output, we looked at multiple studies on the subject (Cheng et al., 2006; Esch et al., 2012; Hachem et al., 2012; Lobaccaro et al., 2012; Martins et al., 2014; Peronato, 2014; Pessenlehner and Mahdavi, 2003; Sok Ling et al., 2007; Takebayashi and Moriyama, 2012; Zhang et al., 2012). The main parameters respecting points 1 and 2 were identified as the street width, the buildings shape and height, and the density.

To simplify the parametric modeling of the neighborhood designs, while ensuring a relevant dataset for training the metamodel, we made a distinction between the design variables used in the parametric experiment and the inputs used for training the metamodel. As such, the height, depth and width of individual buildings were taken as variables, as well as the grid orientation. These indirectly affect multiple other parameters at the neighborhood level such as the street width, density, and solar exposure levels of the buildings. To capture these changes, an extensive amount of geometry- and irradiation-based parameters, such as plot ratio, form factor, and mean irradiation, were computed at the neighborhood-scale and used to populate the inputs dataset.

Six base case neighborhood designs were used to generate the variants. Each base case consists of a replicated building typology according to a certain urban layout. A variant of each case is illustrated in Fig. 2. These neighborhood designs come from two studies: M0 to M2 were provided by an architecture and urban design firm with whom we collaborated (Urbaplan), while M3 to M5 were generated as a preliminary dataset and inspired by student projects analyzed in the context of a collaborative study (Rey, 2013). In what follows, we will refer to each base case as typology Ms, as a term inclusive of both the building typology and the urban layout.

Table 1: Variables and constraints. H: height; D: depth; W: width; PR: plot ratio; BR: building footprint; cst: constant.

<table>
<thead>
<tr>
<th>TYPE</th>
<th>H</th>
<th>D</th>
<th>W</th>
<th>MIN</th>
<th>MIN</th>
</tr>
</thead>
<tbody>
<tr>
<td>M0</td>
<td>6-12</td>
<td>8-15</td>
<td>6-24</td>
<td>0.9</td>
<td>50</td>
</tr>
<tr>
<td>M1</td>
<td>9-18</td>
<td>10-20</td>
<td>12-24</td>
<td>0.9</td>
<td>200</td>
</tr>
<tr>
<td>M2</td>
<td>12-24</td>
<td>10-20</td>
<td>12-24</td>
<td>0.9</td>
<td>200</td>
</tr>
<tr>
<td>M3/4/5</td>
<td>3-24</td>
<td>6-22</td>
<td>cst</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

A series of design variants were parametrically generated from each base case by modifying the dimensions of each building, within the ranges listed in Table 1. For typologies M0 to M2, this was done via a random sampling algorithm, which included a con-
strains verification to ensure all generated variants respected the specified minimum plot ratio and building footprint (Table 1). For typologies M3 to M5, we followed the Design of Experiment approach and used a 3-level Box-Behken design to generate the variants (NIST/SEMATECH, 2013). The cases were duplicated for two orientations: the initial one (0°) and a 90° rotation from 0°, as well as for two blind settings: no blinds and blinds activated when the received irradiation exceeds 75 W/m².

**Simulation and outputs (Y)**

The outputs, or values to be predicted by the metamodel, were selected to represent the potential for (i) passive heating, quantified by the floor area-normalized heating need, (ii) overheating mitigation, quantified by the floor area-normalized cooling need and (iii) daylighting, quantified by the spatial Daylight Autonomy (sDA) (IESNA, 2012). These metrics are obtained through full climate-based simulations run in EnergyPlus (Crawley et al., 2004) and Radiance/Daysim (Larson and Shakespeare, 2011) Reinhart, 2015), using the EnergyPlus weather data file for Geneva, Switzerland. The simulation settings reflected poorly insulated residential buildings (high U-value), but with significant internal loads. Standard values will be used in future work to reflect best-practice buildings.

In this paper, we focus on the floor area-normalized heating need as the main output for which results will be presented. The annual heating need per zone and building was obtained via Archsim (Dogan, 2014), a Grasshopper (McNeel, 2013) plug-in based on EnergyPlus (Crawley et al., 2004). We refer to this metric simply as ‘heating need’, implying that it is the value summed over all buildings in a variant and normalized by the total floor area (kWh/m²).

**Data exploration and metamodel fitting**

Before fitting the metamodel, the recorded data is examined for potential anomalies and correlations between the inputs and outputs and among inputs, which respectively help identify the relevant and redundant inputs to use when fitting the metamodel. The metamodel is then trained and tested by following the sequence illustrated in Fig. 3. The data acquired through the series of parametric modeling and simulation is equally split into a training and testing set. Multiple linear regression is applied on the training data to estimate a metamodel of the form:

\[ y = f(x) + \epsilon = \beta_0 + \sum_{i=1}^{p} \beta_i x_i + \epsilon \]  

where \( x \in \mathbb{R}^p \) with \( p \) the number of inputs, \( y \) is a measurement, \( f(x) \) is the model output, \( x \) the input values, \( \beta \) the unknown coefficients and \( \epsilon \) the approximation and measurement (random) error. To estimate the model coefficients, we minimize:

\[ \sum_{i=1}^{N} (f(x_i) - y_i)^2 + \lambda \|\beta\|^2 \]  

where \( N \) is the number of training samples and \( \lambda \) a regularization parameter which penalizes large coefficient values likely to appear when overfitting. This is particularly relevant to our problem since some of the inputs are likely to be correlated, despite precautions taken to mitigate this risk in the previous phase. In such cases, a large positive coefficient on one input can be canceled by an equally large negative coefficient on a correlated input (Friedman et al., 2001). Starting with 500 values of \( \lambda \) between 0 and 1000, we use k-fold cross-validation to find the best \( \lambda \). We split the data in \( k=10 \) sets, take \( k-1 \) sets for training, then test the fitted model on the remaining set. The \( \beta \) minimizing equation 2 can be obtained as:

\[ \hat{\beta} = (X^T X + \lambda I)^{-1} X^T y \]  

where \( X \in \mathbb{R}^{N \times p} \). The difference between the predicted and the \( Y \) values is quantified by the root mean square error (RMSE):

\[ RMSE = \sqrt{\frac{\sum_{i=1}^{N} (y_i - f(x_i))^2}{N}} \]  

The best \( \lambda \) corresponds to the value yielding a minimum RMSE averaged over the k-fold iterations. Once we have fitted the model over the entire training set using \( \lambda_{best} \), 2-fold cross-validation is used once again to estimate the prediction error, which represents the performance of the model over unseen data (Hastie et al., 2009). Along with the RMSE, we also compute the percentage error (PercErr), which complements the
RMSE by providing a relative reference to the order of magnitude of the output values:

\[
PercErr = 100 \times \frac{\sum_{i=1}^{N} |f(x_i) - y_i|}{N}
\]  

where \(H_{lim} = H_{lim0} + \Delta h/FF\)

\[
H_{lim0} = 55 \text{ MJ/m}^2 \quad \text{and} \quad \Delta h = 65 \text{ MJ/m}^2 \quad \text{for collective housing, and} \quad FF \quad \text{is the form factor (total floor area over total envelope area).}
\]

\[\text{SIA limit range} \quad \text{M0} \quad \text{M1} \quad \text{M2} \quad \text{M3} \quad \text{M4} \quad \text{M5} \]

\[\text{Number of occurrences} \quad \text{Heating need per floor area (kWh/m²)} \]

\[\text{Figure 4: Distribution of simulated heating need for each typology. The interval between the} \quad \text{over all minimum and maximum SIA 380/1 limit (SIA, 2009) is delimited} \quad \text{by the hatched area (see eq. 6).} \]

The extensive list of geometry- and irradiation-based parameters recorded is listed in Fig. 3 which quantifies their correlation. These inputs represent parameters that are likely to affect the energy performance of the neighborhood as proven in the literature as cited previously and earlier work by the authors (Nault et al., 2015; Peronato, 2014). Light (yellow) and dark (blue) squares represent a perfect positive and negative correlation respectively. This analysis helps reduce the dimensionality of the inputs dataset by eliminating redundant parameters. The ones in bold font are further used in the training of the metamodels presented in the next section.

**Performance of metamodel**

We here present the main results obtained when training a metamodel over distinct (sub)sets of typologies and input parameters. Trials were made for the following typology groups: the complete set (‘All’), all except the adjacent building typology M0 (‘M1toM5’), all block typologies (‘M0to3’), all detached blocks (‘M1to3’), and finally the non-block typologies (‘M45’).

Figure 6 presents the performance of each trained metamodel; a boxplot of the RMSE and PercErr, and the predicted (by the metamodel) against reference (simulated) values for the heating need metric.

The lower graphs of Fig. 6 also provide information on the domains which are lacking data, i.e. the regions looking at how much accuracy is lost when increasing the number of parameters considered. We begin with a unique input (1 X: form factor), to which we add the south facade and window-to-floor ratios and floor area-normalized south facade irradiation (4 Xs). We then add the window-to-wall ratio and replace the south facade irradiation parameter for the facade and roof equivalents (6 Xs). Finally, the last and largest subset includes the previous 6 parameters complemented by the plot ratio and mean envelope and south facade irradiation (9 Xs). It is to note that this iterative process, which included multiple other scenarios, was done in a manual way and partly based on the correlation analysis.

A better performance is typically achieved for the smaller typology subsets, e.g. M1to3 and M45, which is to be expected considering the similarities in terms of morphology and output distribution (Fig. 4). By looking at how much accuracy is lost when increasing the typologies considered, we can assess the generalization potential of the metamodel. For instance, according to the targeted performance level (RMSE, PercErr), we can determine if a unique metamodel would be sufficient for dealing with various typologies, or if it would be preferable to rather have a metamodel per (or per group of) typology(ies).

The lower graphs of Fig. 6 also provide information on the domains which are lacking data, i.e. the regions

\[\text{Figure 5:Correlation level between all parameters in} \quad \text{the initial set of potential inputs. The ones in bold are} \quad \text{used in the results presented later.} \]
Figure 6: Comparison of metamodels trained with different groups of design variants (Ms) and sets of input parameters (Xs). Top: boxplot of root mean square error (RMSE) and percentage error (PercErr). Bottom: predicted (by metamodel over $R = 100$ training runs) versus reference (simulated) heating need values. 1 X: form factor; 4 Xs: form factor, south facade ratio, window-to-floor ratio and south facade irradiation per floor area; 6 Xs: form factor, south facade ratio, window-to-wall and window-to-floor ratios, and facade and roof irradiation per floor area; 9 Xs: plot ratio, form factor, south facade ratio, window-to-wall and window-to-floor ratios, facade and roof irradiation per floor area, mean envelope irradiation and mean south facade irradiation.
on the graphs where there are fewer points and where points are further away from the diagonal line. Increasing the amount of reference data in these regions would allow improving the metamodel’s performance. The metamodels also provide a way to assess the level of influence of each parameter considered. Figure 7 shows the partial dependence plot of each parameter used in the 9 Xs metamodel fitted with the complete typologies dataset. The partial dependence of a parameter represents its average effect on the output after accounting for the average effects of the other parameters (Hastie et al., 2009). They are the metamodel coefficients $\beta_i$ in equ. 1. The dark line represents the mean while the lighter dashed lines indicate the 95% confidence interval (2 times the standard deviation). The histogram of the corresponding parameter has also been plotted to show the distribution of the training data. We observe that the heating need:

1. decreases proportionally with the plot ratio (i.e. density), form factor (i.e. compactness), window-to-wall ratio (i.e. facade openings), facade irradiation per floor area and mean envelope irradiation (i.e. solar exposure)
2. increases proportionally with the south facade ratio, window-to-floor ratio, roof irradiation per floor area and mean irradiation on the south facades

The influence of each parameter, i.e. the slope, is conditioned by the range spanned by the parameter and output values. This factor must be kept in mind when comparing the relative effects; at first view, the roof irradiation per floor area appears significantly more influential than the window-to-floor ratio, but this conclusion could be reversed if the latter parameter spanned a wider range of values. Moreover, the confidence interval of the window-to-floor ratio is about twice as large as the one for the roof irradiation per floor area. The distribution of the parameter values (frequency of occurrences) also influences the fitting results. This is reflected by the differences observed between the typology (sub)sets in Fig. 6, as the parameter distributions differ between typologies.

Another aspect to consider when interpreting these plots is the potentially counter-acting effects of a pair of parameters. For example, the window-to-wall and window-to-floor ratios appear to provoke a similar change in the output over their respective range. With this change being of opposite directions, there is a chance that the effects do not reflect a causal relationship with the output, but are rather artificially caused when creating the metamodel. To help identify the potential artifacts, we can look at the correlation matrix of Fig. 5 where we see that the window-to-floor ratio is negatively correlated to the form factor, or compactness level of the design, which is a strong indicator of the heat losses. Thus, it is possible that the positive trend observed between the heating need and the window-to-floor ratio is caused by this negative correlation with the form factor; as the design becomes less compact, the heating need increases, but so does the window-to-floor ratio due to its association with the form factor. This relationship, and others observed between the input parameters, emerges from the parametric modeling procedure. As such, the metamodel might be more robust if we remove some of the least significant parameters, despite a loss in its performance (in terms of RMSE and PercErr). These decisions must be taken by thoroughly examining the data and using our intuition and understanding of the phenomena causing variations in the energy consumption at the neighborhood scale.

A limitation of the linear model assumption can also be seen from Fig. 7 for some parameters, e.g. the mean envelope irradiation, the lower boundary of the confidence interval crosses the x=0 axis, which means that not only null output values could possibly occur, but even negative ones, which is unrealistic.

**Computational cost**

While a full energy simulation takes between 1 and 5 minutes per variant, depending on the size and morphology of the neighborhood design, the duration of the metamodel’s prediction process is in the order of seconds (max $\sim$1 minute). The main time-consuming task is the irradiation simulation (with 2 ambient bounces). These times were recorded for simulations run on an Intel Quad Core 3.70GHz computer with 16 GB of RAM. It is to note that the time savings could be larger for the daylight performance criterion (not presented here), due to the particularly expensive daylight simulation which is around one hour per variant. In addition to time savings, our approach requires a simpler 3D model, i.e. empty boxes as opposed to the detailed zoning required for full energy simulations.

**CONCLUSION**

This paper presents a prediction-based approach for assessing the performance of neighborhood designs. Results show that by carefully selecting the most relevant input parameters when fitting the model, to account for both morphology and solar exposure, we can achieve a prediction performance of the heating need with a root mean square error and percentage error below 5 kWh/m² and 5 % respectively. The outcome remains limited by the assumption of a linear model, which could lead to negative outputs and thus unrealistic values, by the manual parameter optimization, which may not provide the best metamodel, as well as by the dataset used for fitting. However, the improvement seen in the metamodel’s performance, when playing with the training data, highlights its validity within certain boundaries in terms of typology, climate, and design parameter ranges. We achieve significant savings in terms of computational time, particularly valuable when assessing multiple variants in the exploratory and com-
Figure 7: Partial dependence plot and histogram for each of the 9 parameters in the 9 Xs metamodel trained over the full dataset (‘All’). The slope of the mean (dark line) represents the coefficient in the metamodel function ($\beta_i$ in equ. 7). The dashed gray lines represent the 95% confidence interval.

parative design phase. We conclude that the proposed approach is a promising alternative to complex simulation and has great potential for becoming the underlying engine in a design decision-support framework.

In future work, the dataset will be extended to include simulation results from various climates and simulation settings (e.g. materials). We will test different machine learning techniques e.g. Gaussian Processes and optimize for the input parameters.

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