6 Modelling Methodologies: Opportunities and Limits

Chapter Summary

This chapter describes in detail the methodologies of modelling and their limits, as a preparation for exploring the specific model to be proposed and evaluated.

This chapter is drawn from the peer-reviewed publication "Counting Urban Carbon" (Mehaffy, 2014).

Before we can turn to the specifications of a new urban design decision support model, we must first ask fundamental questions about methodology. After all, there is a profound problem facing anyone seeking to develop models to guide design choices. It lies in the epistemological limits of all models, which we will discuss here in more detail. Following that discussion, we can examine some of the modelling methodologies that have been developed in part to respond to these limitations, and to provide the more robust capability that we seek.

First, we must recognize that a modelling tool is, by definition, a prediction of what will happen in the future, when conditions in reality are sufficiently aligned with the parameters of the model. But the data on which such a model relies for its development is, by its nature, from the present or the recent past. In relying upon previous data, we must apply our own theories – the predictive elements of our model about how the system will behave – to generate a prediction. If our model is not a simple extrapolation (which is rarely correct), then we must rely upon a more complex set of abstract ideas about the interaction of factors.

Of course, any such abstraction is precisely that – an abstraction, which is fundamentally "an omission of part of the truth," in the memorable words of the philosopher and mathematician Alfred North Whitehead (1938). Our challenge is not to create a perfect copy of reality, but to apply such abstractions (including models) in a way that their corresponding features provide useful guides to the structure of the phenomenon of interest, without their omissions becoming problematic. This standard of usefulness must ultimately apply to all models.

However, Whitehead warned, we must be clear about what our abstractions can and cannot do, and the need to attain what he termed a "right adjustment of the process of abstraction". Failure to do so may lead us to what he called "the fallacy of misplaced concreteness" – the often mistaken assumption that aspects of our abstractions will correspond to aspects of reality. An example is the tendency to over-estimate the predictive validity of a theoretical model – a common problem in a number of professions today (Taleb, 2005; Kahneman, 2002; Tversky and Kahneman, 1974).

Whitehead's work is part of an extensive literature on the epistemology of modelling, and the broader capabilities and limits of abstract systems – including language itself – whose cautionary lessons must form the foundation of the robust modelling methodology we seek. In particular the Twentieth Century brought important work in identifying the inherent incompleteness of information as a fundamental limitation of any such model.

Especially notable among this literature is the work on undecidability and incompleteness by the mathematician Kurt Gödel (1931). Gödel famously applied a brilliant analysis of symbolic logic to Whitehead's own logical system, presented in his masterwork *Principia Mathematica* (developed with his colleague Bertrand Russell, 1912). Somewhat ironically, in view of Whitehead's own later work, it was Whitehead and Russell's intention to create a complete logical system to represent all of mathematics. But Gödel proved, with unassailable logic, that it must be incomplete – and so too must any such formal system. The implication is that any referential system – that is, any system that refers by formal representation to some other system, including any model – must be incomplete. Furthermore, this incompleteness is not a trivial distinction, but it goes to the core of any referential system.

The philosopher Ludwig Wittgenstein (1953) made a similar observation about the nature of language itself. In his earlier work (1921) he had built on Russell's own work to develop a theory of the correspondence of linguistic acts to structures in the world, as maps correspond to the regions they represent (a "picture theory" of language, as he put it). His later work, however, recognized that there is no such simple mechanical coupling of a linguistic model to its subject; indeed, he formulated a "rule-following paradox" that showed, not unlike Gödel, that language could not be generated by a rigid set of rules of correspondence to reality. Rather, the linguistic system must function as a kind of "game", or an analog system with its own internal rules, in which useful but quite loose correspondences may (or may not) occur. To think otherwise, Wittgenstein warned, is to fall victim to a kind of "bewitchment of intelligence", of just the sort that language (and especially the misuse of language) is prone to encourage.

Unfortunately we can still see examples of Wittgenstein's "bewitchment of intelligence by means of language" and Whitehead's "fallacy of misplaced concreteness" in many modelling methodologies today – or what is just as unfortunate, in their uncritical application by over-specialized professionals. These faulty outputs become the uncritical basis for rigid, poorly optimized design decisions, with little scope for refinement and fine-grained support.

As the urban theorist Jane Jacobs (1961) pointed out, such models actually fail to account sufficiently for what she described as "the kind of problem a city is" – a problem that has the dynamic behaviours of living systems and their processes. Such systems cannot be entirely reduced to linear, single-variable analyses or statistical models – though these approaches have their limited place. However, she argued that their misuse by planning specialists damages the inherent capacity of these cities to self-organize in benign ways. The inevitable result is the grim damage that is readily observable in great cities of the 1960s, as she documented in her landmark work *The Death and Life of Great American Cities*.

§ 6.1 Accounting for Complexity and Self-Organization

Jacobs' analysis alluded to yet another fundamental problem with the modelling of complex phenomena like urban systems. It is that the phenomena we are modelling do not sit frozen, but have the unfortunate habit of self-modifying in response to dynamic events, and in unpredictable ways. That is, they are complex adaptive systems that are continuously evolving and, to some degree, self-organizing. While some of their features may remain relatively static, many of them – particularly those relating to socio-economic interactions – are exceedingly dynamic. Often they have "non-linear" characteristics, i.e. their behaviour is not proportional to the quantitative factors that influence it. Clearly we must somehow account for this dynamism in any model as well.

The development of transportation modelling illustrates the nature of the problem. Earlier transportation models treated the actions of individual vehicles as simple and predictable elements that seek only to continue on their current path at the maximum possible rate. The errors of these models, and the failures of the systems constructed in response – particular the failure to alleviate traffic congestion for any but a short period – are now well documented (Supernak, 1983). Of course, human beings are decision-making agents in their own right, and they are able to decide to take alternative routes based upon dynamic conditions – or not to travel at all. One consequence of this dynamic environment is the phenomenon of induced demand: the more supply is increased, the more demand may grow in order to consume more of it (Noland, 2001).

The same limitation affects the systems that generate greenhouse gas emissions. As Mayumi and Giampietro (2006) pointed out, the socio-economic systems that are ultimately responsible for greenhouse gas emissions are themselves self-modifying, and because the number of variables is large, the ability to predict actual outcomes is greatly reduced.

Jacobs (1961) noted the importance of large numbers of variables in playing a role in the complexity of cities. But she argued that it is not only the number of variables, but the way they are interrelated within a structural characteristic she referred to as "organized complexity." She noted the progress made in the life sciences in understanding how the elements of a system modulate one another's behaviour so as to form an "emergent" pattern.

In the subsequent decades, this progress accelerated notably, as problems in many fields were seen to be understandable as problems of complex adaptive and self-organizing systems. The progress was perhaps most dramatic in the field of biology and genetic processes. For example, Farmer et al. (1987) were able to show how so-called "network models" could explain the complex interactions of immune systems and other biological phenomena, and they applied the insights to other systems as well. Kauffman (1993) also showed that self-organisation processes are capable of accounting for the evolution of complex biological structures. But self-organisation was readily seen in other systems. Nicolis and Prigogine (1977) described the self-organisation of non-equilibrium chemical systems. Kauffman (1995) described broader insights from self-organisation and complex adaptive systems.

FIGURE 6.1 Self-organisation is seen in many natural systems including this bird flock. Each bird follows a local set of rules to adjust its position to the other adjacent birds, and the system "self-organizes" into an ordered structure. Similar phenomena have been extensively studied in urban systems and their economies. Photo credit: Titus Tscharntke

A number of authors have also applied these lessons to urban systems since Jacobs. Salingaros (1998, 2005) described the "urban web" as an interactive network with dynamic and self-organizing aspects. Batty (2007, 2009) described the complex and fractal structure of cities, and proposed modelling methodologies to account for this structure. Allen (1997) described cities and regions as self-organising systems, arising from the complex interactions of individual agents. Portugali (1999) described self-organization processes in cities as a form of rule-based "game".

In these and related findings, the topic of self-organisation poses profound epistemological limitations – but also opportunities (Kauffman, 1995). If we can understand the dynamics of these processes, we might well find ways of enhancing their desired results, and suppressing their undesired results. This indeed has been a fertile area of research. In fact, a number of modelling methodologies have been developed so as to account for and exploit these dynamics. We discuss several of them in more detail below, followed by a discussion of their relevance for carbon reduction urban design modelling more specifically.

§ 6.2 Methodologies for modelling under complex and uncertain conditions

In recent decades a number of innovations in modelling methodology have emerged to incorporate the epistemological insights of earlier decades. We survey several of the most relevant up to the present day, and draw conclusions for current work in development of urban design support modelling.

§ 6.2.1 Bayesian Methodology

One of the most important developments in the methodology of statistical modelling has been the development of Bayesian methods, originated by the English mathematician Thomas Bayes and further formalised by the French mathematician Pierre LaPlace via what is known as Bayes' Theorem. Subsequently a methodology has been developed around the use of the theorem with applications to modelling, known as Bayesian methodology (Rupp, Dey and Zumbo, 2004).

In contrast to "frequentist" methodology, which seeks to confirm or reject a predictive hypothesis purely on the basis of the frequency of data, Bayesian methodology allows for successive estimations of the probability of truth of such a hypothesis. There is a strong relationship to what is known as "fuzzy logic" in the field of logic, but there is one key difference: whereas Bayesian methodology is concerned only with uncertainty around a given set of data, fuzzy logic accepts the premise, for strategic reasons, that the logical consistency of the data itself may not hold (Zadeh, 1973). Fuzzy logic is an important development in complex systems and decision processes, but it is less applicable here than Bayesian methodology.

In Bayesian methodology, a crucial element of the calculation is the knowledge of probability *prior* to the current data calculation, known in the field as the "Bayesian prior." This key assessment can be made on the basis of what is known, or only believed, about the probability of the predictive hypothesis. This can include an explanatory theory of how the system in question is predicted to behave, or even a heuristic that is drawn from past experience. The methodology relies upon iteration, and at each successive step the Bayesian prior will be updated on the basis of new information and new assessments. In this way, a Bayesian methodology is capable of learning and growing more accurate over time.

It is a crucial feature of the methodology that the initial accuracy of the Bayesian prior probability need not be high for the process to provide useful results – as long as the system is capable of improving based upon later outcomes. (This idea is captured in the elegant little poem titled "The Road to Wisdom," by the physicist and mathematician Piet Hein: "To err and err and err again, but less and less and less.")

Comparisons have been drawn between Bayesian methodology and the iterative way that the scientific process itself works. As we will see, there is also a comparison to the use of design patterns and pattern languages, which function as "structured essays" that can be improved iteratively over repeated usage, testing and improvement. (See Appendix.)

§ 6.2.2 "Improper" linear models

Although linear models – those that simplify a prediction to a simple linear scale of probability – are often significantly inaccurate, they may still be more accurate than human judgment alone, including the judgments of highly trained professionals (Kahneman, 2002). This may be because, like all models, linear models combine inaccurate features with features that may be accurate enough to be useful in some decision-making contexts. The question is not whether they have any inaccuracy – all models must, as Gödel demonstrated – but whether they nonetheless provide useful capabilities.

The usefulness of so-called "improper linear models" was made clear in a very highly cited paper by the psychologist Robyn Dawes, titled "The robust beauty of improper linear models in decision-making" (1979). In it he demonstrated that, in certain contexts, "improper" models (that is, models in which the variables are not properly weighted in relation to one another) can nonetheless be useful. These contexts are typically where data is limited and "noisy" (inaccurate) and where there may also be many variables of data. In such a case it may be more effective to simply aggregate the factors without giving them weight. In fact, the research shows very clearly that such models can be remarkably effective, and considerably more accurate than human judgment, even highly trained expert human judgment.

It is a remarkable fact that this is so. The reason, according to Dawes, is rooted in the subject of epistemological limits as we discussed previously. While models can suffer from inability to cope with complexity and dynamic self-organization, it appears that human judgment is even more prone to error. As later work by Kahneman (2011) showed, we make decisions with cognitive systems that are extremely vulnerable to biases and distortions. When it comes to phenomena like climate change, these biases can result in the familiar patterns of inaction and apparently irrational response. In such cases improper linear models, for all their limitations, often perform better than human judgment.

A rudimentary example of an improper linear model, according to this definition, is the urban sustainability rating system known as LEED-ND, or Leadership in Energy and Environmental Design for Neighborhood Development. The system uses a point system for scoring a range of urban sustainability metrics. It has been criticised, probably rightly on the merits, for ranking the points in an arbitrary way – "improperly" according to this definition (for example, in the critique of Sharifi and Murayama, 2013). Yet Dawes' work suggests that LEED-ND may well be a good interim model to use, at least until such time as better models are developed.

§ 6.2.3 System Dynamics Modelling

AltThe fundamental problem of dynamic interaction and feedback was recognized in the 1950s by Professor Jay Forrester of the Massachusetts Institute of Technology (1957, 1961). His methodology, called "system dynamics," explicitly built in recognition of the effects of feedback and time delays with the behaviour of systems, and the methodology sought to capture and predict the outcome of such interactions.

Forrester's stepwise, iterative modelling methodology can be described as follows:

- First, define the boundary of the phenomenon to be modelled, using existing boundaries as much as possible.
- Second, identify the most important "stocks" (metrics) and the flows (movements of quantities) that will change these stock levels.
- Third, identify inputs that will influence the flows.
- Fourth, identify the feedback loops in the flows and the inputs.
- Fifth, draw a "causal loop diagram" that links the stocks, flows and inputs.
- Sixth, write equations (or computer programs) that will calculate the flows.
- Seventh, estimate the parameters and initial conditions, using the best information available.
- Eighth, run the simulation of the model and analyse the results.
- Finally, if iterations are required, cycle back to the point of the next iteration.

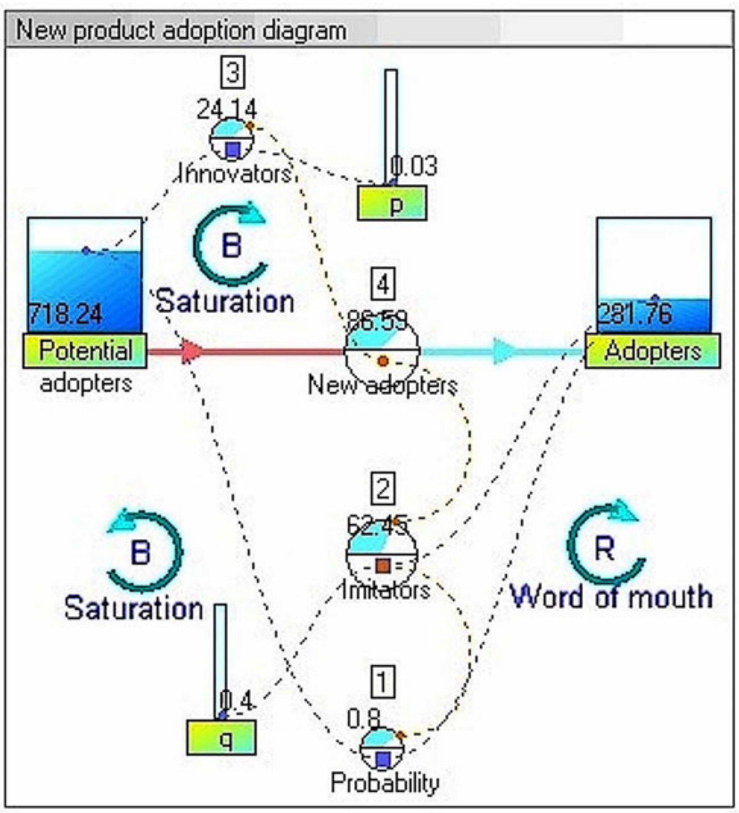

FIGURE 6.2 Diagram of a dynamic model of the interaction of factors in the adoption of a new product, as it is influenced by word of mouth, imitation, innovation, and other factors. Source: Patrhoue/Wikimedia Commons, After Sterman, 2001

.Forrester's modelling methodology became popular in business management and industrial process engineering, notably as a tool to optimise quantities and delivery times. Initially a manual method, the process was computerized in software such as SIMPLE and DYNAMO, and it became an industry standard tool. The modelling was expanded into urban systems when Forrester was asked by Boston mayor John Collins to collaborate on a project at MIT, resulting in the book *Urban Dynamics* (Forrester, 1969).

Forrester was drawn into global systems modelling in his work for The Club of Rome's 1972 report *The Limits to Growth*. That work certainly focused public attention on the ecological parameters of socio-economic systems, and the implications of their limitations. But its notable inaccuracies of prediction (for example, it under-estimated ecological capacity) also did damage to the reputation of such large-scale models. In fact, the following year, a "requiem for large-scale models" was published in the *Journal of the American Institute of Planners* (Lee, 1973).

Other critics pointed out the value-laden assumptions in Forrester's modelling. Kadanoff (1971) published a critique of Forrester's book *Urban Dynamics*, making the argument that Forrester's choice of modelling elements shaped the outcome. Harris (1972) argued that single projections, including those proposed by Forrester, are extremely unreliable because their boundary definitions isolate the entity under study from its environment. He suggested that Forrester's modelling, while highly influential in business process planning, had little effect on urban planning practice.

§ 6.2.4 Artificial Neural Networks and Bayesian Belief Networks

The recognition of limitations imposed by self-organizing phenomena has inspired a class of models that are able to self-organize on their own, and, in effect, "learn." Notable among these are "artificial neural networks," which seek to mimic the learning processes of neurons in biological systems (Rumelhart and McLelland, 1986). This approach to modelling is "connectionist" – that is, it relies upon the evolving set of connections between the elements of the model, which are not defined statically as in Forrester's system dynamics.

This work has begun to be applied to modelling, and to greenhouse gas modelling specifically. For example, Radojević et al. (2013) published a report on a project to forecast greenhouse gas emissions in Serbia using artificial neural networks. However, much more remains to be done in this promising area .

Bayesian belief networks are similar in that they have the capacity to learn by identifying and evaluating inferences within a modelling environment of uncertainty. But they do so using Bayesian methodology, which as we have seen, deals with uncertainty not by identifying "true-false" relationships, but (evolving) degrees of probability based on incomplete knowledge and belief. In such a model, a certain quantitative relationship between A and B might be probable to a certain degree (say, residential density and number of kilometres driven), and another relationship between B and C might also be probable to a certain degree (say, number of kilometres driven and types of automobiles owned), but with variable degrees of probability. The resulting network can model the total degree of likelihood for the condition in which A, B and C interact (say, how residential density relates to types of cars owned, and how both affect kilometres driven).

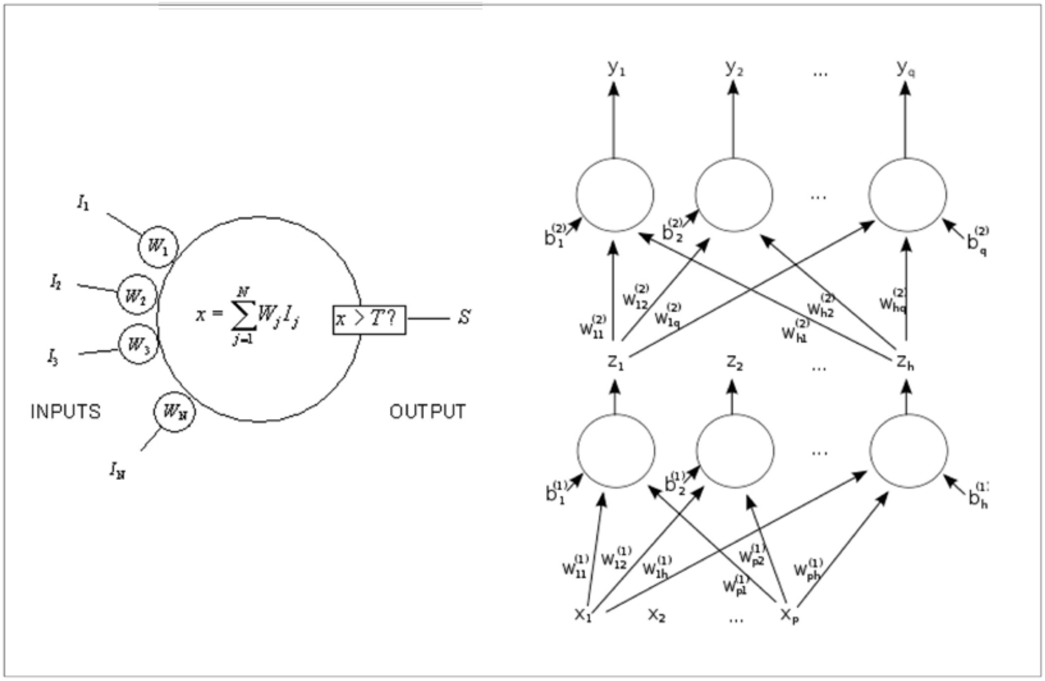

FIGURE 6.3 Artificial Neural Networks solve optimisation problems by mimicking the way natural neurons work. Left, each neuron receives inputs from other neurons and decides whether to "fire" based on a threshold value. Right, the network of neurons is able to "learn" the pattern that produces the intended output. Source: Left, after Ivan Galkin, U. Mass Lowell. Right, M.C. Strother.

Bayesian belief network models have been used in ecological modelling and conservation (Marcot et al., 2006) and the effects of variable greenhouse gas emissions on sea ice and polar bear populations (Amstrup et al., 2010). A Bayesian Belief Network has also been used successfully to model land use decision behaviours (Aalders, 2008). Again, more remains to be developed in this promising field.

§ 6.2.5 "Dynamic Structural Models"

Several fields, notably econometrics, apply the concept of a "dynamic structural model," in which the behaviour of an individual (a person or object) is predicted based upon a dynamic interaction of structural conditions and preferences (Aguirregabiria, 2011). In this sense, the individual person or object is embedded within a dynamic system and their behaviour is understood as an interaction with the other factors.

In computer systems engineering and other related fields, the same term is used to describe an "object-based" modelling process. The systems that are modelled are not seen fundamentally as collections of discrete mechanical elements, but rather, as whole systems that are "decomposed" into smaller systemic wholes according to their functional sub-systems. These elements of "dynamic structural models" are more readily able to retain the larger systems attributes that are essential in the generation or "instantiation" of new applications (IBM, 2014).

§ 6.2.6 Pattern Languages

In software, one of the best known such object-based modelling systems is pattern language programming (Coplein and Schmidt, 1995). Pattern languages, developed by architect Christopher Alexander, have been used successfully as object-based models of software design since the early 1990s. In fact they are now ubiquitous within computing, and they form the basis of many common software systems (such as the Apple Mac OSX and the iPhone Cocoa language). Pattern languages have spread into many other domains as well, including human-computer interaction, service design, business administration, education, and many other fields. In some cases innovations in software design have led to innovations in other fields; a notable example is the development of the "Scrum" and "Agile" methodologies, which began in the software world and spread to become mainstream management methodologies (Beedle et al., 1999; Mehaffy 2010).

The reason that pattern languages, invented for architectural design, fit so well within the object-based approach of computer software is that they were explicitly developed as flexible, networked, language-like design models (Mehaffy, 2010). Their inventor, architect Christopher Alexander, was trained as a mathematician and physicist before earning the first Ph.D. in architecture at Harvard University. However, he spent time working on early generations of computer decomposition software. He also worked closely with leading cognitive psychologists at MIT, including George A. Miller, and his Ph.D research included cybernetics, cognitive psychology, linguistics and philosophy.

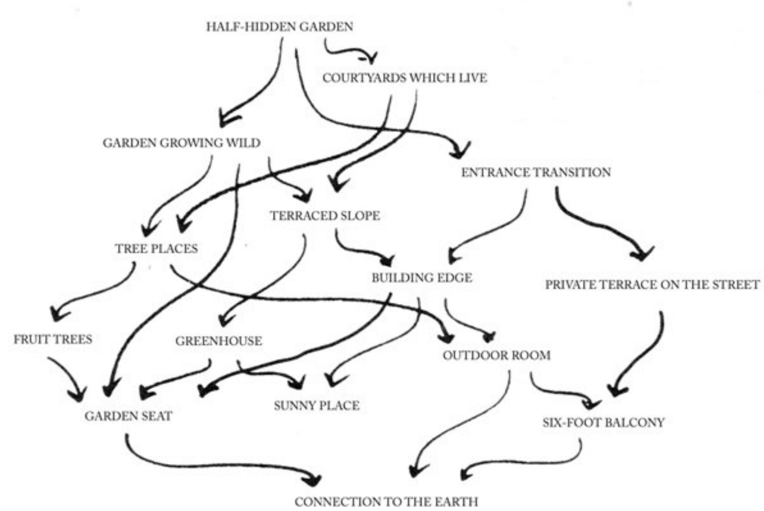

FIGURE 6.4 Pattern languages have been used in many fields of software and hardware design, following their invention in the field of architecture. The elements and their linkages form a web-network, which usefully mimics the web-network structure of design problems. (Credit: Christopher Alexander.)

Like Wittgenstein, Alexander became convinced that language was not a perfect decomposition of an orderly hierarchical reality, but more like a "game" with its own set of objects and rule-based interfaces, only loosely coupled to the world to which it referred. It had ambiguities, overlaps, and the complexity of web-networks – as did, too, the phenomena it sought to describe.

So, too, designs must not seek to be perfectly rigid hierarchical structures made up of collections of elements, but rather, they must be systems with language-like ambiguities (Alexander, 1965). The value of such a design model was in its ability to capture the same web-like structure of the world, and to be able to explore a wide range of design possibilities in a powerful and flexible way – not unlike the power and flexibility of natural languages.

Each pattern is, in a sense, an element of a predictive model which asserts that a given configuration will work in a predictable way, within a context of other patterns. Crucially, the pattern is able to be tested and falsified, and then modified to become more accurate. In this sense, a pattern states a kind of Bayesian prior, which can be used to create a prediction of whether a given design will actually work. Over time, and within a community of users, the patterns can become more accurate and effective.

One of the developers of pattern languages in software, Ward Cunningham, took this capability a step further. He developed a flexible new tool for collaboration, using easily editable pages as hyperlinked objects. His invention, Wiki, is also now a ubiquitous tool, leading to the development of Wikipedia and thousands of other corporate and private Wikis (Mehaffy, 2010).

For Cunningham, a Wiki page *is* a kind of pattern, and a Wiki compendium is, in a sense, a pattern language. In both cases the pages are "structured essays" that describe what is asserted to be a valid relationship. But in both cases, that relationship can be tested, corrected and made more accurate over time (see the Appendix for more discussion of this central software methodology).

It is a key capacity of pattern languages that, like natural languages, they are shared and evolved by a community of users. For Cunningham, this capability was an essential strength of Wiki, and was clearly a critical ingredient of the success of Wikipedia. Cunningham is now working on a new generation of Wikis that will, in addition, have the capacity of data management and manipulation, as well as a more distributed, "federated" structure (Mehaffy, 2013; Cunningham and Mehaffy, 2013).

The next chapter will describe the workings of this Wiki structure in more detail, and will examine a prototype decision-support tool that utilizes its capabilities. First it is necessary to examine another existing methodology for evaluating design solutions – one that will also form a part of the basis for the new tool we will discuss.

§ 6.2.7 Scenario modelling

A simpler modelling methodology that is also able to incorporate aspects of the other methodologies discussed herein is the use of so-called "scenario-modelling". This methodology has become more common in recent years (Schoemaker, 2004; Mehaffy, 2013), notably in the fields of urban design and planning. This is in large part because a range of concrete possibilities can be more readily explored and evaluated, not only on the basis of one criterion like greenhouse gas emissions, but with a balance of broader criteria.

As with all design, the goal is not merely to create some wholly new structure with desirable attributes, but – as the noted design theorist Herbert Simon famously described it – to effect a course of action that successfully changes an existing state into a preferred one (Simon, 1962). This implies an ability, on the part of the designers, to explore a range of alternative design decisions and their likely outcomes, so as to judge their preferability. That is, it implies a capacity for usefully reliable prediction.

It is in this environment that scenario modelling has arisen as an urban design decision-support tool . In essence, a designer, or design team, prepares a series of design alternatives, which serve to outline the range of choices that are believed to be available for the design. The modelling process then provides a set of comparative predictive results of those choices, and thereby provides guidance in directing the design process. In so doing, the process works to solve an optimization problem with regard to a set of inter-dependent variables – such as greenhouse gas emissions, residential density, urban paving area and the like (Condon, Cavens and Miller, 2009).

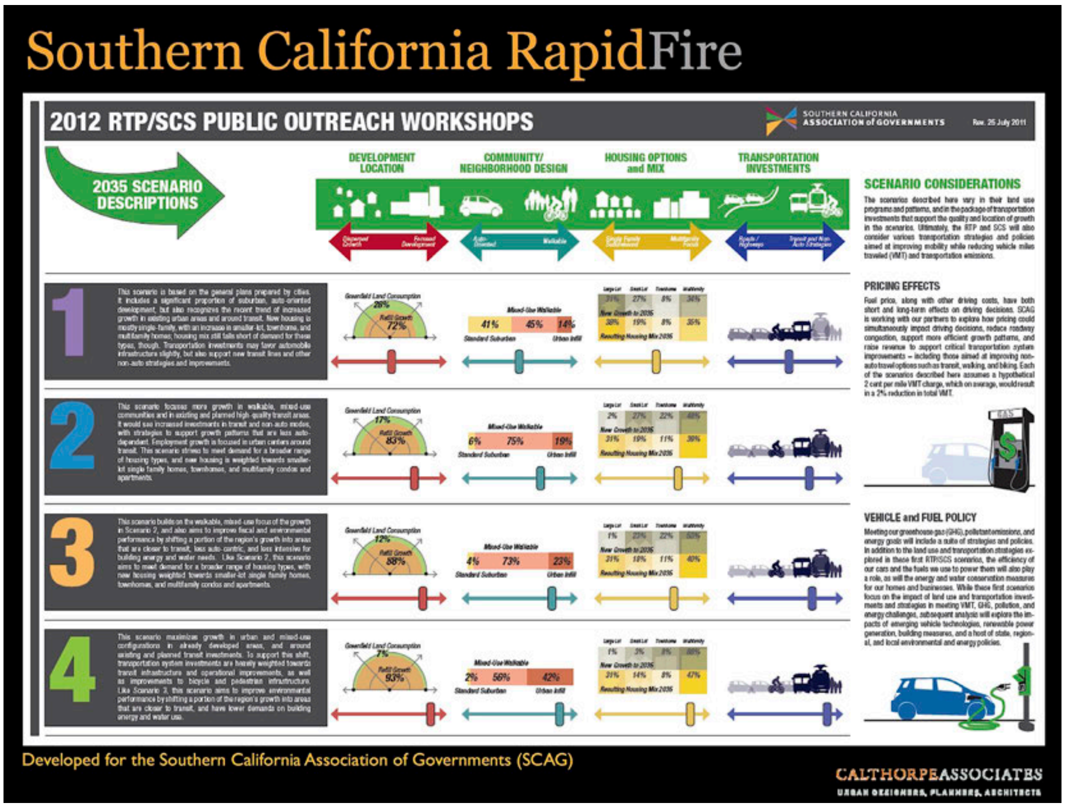

FIGURE 6.5 Scenario modelling has been developed on computer platforms using open-source methods, such as RapidFire, shown here, developed by Calthorpe Associates for use in California's greenhouse gas reduction planning work. In this user interface, stakeholders are able to choose their preferences within comparative scenarios, and then see the predicted results of their choices. Credit: Calthorpe Associates.

A question immediately arises as to which variables are selected, and how the preferential condition is determined – and by whom. By definition, the designers are optimizing relative to normative definitions of "preferred states" that they themselves have accepted. For example, more reduction of greenhouse gas emissions is better, but perhaps not at the expense of an excessive level of residential density, which may be an "unpreferred state."

But the next question must be, of course, on whose authority do they choose those normative definitions? This was the problem raised by urban design pioneer Kevin Lynch, writing in his book *Good City Form* (1984). He argued that such normative values are an inevitable part of all design, and what is critical is that they are transparent, critically examined, and subject to democratic process. The goal is not to have "the right model" of good city form in any objective, predetermined sense, but to have a model that has been openly and critically assessed, with the benefit of public scrutiny and evaluation.

A key strategy for doing so has been to employ scenario-modelling tools within so-called "public involvement" processes, where citizens and stakeholders have at least a theoretical opportunity to participate in shaping the normative values of the urban design modelling and decision-making process. Examples are so-called "envisioning" processes, where stakeholders are brought into a process of design scenario development and given choices about preferred outcomes, which are then analysed with predictive modelling (Lemp et al., 2008). Subsequent iterations can refine the outcomes according to the preferences of those engaged in the stakeholder involvement process, as well as other required parameters of the outcome (e.g. legal and regulatory requirements).

These public involvement processes can take the form of collaborative workshops or "charrettes" (Condon, 2007). The goal of these charrettes is to actually engage a range of designers, technical experts, and stakeholders, in developing, assessing and refining design ideas. In a sense, the charrette process is in the business of assessing design scenarios, and for this reason the scenario-modelling process has been found to be well suited to the charrette workshop (Condon, Cavens and Miller, 2009).

It is important to emphasise that the achievement of a preferable state, as Simon described it, need not be accomplished entirely by one act, by one process, or even by one agent. Indeed, in practice this rarely happens. As Gigerenzer described it (2004) we are in an environment of "ecological rationality" and must rely in part upon "fast and frugal" heuristic decision-making methods. Progress will be achieved through successive iterations that often involve multiple parties, who can then learn from the results and refine the successive iterations to become more effective.

This means that in modelling of such design actions, what is necessary is to have generally reliable, but not necessarily precise, guides to actions that are likely to take us sufficiently in the preferred direction with each iteration, while avoiding the reversal of progress by any other factors. Through successive iterations we can get closer still, and at the same time, we can use the feedback we gain to hone the accuracy of our predictions as we progress. Through successive iterations and by many participants, these actions can be refined and improved over time: the process can "learn" and grow more effective. This is an aspect of design that mirrors phenomena in the natural world, as Simon (1962) and other planning and design theorists have described (e.g. Jacobs, 1961; Alexander, Neis and Anninou, 1987).

Another fundamental challenge of modelling is the selection of data and the methodology by which the predictions are generated. As we will discuss in more detail below, the issue of political controversy and inaction in the realm of GHG reductions remains especially acute because the complexity and inherent uncertainty of the information obscures the set of decisions that would likely make progress possible, relative to other goals. Our models, often reliant upon large data sets and statistical inventories, are highly sensitive to small errors in initial assumptions – for example, incorrect selection of relevant factors to compare on an "apples to apples" basis (see e.g. Rypdal and Winiwarter, 2001). These errors become magnified to produce large-scale errors at worst, or inconclusive results at best (Cullen and Frey, 1999). Inconclusive or erroneous results are then cited by self-interested parties to support their policy arguments, leading to greater confusion (Morgan and Henrion, 1990). The result is that there is very little progress, and a great deal of uncertainty, false hope, paralysis – and worse, false claims for failing methods. This undesirable cycle is self-reinforcing and self-accelerating.

§ 6.3 Conclusion

Building on the advances of these existing methodologies in other fields, we can now state the requirements of an effective modelling methodology for resource-efficient urban design decisions, working under the uncertain conditions with which we must cope:

1. ***Such a methodology will be iterative.*** It will not be applied in a single iteration to any degree of effectiveness, but will improve with successive iterations.
2. ***It will be able to regularly make comparisons with empirical results and adjust its predictive data accordingly.*** The iterations will be of little benefit if they do not allow a periodic comparison with empirical results so as to verify or refine the model.
3. ***It will utilize the iterative participation of a community of users in an "open-source" format.*** In this way the improvements can be distributed across a larger community, and the cycle of improvements can be accelerated.
4. ***It will include the most readily identifiable factors, and add other factors as they can be established accurately.*** The accurate weighting of the factors is less important than their inclusion within the model as it goes through iterative refinement and empirical adjustment.
5. ***It will account for the dynamic interactions between factors, without becoming overly complicated.*** The best way to do that is to use a more flexible, web-networked, language-like approach, rather than a mechanical approach to constructing components within a linear or reductionist scheme.
6. ***It will draw on the best available data – but it will also compensate for the inherent uncertainties of the data.*** This means using methods to draw inferences and improve them iteratively (such as Bayesian methodology) and other compensations. It will also mean that the result is treated as provisional and incomplete, but nonetheless, a useful basis for incremental improvement.

It will be noted that the previously discussed modelling methodologies do contain some or all of the features specified above, to varying degrees. But an opportunity now appears to combine the varying benefits of different approaches into a next-generation methodology, as outlined here. For example, in what ways might pattern languages be able to function as artificial neural networks, capable of learning in problem-solving – particularly with the open-source capabilities of a Wiki community? What capacity might such a technology offer for developing more effective design models, and more effective problem-solving capability for complex contemporary challenges?

Such a synthesis methodology therefore suggests the possibility of a promising new kind of design technology – or perhaps it is more accurate to say, an existing technology, given useful new capabilities. That is the opportunity we will examine in the next chapter.

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