Strategically robust urban planning? A demonstration of concept

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Strategically Robust Urban planning? A Demonstration of Concept

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Strategically Robust Urban Planning? A Demonstration of Concept

Abstract

Planning for the future is inherently risky. In most systems, exogenous driving forces affect any strategy’s performance. Uncertainty about the state of those driving forces requires strategies that perform well in the face of a range of possible, even improbable future conditions. This study formalizes the relationship of different methods proposed in the literature for rigorously exploring possible futures and then develops and applies the computational technique of scenario discovery to the policy option of a subsidy for low-income households in downtown Lisbon. The work demonstrates one way in which urban models can be applied to identify robust urban development strategies. Using the UrbanSim model, we offer the first known example of applying computational scenario-discovery techniques to the urban realm. We construct scenarios from combinations of values for presumed exogenous variables – population growth rate, employment growth rate, gas prices, and construction costs – using a Latin Hypercube Sample (LHS) experimental design. We then data mine the resulting alternative futures to identify scenarios in which an example policy fails to achieve its goals. This demonstration of concept aims to lead to new practical application of integrated urban models in a way that quantitatively tests the strategic robustness of urban interventions.

Keywords: uncertainty, scenario discovery, robust decision making, UrbanSim, regional planning, metropolitan area networks
Introduction

City planning is predicated upon a desire to understand the future. Planning and investment decisions require some knowledge of cause-and-effect. In this context, the field has had a complex relationship with complex models. Enthusiasm for large-scale computational models, exemplified by Lowry’s (1964) seminal work, was later tempered (e.g. Lee, 1973). While model development and applications have ebbed and flowed over time, constant increases in computational power and simulation capabilities continue to strengthen possibilities for large-scale applications. Micro-simulation has become more important, aided by enhancements in computing power, behavioral theory, and econometrics (Timmermans, 2003; Wegener, 2004). Public concerns about issues such as environmental impacts and social equity have led to broader assessments of a range of policies, not just large-scale infrastructure investments, but also road pricing, travel demand management, zoning, etc. At the same time, a history of being blindsided by the unforeseen has led to continuing concern about accounting for uncertainty (e.g. Lee, 1973; Rodier and Johnston, 2002).

Uncertainty, in this context, arises from a range of factors, from initial modeling decisions, to behavioral representation, to data. In this paper, we explore uncertainty related to forecasting exogenous factors. Specifically, we examine model input values under deep uncertainty, a condition in which relative probabilities cannot be easily assigned to different combinations of input parameters. In other words, the probability distributions of model inputs are so unclear that characterizing the probability of different scenarios, even broadly, is very difficult (Kwakkel, 2010; Walker et al, 2003).
The importance and relevance of this particular form of uncertainty are evidenced by the use of scenario-planning techniques for urban transportation planning purposes. Scenario planning, famously adapted from military applications to the private sector by Shell in the early 1970s, was being adapted to urban- and transportation-related planning applications by the early 1980s (Zegras et al, 2004) and is increasingly used today. For example, Bartholomew (2007) reviews 80 recent applications in over 50 USA metropolitan areas. Bartholomew’s review reveals, however, that many of these applications have focused on “visioning” – i.e., identifying the future “we want” – rather than formally accounting for uncertain exogenous forces and developing plans that prove robust across wide ranges of these forces. We believe that scenario planning should be applied towards these latter ends, understanding and planning for the uncertain, in order to improve urban land use and transportation planning. This would enable the development of strategies that meet minimum goals under a range of unknown future conditions – a characteristic called “strategic robustness.” Such an approach is not inconsistent with “visioning” exercises. For example, one could backcast from a desired future vision and test the reliability of strategies – under different exogenous conditions – in achieving that “vision.”

In this paper, we demonstrate a quantitative approach to strategic robustness in urban planning by: 1) formalizing the relationship between qualitative and quantitative methods for rigorously exploring the space of possible futures to enable strategic decisions based upon this information, and 2) applying the scenario-discovery technique (Bryant and Lempert, 2010) to UrbanSim, a modular land-use model that can be integrated with a transportation model (Waddell, 2002). The focus on robustness across ranges of model inputs speaks directly to
concerns about the use of point estimates in transportation-demand forecasting (e.g. Ashley, 1980; Zhao and Kockelman, 2001). The approach shown here can be characterized as a combination of data “farming” – whereby multiple UrbanSim model runs are used to “farm” a range of possible alternative futures – and data “mining” – whereby the range of “farmed” futures are “mined” to identify scenarios in which a particular policy or set of policies fails to achieve established goals. We use the Lisbon, Portugal, metropolitan area as the empirical setting and test a low-income housing subsidy policy in the city center. Section two of this paper introduces several different techniques for incorporating uncertainty regarding exogenous forces into urban modeling. Section three provides details on the specific approaches we employ for data farming and data mining. The fourth section introduces the empirical case, the computational environment, and describes the application and its results. Finally, the conclusion presents implications and areas for future research.

Planning in an uncertain world: a basic background to potential techniques

Planning for the future inevitably involves accounting for the effects of exogenous driving forces. In the urban context, these forces are generally categorized as economic, social, political, technological, and environmental (Zegras et al, 2004). For quantitative models of the future, driving forces shape the values which serve as model inputs. For example, “economic conditions” may include inputs such as “employment growth rate” and “gas prices,” with poor economic conditions characterized by low employment growth rate and high gas prices. Mathematically, model inputs can be characterized as a vector $\mathbf{x}$ of length $K$ where $\mathbf{x}$ is composed of the inputs $x_1, x_2, \ldots, x_K$ (Bryant and Lempert, 2010). Considerable uncertainty
usually underlies the states and probability distributions of these inputs. The range of a system’s inputs and outputs defines the space of possible futures, hereafter known as the futures space. This space allows characterization of the system’s output in response to inputs, which may be envisioned as a surface in this space.

Planners aim to define ways to intervene in the urban system in order to achieve certain objectives. Many planners are engaged in constrained optimization – trying to do the best (however “best” is defined) subject to various constraints (legal, financial, technological, etc.). However, when confronting deep uncertainty, planners should also concern themselves with robustness – identifying strategies that perform well across a range of possible future conditions (Serra et al, 1996). Lempert and Collins (2007, pp. 1016-1017) identify three possible definitions for a robust strategy:

1. “trades a small amount of optimal performance for less sensitivity to violated assumptions;”
2. “leaves options open,” in other words avoids or delays making irrevocable decisions; or,
3. “performs reasonably well over a wide range of plausible futures.”

We use the third definition and, in this paper, focus upon discovering the areas of the futures space in which a strategy is not likely to perform well. In other words, we focus on satisficing, the satisfaction of a minimum goal, as opposed to optimization.

Optimization and robustness are not mutually exclusive. Given two equally robust strategies, optimality is a good method for choosing between the two. However, in cases where the underlying distributions of parameters are unknown, robustness can guide the initial choice.
of the strategy portfolio. Depending on time and other constraints, strategies can be repeatedly analyzed, with robust strategies selected and improved. Choices can then be made between strategies that achieve similar objectives but are sensitive to variations in different inputs (Lempert et al., 2006). The selected “robust” strategies can be optimized within the bounds dictated by maintaining robustness.

A second concept related to robustness is that of scenarios of interest, which refers to those combinations of model inputs that produce very negative or very positive results. Consider the formulation:

\[ y = f(s, x) \] (1),

where \( f() \) is the system of interest, \( s \) is the vector characterizing the strategy under consideration, \( y \) is the vector of the strategy results, and \( x \) is the vector of inputs characterizing the scenario (Bryant and Lempert, 2010). To test a given strategy for robustness, \( s \) is held constant while \( x \) varies according to the exploration technique chosen to elaborate the futures space. The set of scenarios of interest, \( I_s \), may be defined as:

\[ I_s = \{ x_i | f(s, x_i) \geq y_{Interest} \} \text{ or } \{ x_i | f(s, x_i) \leq y_{Interest} \} \] (2),

where \( x_i \) is a vector of inputs for which the output vector \( y \) passes a given threshold, \( y_{Interest} \) (Bryant and Lempert, 2010). In general, the direction of the inequality is chosen so that \( I_s \) is the minority of the total set of modeled scenarios. This minority property facilitates determination of the range of inputs in \( x \) that cause inclusion into \( I_s \) and is consistent with the idea that these scenarios are exceptional.
The related concepts of robustness, optimality, and scenarios of interest frame the different techniques available for elaborating the futures space for planning purposes; each implies different degrees of computational intensity (Error! Reference source not found.). Experience/intuition-based exploration relies on users to generate scenarios, while orthogonal exploration examines how the output of a baseline scenario reacts when parameters are changed one-by-one. Latin-Hypercube-Sample (LHS) exploration enables a more “evenly” sampled examination of the futures space. Relative to LHS, Pseudo-Full-Factorial (PFF) exploration increases the density of sampling; LHS and PFF exploration fit within a larger group of methods known as Exploratory Modeling and Analysis (Agusdinata, 2008; Agusdinata and Dittmar, 2009; Agusdinata et al, 2009; Bankes, 1993; Van der Pas et al, 2010). Our typology thus provides a unified characterization of sampling methods across a range of computational requirements. The following section presents these methods in more detail.

**Figure 1.** Futures exploration approaches.
Experience/intuition-based exploration

These techniques derive directly from the Shell scenario planning tradition (e.g. Wack, 1985) in which experts and/or stakeholders identify combinations of a system’s fundamental external driving forces and their likely effects on a particular concern. The idea is to construct a wide span of internally consistent scenarios to increase awareness of possible futures. These “interesting” possible futures explicitly aim to take systemic factors into account (Bryant and Lempert, 2010; Zegras et al, 2004). Zegras et al (2004) review several attempts since the early 1980s to apply scenario planning methods in urban transportation-related applications, including in Sydney, Baltimore, and Seattle.

If the system of interest can be modeled, the experience-/intuition-based driving forces can be translated into model input parameters for computational simulation, which can provide several benefits (Kemp-Benedict, 2004; Kok and van Delden, 2009):

- forcing the “clarification of terms and mechanisms” used in the scenarios, exposing any logical faults and contradictions in intuition;
- providing “a feel for the scope of possible outcomes within a narrative framework;” and
- making a study more “replicable, extensible, and transferable” (Kemp-Benedict, 2004, p. 3)

Nonetheless, scenario translation into computational modeling presents difficulties, such as:

- quantifying driving forces into specific input parameters,
- concretizing loose terms (such as “changes in attitude”) into model-able input parameters,
• avoiding model artifacts (interactions of modeled elements giving unrealistic results) 
  (Cole and Chichilnisky, 1978), and
• interpreting the sensitivity of simulation results, such as the sensitivity of model outputs 
to small changes in the values assigned to the driving forces.

Relevant attempts to model intuition-produced scenarios include: public transportation 
ridership (Rutherford and Lattemann, 1988), urban growth (Barredo et al, 2004; Lemp et al, 
2008), forestry-urban interaction (Walz et al, 2007), water-quality-urban interaction (Jantz et al, 
2004), desertification (Kok and van Delden, 2009), climate change (Solecki and Oliveri, 2004), 
and international/national development (Cole and Chichilnisky, 1978). Most quantify scenarios 
using historical/economic research and/or intuition. Overall, the literature lacks a strong body 
of work on how exactly to use experience/intuition-based techniques to assess strategic 
robustness (Lempert et al, 2003).

Orthogonal exploration

Orthogonal exploration calculates the elasticities of output response to changes in inputs. In 
order to calibrate an equation based upon these elasticities, a series of model runs orthogonal 
to each other are carried out, with the coordinates of one base run serving as the origin of the 
right angles. Elasticities are derived from these limited runs. Bowman et al (2002) provide one 
example of this approach that has been applied to transportation models. They estimate 
elasticities based upon reference deviations and effectively predict the local output of far more 
complex models. The savings in computational time are obvious.
**Latin-hypercube-sample (LHS) exploration**

A Latin-Hypercube-Sample (LHS) experimental design distributes model simulation points across the futures space in a manner that decreases variability of results (Helton and Davis, 2002; McKay et al, 1979). Latin hypercube sampling “roughly speaking...stratifies each marginal distribution of $x_1, ..., x_K$ as much as possible but otherwise picks the $x_j$’s randomly” (Stein, 1987, p. 144). Essentially, LHS is a special type of non-orthogonal sampling for Monte Carlo analysis – no run is orthogonal to any other run in the LHS. McKay et al (1979), Stein (1987), and Helton and Davis (2002) provide more information on LHS and its attractive properties relative to stratified and random sampling (two techniques that similarly attempt to address limited computational power).

Outputs from the LHS experimental design, characterized into binary failure and success cases, can then be datamined through methods such as Patient Rule Induction Method (PRIM) (Friedman and Fisher, 1998), Classification and Regression Tree (CART) (Breiman, 1993), and rough-set analysis (Agusdinata, 2008; Pawlak, 1997). This approach, known as “scenario discovery”, identifies ranges of input values for which thresholds of failure or success are passed, delineating danger or high-reward zones (Bryant and Lempert, 2010) and avoiding bias in the selection of scenarios to simulate. A prominent example of such bias includes the tendency to predict consistent trends over surprising events or combinations of inputs (Lempert et al, 2003).
**Pseudo-full-factorial (PFF) exploration**

The most computationally intensive of the four approaches, a PFF is similar to an LHS experimental design but samples a greater number of points from the futures space. Construction of the PFF divides the overall hyperspace defined by the range of the parameters that make up $x$ into constituent boxes, then samples within each box. We adopt the “pseudo” qualifier to reflect that the futures space is generally continuous, while the simulations conducted are discrete points. A PFF thus gives a much more detailed view of the futures surface than that given by the LHS, but at high computational cost. As the number of parameters increases, any significant stratification of the variable values becomes infeasible for all but the simplest models. Agusdinata (2008, pp. 68-69) provides a helpful discussion of specifics of factorial design vs. LHS and Monte-Carlo sampling.

**Adapting the latin-hypercube-sample (LHS) method**

We chose LHS for our analysis as the technique matched our computational resources\(^1\) while avoiding the pitfalls presented by intuition- and orthogonal-based futures exploration. The following subsections discuss several considerations in our use of the technique.

**Appropriate density for a LHS**

Theoretically, confidence intervals can be obtained for LHS results, although in practice this can be difficult (Helton and Davis, 2002). No metrics have, however, been designed to assess the

---

\(^1\) As shown below, our model is computationally expensive.
density of LHS experimental designs, where density is the number of points over the given futures space.\(^2\) Towards this end, we propose a relative density metric, \(J\):

\[
J = \sqrt[n_S]{K}
\]

where:

- \(n_S\) is the number of intervals (equal to the number of runs to be carried out).
- \(K\) is the length of the input vector \(x\).

This metric represents the number of stratifications of a PFF that could be constructed from a given LHS and enables the comparison of the former with the latter. The \(J\) value found can be judged by a subjectively decided ideal or relative to other analyses. Higher \(J\)'s correspond to higher sampling densities, non-linearly; as the LHS approaches a vacuum, \(J\) asymptotically approaches 1. We reviewed the literature that involved the LHS experimental design, focusing especially on scenario-discovery/futures-exploration, and derived \(J\) values which generally indicated relatively sparse samplings of the futures space in these studies (Table 1).\(^3\) Of course, since LHS is designed for cases in which the PFF is computationally infeasible, this sparse sampling is unsurprising. No hard-and-fast rule defines a “too-low” level of \(J\). In cases in which only a few members of \(x\) are actually important in determining the model’s output, even an \(x\) with a large number of parameters may be acceptable. However, Table 1 demonstrates that some applications have approached \(J = 1\), indicating a very sparse density of points in the futures space and suggesting conclusions drawn from such studies might vary if the LHSs were to be resampled.

\(^2\) The closest work we have seen in this vein is Agusdinata and Dittmar (2009), which looks at the effects of sample size on CART misclassification errors for a carbon emissions model.

\(^3\) We concede that \(J\) does not compare the length of the ranges from which the \(x\) component is sampled from paper to paper, but this comparison is likely not feasible.
Table 1. Comparison of sampling densities found in various LHS applications.

| Source                          | $|x|$ | Size of LHS | $J$ |
|---------------------------------|-----|-------------|-----|
| McKay et al, 1979               | 4   | 16          | 2.00|
| Stein, 1987                     | 6   | 100         | 2.15|
| Helton and Davis, 2002*         | 57  | 300         | 1.11|
| Lempert et al, 2003*            | 43  | 5000        | 1.22|
| Groves and Lempert, 2007*       | 16  | 500         | 1.47|
| Bryant and Lempert, 2010*       | 9   | 100         | 1.67|
| Agusdinata and Dittmar, 2009*   | 18  | 10,000, 50,000, 75,000 | 1.67, 1.82, 1.86|
| Our application*                | 4   | 100         | 3.16|

Notes: Papers marked with a * apply LHS to futures exploration. Helton and Davis actually use three LHS designs each of 100 points. Lempert et al (2003) discards, before further analysis, more than half of the generated 5000 LHS points as unrealistic.

In comparison to other applications, ours compares favorably in its $J$ metric, despite an LHS size (number of runs) low in absolute terms.

Range of variables in $x$

Generally, the easiest manner of creating an LHS of desired size is to use an LHS generator like that available for the statistical program R (Carnell, 2009). This generator takes as inputs the desired number of parameters and runs and produces an LHS, assuming each parameter has a range of 0 to 1 with constant probability of achieving any value in this range.

To convert this general LHS into one specific to the parameter ranges for the model at hand, one can use a cumulative distribution function (CDF) (Helton and Davis, 2002), which
allocates the computational intensity to be applied to the different portions of the parameters’ ranges. If the true CDFs of occurrence for each component of \( x \) can be estimated, computational intensity can be allocated by the actual probability. Salling and Banister (2010) propose options for possible distributions. However, complete allocation of computational power by assumed probability of occurrence is not recommended when exploring futures space. Since data produced by the LHS will be mined to identify scenarios of interest, a fairly even distribution of points across the futures will allow clusters to be identified.

The CDF proposed here allocates most computational power evenly across possible, even improbable, values chosen for each member \( x_k \) of \( x \). A small amount of residual computational power is allocated to more extreme values, using a normal distribution.\(^4\) Figure 2 provides an example. The range of construction costs of 350 Euros/m\(^2\) to 650 Euros/m\(^2\) bounds the possible and even the improbable. Values in this range have equal probability density, and occupy the inner four standard deviations of a normal distribution. The tails of a normal distribution are added beyond this range, representing more extreme values, with a lower probability (4.55%) of being sampled. Each value in a generic LHS that stratifies variables on a 0 to 1 scale can then be converted to a specific value in the parameter’s range using the CDF. In our example, a value of 0.4 in the general LHS corresponds to 469 Euros/m\(^2\) of construction costs.

\(^4\) We thank Moshe Ben-Akiva for suggesting this approach.
Figure 2. Sample exploratory cumulative distribution function (CDF) used for construction costs with the cost corresponding to a probability of 0.4 identified.

Data mining: analysis of the data created by the LHS design

For the purposes of strategic robustness we are interested in meeting minimum criteria – “satisficing” rather than optimizing. For this purpose, model outcomes can be classified into binary states of success or failure with these generated futures, then “mined” using techniques such as PRIM, CART, or rough-set analysis. The shape of the failure (or success) response in the
futures space will, for complex models, likely be somewhere between a clearly delineated surface and a non-surface corresponding to complete mixing of success and failure cases. A delineated surface would correspond to a very clear association of model inputs to outputs, which may be reasonably approximated locally by equations such as that proposed by Bowman et al (2002). A thorough mixing of success and failure cases that defies classification would correspond to a strategy whose success or failure can be best summarized by a probability rather than any further analysis (Bankes, 1993). In such a case, the varied inputs are likely not controlling the model output.

Lempert et al (2008) discuss the relative merits of CART vs. PRIM. Here, we briefly discuss PRIM, the technique we apply in our example. A bump-hunting technique, PRIM seeks areas of the data space that have unusually high or low means. So, if scenarios of interest are classified as a 1 and scenarios not of interest are classified as a 0, a high mean reflects a high density of scenarios of interest. PRIM separates these “interesting” areas from the less interesting areas by means of rectangular, cubic, or hyper-cubic boxes delineating ranges of input values (Friedman and Fisher, 1998). We use PRIM for its ease of use and user-directed nature (Bryant and Lempert, 2010).

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5 Rough-set analysis is seen less often in the scenario discovery / exploratory modeling literature.
Application

We demonstrate LHS-based scenario discovery in urban planning using Lisbon, Portugal, as the empirical setting and UrbanSim as the basic modeling tool. This application illuminates the potential value of this technique in the context of a specific urban-systems model.

Context

Lisbon, Portugal’s capital city, is located on the country’s west coast. Figure 3 shows the region of the Lisbon Metropolitan Area (LMA) we model while Table 2 presents basic statistics. Since 1980, the city proper, especially the city center, has been losing population; in 2008 the city had less than 490,000 persons. Despite this, housing prices are highest and supply is most limited in the city center, discouraging residence by younger households (Oliveira and Pinho, 2010).
Figure 3. Lisbon Metropolitan Area.
Table 2. LMA Demographics, Socioeconomic and Transportation Characteristics.

| Population | Land area, square mile | 1,243 |
| Population | Population, year 2000 | 2,682,687 |
| Population | Population density, person/sq mile, 2000 | 2,159 |
| Population | Households, 2000 | 1,014,259 |
| Population | Persons per household, 2000 | 2.64 |
| Housing units, 2000 | 1,305,756 |
| Homeownership rate, 2000 | 70.43% |
| Median value of owner-occupied housing units, 2000 | $124,038 |
| Median household income, 1999 | $26,099 |
| Per capita money income, 1999 | $14,248 |
| Persons below poverty line, percent, 1999 | 7.00% |
| Mean travel time to work (min) workers age 16+, 2000 | 32.10 |
| Means of transportation to work, 2000 | Workers | % Share |
| Total | 1,151,364 |
| Transit (excluding Taxi) | 393,348 | 34.2% |
| Light Vehicle | Drove Alone | 449,471 | 39.0% |
| Carpool | - | - |
| Bicycled or Walked | 187,616 | 16.3% |
| Worked at Home | 27,345 | 2.4% |
| Other (including Taxi) | 93,584 | 8.1% |

Computational environment

We use UrbanSim, an open source land use model which can be linked directly to a travel demand model (Waddell, 2002) to simulate the LMA. UrbanSim is a disaggregate, discrete-choice-based, dynamic, “disequilibrium” (i.e., supply and demand are not perfectly balanced).

6 Available at: http://www.urbansim.org/Main/WebHome
model of household location choice, real estate development, job location choice, and real
estate prices. Transportation feeds into the model via estimated “accessibilities” that enter in
the relevant location and development choice models. UrbanSim is implemented in Python and
can be run in a Windows, Macintosh, or Linux environment. We ran UrbanSim in Linux.

The LMA-calibrated UrbanSim is linked to a four-step transportation model
implemented in TransCad and exogenous to the land-use model. The population and
employment inputs into the transport model are aggregated at the level of the freguesias (akin
to civil parishes). The model is based upon Lisbon’s 1994 transport network with the Vasco de
Gama bridge, opened in 1998, added. The Transcad model thus approximately replicates the
LMA infrastructure from 1998 to the present. This model generates AM-peak (8-9 am) auto
car travel times. Using these measures, UrbanSim calculates the accessibility measure for 206
freguesias based upon modeled travel time and job locations. Households choose residences to
maximize utility based upon preferences, prices, and relevant attributes. The demographic sub-
model generates jobs and population based upon census data, with exogenous growth rates
which can vary from year to year. New households are generated according to three income
strata, with all three strata growing at the same specified rate. Instead of firms, UrbanSim in
our implementation models job location choice, based upon a freguesia’s current number of
jobs, accessibility to people and jobs, and building density. Jobs and households, then, influence
each other through accessibility and effects on property prices and location choices. Overall,
while relatively crude (e.g., no representation of public transport; poor representation of firm
location choice), the LMA UrbanSim-Transcad implementation serves our purpose of
demonstrating the data-farming and data-mining approach as it might be applied with such models; the limitations of the model itself does not reduce the value of the demonstration.

**Specification**

As noted, city center population loss and housing unaffordability pose significant problems for Lisbon. We examine a policy aimed at altering this pattern: a residential subsidy (constant over five years) designed to induce lower income groups to live in the city center.\(^7\) This policy is model-able in UrbanSim, the goal is reasonable, as is the strategy (such subsidies could be implemented as a tax credit with approximately the same effect), and the output is intuitive. Table 3 formulates the goal, strategy \(s\), input parameters \(x\) and output \(y\). We selected the four input parameters for this demonstration due to their exogeneity and ease of manipulation within the model.

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\(^7\) This represents a “static” strategy as opposed to an adaptive one (Agusdinata, 2008, p. 9).
Table 3. LMA Scenario Discovery Formulation Key Characteristics.

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<th>Characteristic</th>
<th>Description</th>
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<tr>
<td>Time Period</td>
<td>2001-2006: Historical data and projections available</td>
</tr>
<tr>
<td>Goal</td>
<td>Make Lisbon’s city center more affordable for lower-income households</td>
</tr>
<tr>
<td>Strategy (s)</td>
<td>20% subsidy for low-income households moving to the city center</td>
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**Input parameters (x)**

1. **population growth rate**: represents demographic driving forces and political driving forces vis-à-vis immigration;
2. **employment growth rate**: represents economic driving forces;
3. **cost of construction**: represents technological and economic driving forces;
4. **travel-cost coefficient**: an addition to the accessibility calculation that represents gas prices, or people’s attitudes towards travel (increasing or decreasing real or perceived costs per distance).

**Output (y)**

1. \( \Delta H^{LI} = H_L^{Subsidy} - H_L^{Base} \), where \( H_L^{Subsidy} \) is number of low-income households in the city center, and \( Subsidy \) and \( Base \) connote estimated with and without subsidy conditions, respectively.
2. \( \Delta N_{Jobs} = N_{Jobs,Subsidy} - N_{Jobs,Base} \), where \( \Delta N_{Jobs} \) is the increase or decrease in jobs in the city center.

For the ranges of input parameters from which each \( x_i \) is drawn, we looked for values that bound the probable to minimize potential bias in the discovery of strategy vulnerabilities and successes. In the first stages of such explorations, erring slightly towards wide ranges is wise. After a preliminary stage, more points within detected ranges of interest can be simulated (Bryant and Lempert, 2010). For our LMA application, Table 4 presents the “bounding” ranges decided upon for the input parameters. We use the CDF proposed in Figure 2 to ensure sampling of some more extreme values outside these ranges, thus permitting minimal investigation of scenarios of interest even in the event of underestimation.

<table>
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<tr>
<th>Input parameter ($x$)</th>
<th>Precedent/Justification</th>
<th>Bounding</th>
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<tbody>
<tr>
<td>Population</td>
<td>1% Year-on-Year (YoY) (2001-2006)</td>
<td>0.5% to 1.5% YoY</td>
</tr>
<tr>
<td>Employment</td>
<td>-2% to 2% YoY (2001-2006)</td>
<td>-2% to 2% YoY</td>
</tr>
<tr>
<td>Construction Costs</td>
<td>Observed increase of approximately 80 Euros/m$^2$ over the 2001-2006 period from a baseline of 500 Euros/m$^2$</td>
<td>350 Euros/m$^2$ to 650 Euros/m$^2$</td>
</tr>
<tr>
<td>Travel Cost</td>
<td>Upper bound: 50 Euro/tonne carbon tax (0.119 Euros/liter of gasoline or 0.1271 min/km)</td>
<td>-0.119 Euros/liter to 0.119 Euros/liter (a negative value is a gas subsidy)</td>
</tr>
</tbody>
</table>
The mean value of 1.0% for the population input parameter range was based upon the observed population growth rate over the 2001-2006 period. The bounds were calculated based upon the observed range of 1% between the high and low forecasts that the Portuguese Statistical Agency predicted for the LMA in the 2001-2006 period. The employment data for the LMA over 2000-2006 saw a fluctuation of about -2% to 2% and these bounds were thus taken. A decrease of 2% in employment or a similar increase within one year seemed sufficiently extreme. Construction costs increased by approximately 80 Euros/m² over the 2001-2006 period; we chose a range within 150 Euros/m² of the 2001 baseline of approximately 500 Euros/m² (i.e., 350 to 650 Euros/m²). The upper range of travel costs was based upon our judgment of the reasonable upper range of carbon taxes currently discussed. The European Commission recently proposed a carbon tax of 20 Euros/tonne (Weisbach, 2011) and estimates suggest that a carbon price in the range of 50 to 100 Euro/tonne would achieve reductions of 20 to 50% of developed countries’ CO₂ emissions relative to the baseline in 2050 (IPCC, 2007). We chose 50 Euros/ton as an upper limit for what is politically practicable and, in order to also account for the possibility of a decrease in global oil prices that would function effectively as a subsidy, the lower edge of the range was taken, somewhat arbitrarily, as the negative of the possible carbon tax. Using our calculation of LMA citizen’s valuation of travel time, these gas taxes/subsidies were converted to equivalent increases/decreases in the time of a trip.

The ranges of these input parameters can be critiqued as somewhat arbitrary, although our CDF does compensate partially for this by allowing a few more extreme values. Our goal here is, however, a demonstration of concept; these ranges could be adjusted in future applications.
The LHS exploration technique

In constructing the LHS for the four input parameters, we assumed that they could be sampled and combined independently. An LHS of 100 simulation points was created, applying the ranges in Table 4 and the CDF described above (e.g., Figure 2), using a 4.55% probability of drawing more extreme values than the range specified.

Following construction of the LHS, UrbanSim was used to simulate the period of 2001–2006 for each simulation point for two cases: business-as-usual and subsidy. Thus, each simulation point has two realizations: the future for a given set of parameters with and without the subsidy. The same “seed” dictating the computer’s procedure for stochastic processes was used for all 200 of these runs. These business-as-usual/subsidy pairs reveal the estimated effects of the subsidy. Each run took approximately 12.5 minutes to run on a high-end machine,\(^8\) which meant that the 200 runs took approximately 42 hours. Although some examples of scenario discovery and LHS in the literature use many more runs, our LHS compares favorably to these other studies in terms of “density” in multi-dimensional space (Table 1).

Analysis of LHS experimental results

In all cases simulated, the subsidy significantly increased the number of low-income households in the city center. The range of increases over business as usual ranged from 8,075 to 10,132 households, or 153% to 162%. The subsidy strategy thus substantially increased the number of

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\(^8\) A Dell desktop with 7.8 GB of installed memory and 8 Intel Xeon CPU processors (E5530 @ 2.40 GHz), running Ubuntu 9.10.
low-income households in the city center and can be qualified as robust for a goal of increasing low-income households in the city center by approximately 8,000 households or 150%. However, to apply the scenario-discovery technique in an interesting manner, an arbitrary goal was set: achieve an increase of at least 8,650 households (in this demonstration of concept, for the sake of simplicity we omit discussion of confidence intervals for individual scenarios; however, with lower computational costs these could be estimated by rerunning the simulations with a range of different seeds). Thus, all scenarios that achieved fewer than 8,650 households were designated as failure scenarios for the subsidy strategy. By this definition, failure scenarios were 25% of simulated cases. These scenarios were marked with a “1”, with all others marked with “0.” We then applied PRIM, using settings as recommended in Friedman and Fisher (1998). The most cogent definition for the box capturing the failure scenarios was population growth rate less than 0.99% Year-on-Year (YoY) and gas tax (subsidy when negative) greater than approximately -0.06 Euros/l: this box captured 92% of all failure cases (Figure 4). However, this box also captures a relatively large number of “successes.” Defining “purity” as a given box’s percentage of cases of interest out of total simulated cases (Bryant and Lempert, 2010), this box’s purity was 46%. Thus, the box captures most failure scenarios but at somewhat low purity, representing an area where the subsidy strategy will more likely exhibit problematic behavior relative to the rest of the futures space.

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Figure 4. Visualization of the failure box for movement of low-income households to city center, 3 of 4 dimensions displayed. Inspired by Groves and Lempert (2007).

This box definition confirms that UrbanSim is producing intuitive results. A lower overall population growth rate indicates fewer total people, which would reasonably lead to lower absolute values of people moving into the city center. Lower gas subsidies/higher gas prices may make the city center more attractive, driving up relative prices and causing the rich to move in. Indeed, other tests with increased gas tax found increased housing costs and number of high-income households in the city center.

The results suggest that performance of the subsidy as a city-center job-production strategy is less robust than the strategy’s performance in increasing low-income households in the city center. Across the futures space, the subsidy resulted in a net city center population increase of approximately 6,000 total households—an increase in low-income households but fewer medium- and high-income households. One might guess that the population increase in
the city center would increase the number of jobs there. However, the simulations across the futures space produced a wide range of responses to the subsidy in this regard: from an increase of 3,831 jobs to a decrease of 332 jobs. This wide range makes job creation an interesting metric by which to judge the effects of the subsidy.

To demonstrate the concept, failure scenarios for job creation were defined as those in which the subsidy failed to increase jobs in the city center by 1,000 jobs. All simulated scenarios that did not produce increases of 1,000 jobs or more were designated as failures—23% of total simulated cases. The rule that best balances high support, mean, and purity in finding failure scenarios is employment growth rate greater than 1.16% YoY. In total, 90% of all failure cases were captured by this rule (Figure 5). This rule also has very high purity: 96% of the simulations in this box were failure scenarios.

Figure 5. Visualization of the failure box for job growth in the city center, 3 of 4 dimensions displayed. Inspired by Groves and Lempert (2007).
While the explanatory power of this box definition is strong, the meaning of this rule is not completely intuitive. In effect, the rule says that above a certain level of employment growth, the subsidy will not create jobs in the city center, although it also will only rarely decrease them. Perhaps a tipping point of employment growth exists, beyond which the outer areas add enough jobs to become major centers of job attraction. Spatial visualization of a number of scenarios of interest supported this explanation: we observed concentration of jobs into a few outer areas for a number of high-employment-growth scenarios. This finding warrants further investigation both of our model and of our general assumptions regarding the effects of employment growth.

Discussion and conclusions

To improve methods for accounting for uncertainty in urban planning, we provide a theoretical framework to organize qualitative and quantitative methods of futures exploration, according to the number of futures considered and relative computational intensity. We then demonstrate one method that operationalizes the concept of strategically robust urban planning, using LHS experimental design and an urban simulation model to “farm” alternative futures and applying PRIM to “data mine” those futures. Our demonstration examines the general influence of exogenous forces in determining “danger regions” — where policies may perform poorly — and characterizes these danger regions through a method that emphasizes high interpretability. The analysis thus sheds light on both the computational model and the real-world processes that it attempts to simulate. The model runs were not prohibitively time-
consuming on a high-end machine; expanding the simulations to longer time scales and more complex models should be possible.

Towards that end, a number of issues remain for investigation. First, the UrbanSim model used in this analysis represents a simplified calibration for Lisbon. Data availability precluded a model involving multiple travel modes and time periods and longer timeframes. The transportation system and firm location choice representations are particularly crude. Our work is a demonstration, not a true indication of robustness for subsidies in Lisbon. More complex models will require additional work on automation in the data-farming phase. Furthermore, in terms of data-mining, the simple performance metrics (e.g., number of households) utilized in our demonstration are unrealistic, and inappropriate, for actual urban policy making, which inevitably requires satisfying a number of objectives (environmental, equitable, economic). Multi-criteria analysis, with a singular indexed performance value, could help satisfy this need. In addition, stochasticity, including that inherent to certain UrbanSim sub-models, has been neglected here. Confidence intervals could be calculated, whereby “successful” outcomes would have to cross a given threshold with a specified level of confidence. In terms of the input parameters chosen, only four could be adjusted easily in our UrbanSim implementation. These inputs may not correspond to all driving forces of interest. Future research could, for example: aim to develop a hierarchical approach to identifying external forces of interest; expand the variables modified in a given simulation by including behavioral parameters in the model(s); and/or account for potential fluctuations in variable values within the time period of interest.
Increases in computational power will certainly enable greater complexity and computational intensity in urban systems modeling. Effectively applying that power remains the challenge. Some might argue for moving towards simpler models, at least before modeling more completely the scenarios of interest identified by these simple models. Undoubtedly, however, others will continue to advance detailed, agent-level, behaviorally based micro-simulation models. Ultimately, irrespective of model approach, we need more rigorous methods to assess model and strategy results. We believe that, just as scenario planning has increasingly entered into the urban and transportation planning realms, the quantitative approach of scenario discovery via data farming and data mining, as demonstrated here, holds great promise for formalizing more systematic approaches to identifying strategically robust urban policies.

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