Policy Modelling: Problems and Prospects

Scott Moss*

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Policy modelling is the application of agent based social simulation to the analysis of social policies. While agent based modelling has been seen as a promising technique for policy analysis in a number of applications such as water demand and land use management, it has not become an important tool of business and public policy analysis more widely.

The purpose of this paper is systematically to set policy modelling in a wider scientific context than has been attempted previously and to use that context to explore the general conditions in which policy modelling is appropriate and the problems to be faced in convincing working policy analysts why and when it is the most appropriate tool of analysis available to them.

1 Qualitative and quantitative approaches

Approaches to policy analysis in general are based on either qualitative research or statistical (including econometric) and mathematical modelling. Most qualitative research is not formal while all statistical and mathematical models are of course formal in the sense that they are constructed using techniques with proved logical (in this case, mathematical) properties.

Core approaches to qualitative research are soft systems methodology (Checkland, 1981) and grounded theory discovery (Glaser and Strauss, 1967) – both of which have been developed in relation to the analysis of organisations.[1] Practitioners of these approaches seem to dismiss formal approachs as "mathematical modelling" that is inherently remote from reality and the problems that qualitative researchers are addressing. Nonetheless, they have in common three features that are of interest to policy modellers: they start from detailed, evidential accounts of the target organisations; eliciting the evidence requires the participation of stakeholders; relationships among

*The line of thinking that led to this paper was inspired by discussions with Thomas E. Downing of the Stockholm Environment Institute Oxford Office and Ossie Jones of the MMU Business School. Neither has had a chance to object to anything in this paper and I imagine each would take issue with some of the arguments put forward here.

[1]For a description of the relationship among soft systems, grounded theory discovery and agent based modelling, see Pahl Wostl and Hare (2004).

stakeholders are of primary concern. These features are shared by several projects involving the development of agent base social simulation models for purposes of social policy analysis. First among them chronologically (and ongoing) is companion modelling (Bousquet et al., 1999; Becu et al., 2003; Barreteau et al., 2003), an approach that involves iterations between stakeholder engagement and, in particular, role-playing games for purposes of knowledge elicitation and model evaluation. A similar approach was undertaken in the EU projects FIRMA[2] and CAVES[3]. Amongst the models produced for purposes of policy analysis, those reported by Downing et al. (2000), Alam et al. (2007) and Ernst et al. (2007) defined their agents on declarative, rulebased inference engines which captured the qualitative descriptions of relationships and behaviour provided by stakeholders and did so using their own language and terminology. Effectively, we can see a spectrum of models ranging from those that are most qualitatively expressed to those that are least qualitatively expressed because they use numbers (for example real numbers to represent opinions (*e.g.* Deffuant, 2006)). The evidence based models are all closer to the qualitative end of this notional spectrum and therefore (because they are also concerned with relatioships amongst distinct individuals) unambiguously closer to the informal approaches taken by the qualitative researchers concerned with organisational and management studies.

Mainstream economic and econometric models share none of the three features of qualitative and social simulation modelling indicated above. That is, the modellers do not start from detailedn narrative evidence (dismissed by economists as "anecdotal evidence"), they to not engage stakeholders in the elicitation of the evidence used and, apart from some economists producing agent based models otherwise constrained by mainstream economic concepts, they assume away individual differences and influences so that social interaction has no role in their analyses.

The role of social interaction could not be more important because it brings up issues of emergence, complexity, social norms, reputation, influence – itself not an exhaustive list of important social phenomena. Of these phenomena, the most relevant for the present discussion is complexity.

2 Policy and complexity

Social policies are comprised by actions or statements of public authorities that are intended to influence or modify the collective behaviour of individuals. Social complexity is a condition whereby social behaviour cannot

[2]Freshwater Integrated Resource Management with Agents,funded under the fourth Framework Programme (*cf.* Downing et al., 2000; Pahl Wostl and Hare, 2004)

[3]Complexity Agents Volatility Evidence and Scale, funded under the sixth Framework Programme (*cf.* Alam et al., 2007; Ernst et al., 2007)

be understood simply as a scaled-up replication of the behaviour of the individuals comprising the society so that, in consequence, social behaviour cannot be forecast on the basis of individuals' characteristics and predilections alone. Social outcomes, including the outcomes from social policy initiatives, are the result of individual behaviour and social interactions in which individuals influence one another. On the basis of these considerations, it follows that social policy analysis is reasonably considered to be a branch of complexity science.

By social behaviour is meant the outcome of social processes where "social process" is itself an umbrella term covering the behaviour and social interactions of individuals and the sequence of social outcomes of that socially embedded behaviour. The behaviour and interaction are conditioned by social norms and reputations. The patterns of interaction are determined by acquaintanceship and friendship, relationships that are the result of engagement in common activities or kinship or physical proximity. The content of the interaction is naturally related to the nature of social links. Common activities may entail cooperation in the undertaking of tasks, or sharing some resource – both being characteristics of common employment. They might also entail undertaking similar tasks in parallel such as attending church or school or also in employment. Amongst acquaintances, individuals will generally like some more than others. Social psychologists have demonstrated and reported over many years that individuals tend to like best those who are most similar to themselves and individuals are most uncomfortable in disagreement with those they like best.[4] Brown (1965) called this phenomenon the consistency principle.

One consequence of the consistency principle is that individuals can change their habits or views as a result of the influence of those who are already most like themselves and who they like and with whom they tend to avoid disagreement. Some social policies such as those associated with climate change or water management (Downing et al., 2000) seek to create social pressure to induce the establishment of (say) energy- or water-saving social processes. This objective makes two aspects of complexity relevant to any understanding of policy processes.

One aspect of social policy as a branch of complexity science relates to the feasibility of forecasting outcomes with and without policy interventions. The common practice is to offer from one to many forecasts using statistical regressions derived from time series data and calibrated on available sample data. The value of such forecasts depends crucially on assumptions about the nature of an unobservable population distribution and the presumption that observed data are samples from that population. If there is no such population or it is distributed differently from the requirements of regression

[4]For an older but not dated exposition of this phenomenon, see Brown (1965) and for a more recent textbook version see Fraser and Burchell (2001).

and hypothesis testing algorithms, then the presumption that forecasting models can be used to evaluate policy measures is without any scientific foundation. In conditions of complexity, the conditions of application of the parametric statistical techniques used for such forecasting cannot be taken for granted. The pattern of changes in behaviour includes a relatively small number of widespread changes amongst a large number of relatively small changes. The magnitude of any one change episode appears to depend on the situation of each individual and the particular collection of other individuals they influence and who are influenced by them. Because the small number of large changes arise endogenously in the sense that they are not due to random, external events, then as Mandelbrot (1963) pointed out many years ago, it is certainly illegitimate to remove the "outliers" (the few large changes) from the data set. But if they are not removed, then the conditions of application of standard fitting and hypothesis testing techniques are not satisfied (Fama, 1963).

A second aspect of complexity science concerns network structures as either a description of or an outcome from patterns of social interaction. The small world network is an example of a description of social networks in which nodes representing individuals are characterised by a high degree of clustering so that, within a cluster, if any node that is linked to two other nodes, those other nodes are linked directly to each other. There are also links between individuals in different clusters but these are more sparse and certainly do not include the triangular relationships found within clusters. A small world network is characterised by a higher degree of clustering than is found in networks of randomly linked nodes but the longest path (number of connecting links) between any pair of nodes is not longer than in a random network. [5] In general, the formal properties of small world and other "complex" networks have been studied by generating examples from algorithms that do not describe actual social processes. While the existence of actual small world networks has been well established in the literature (newman paper) we know of no previous empirical studies of the emergence and evolution of these networks. In at least one case to be reported here, however, the existence of small world networks is found and the evolution turns out to be of the first order of importance for social policy.

It seems useful in this context to distinguish between processual complexity with its unpredictable, volatile clusters and structural complexity which is manifest by small world (among other types of) network. In section 3, issues of model design that can capture process and structural complexity are explored.

[5] This version of the small world network is due to Watts and Strogatz (1998) but was intended to formalise an empirical result found by Milgram (1967) and by Travers and Milgram (1969). Many small world social networks have been found since the classic study by Milgram.

3 Complexity and policy model design

The definitions of both processual and structural complexity require that any model of the phenomena be able to represent social interactions amongst individuals. Long before complexity science came to be recognised as an umbrella for related objects of scientific investigation, social scientists developing simulation approaches recognised the importance of explaining macro level phenomena that emerged from social processes whereby individual behaviour and social interaction together produced phenomena that could not be explained by the individual behaviour alone. The seminal paper in this regard was undoubtedly by Nigel Gilbert (1995) who argued that the only way to capture the behaviour and interactions was by means of simulation modelling.[6] Gilbert was concerned with the emergence of social outcomes and was not addressing issues of volatility or social network topology. Nonetheless, these manifestations of complexity are emergent features in the sense of Gilbert. That is, complexity is a subset of the class of phenomena that Gilbert was arguing could be addressed only by means of what we would now call agent based social simulation. The agents, of course, are software entities describing the perceptions, reasoning and actions of individuals.

The use of software agents to capture complexity distinguishes agent based social simulation from the ideal of agent based computing as specified in a classic paper by Wooldridge and Jennings (1995) who were concerned that agent interaction should be minimal in order to avoid unpredictable emergent phenomena at system level. Their concern is readily understood in the context of traditional computer science where software development starts with a requirements analysis to determine clearly what the program should do, then a process of verification to ensure that its design is formally capable of satisfying the requirements, then validation of the program code to ensure that it actually does what is required. The practical purpose of this process is to provide software that yields predictable outcomes in all cases. This is an obviously desirable aim for safety-critical programs or for programs intended to perform clearly defined and well understood tasks. However, where complexity is a genuine issue, the context in which software is used might itself be subject to unpredictable volatility and the inability of software agents to interact densely and to influence one another in the evolution of their behaviour could render that design paradigm inappropriate. Plausibly, densely interacting, mutually influencing agents

[6] More than a decade earlier and at a more general level, another sociologist, Anthony Giddens (1984) argued forcefully for the importance of understanding social institutions as an outcome of individual behaviour and social interaction and that, at the same time, institutions tend to constrain behaviour and interaction. This is the "double hermeneutic" and was intended to reconcile controversies amongst sociologists concerning the dominance of institutions over individual behaviour or, alternatively, institutions as simply the result of what individuals do and how they choose to relate to one another.

with complicated reasoning capabilities are appropriate in such naturally complex software environments as grid computing or information filtering (Moss, 2000). Nonetheless, in general we would expect agent based social simulation models that allow for social complexity to be designed with the capacity for agents to interact and influence while more conventional agent based software would limit those capacities.

If social simulation models are to be used for policy analysis, it is of course important that they should describe with some accuracy the social context, the characteristics of the behaviours of individuals in different circumstances and the relationships amongst those individuals. At the same time, prediction cannot be relied upon in conditions of complexity. Whilst, in these conditions, models cannot be relied upon to yield accurate predictions, they are still formal systems and, as such, capture relationships and outcomes that are precise and unambiguous. Precision is useful in ensuring that analysts have to state their assumptions clearly and that they do not rely on emotive phrasing to justify actions that have no basis in understanding or experience.

In conditions where precision but not accurate prediction can be expected of model-based analyses, the value of the models can be no more than to generate clear scenarios. In order to explore the policy space flexibly and broadly, the models need to be open. That is, it must be possible for model operators to explore a wide range of specifications of behaviour and social interaction. This is not just a matter of setting parameter values but of specifying the ways in which individuals reason about their circumstances, how they filter their perceptions, how they choose their friends and other elements of a model that are structural rather than parametric. In order to ensure insofar as possible that the models are actually relevant to the policy context, it is essential to constrain the model design with evidence. Where direct evidence is not available so that some assumptions have to be made about what the direct evidence would look like, then those assumptions need to be constrained by some criteria of plausibility. Who is to decide what is plausible? There are two tests that can be applied here. One is the legal test – would a reasonable person believe that the persons deciding on the plausibility of an assumption are both sufficiently expert and independent of the modelling process. The other test is simply whether the assumptions are deemed plausible by the client – those for whose use the model is being designed and implemented. If the model is to be used for policy analysis, then the clients are the policy analysts and perhaps the politicians who actually introduce and implement the policy. For the modeller to make assumptions without reference to independent experts or clients leaves open the possibility that the chosen modelling technique rather than descriptive accuracy is driving the model design and therefore the model outputs.

4 Prospects for policy modelling

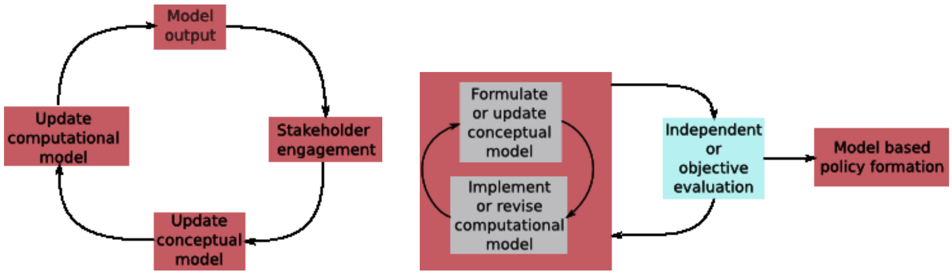
Provided that the problems raised in section 5 can be resolved, the prospects for agent based and evidence driven policy modelling should be promising indeed. Though none of the techniques of policy modelling were designed about qualitative research approaches or with any specific view of structural or processual complexity, it turns out that agent based social simulation as developed by the companion and other policy modellers coheres with both. It is perhaps of especial interest that by providing a link between qualitative research and complexity science, the sort of policy modelling under discussion here will enable us to investigate whether the phenomena studied by the qualitative researchers and the ways in which they study them imply the very complexity that make the applicability of conventional mathematical and statistical modelling uncertain. In other words, there is a natural intellectual alliance to be had between the qualitative research community which exists mainly in university business schools and agent based modellers. If the two communities were prepared to learn from one another, we would have both a well established set of techniques to inform the design and validation of our models and the qualitative researchers would have a complementary set of techniques to lend precision to their analyses.

5 Problems facing policy modellers

The problems to be overcome in realising the prospects outlined above are by no means trivial.

Applications of qualitative research and of evidence driven, agent based policy (including companion) modelling have been almost entirely or entirely at local scale. Qualitative researchers have studied organisations, companion modellers have engaged at village or perhaps water catchment level, the FIRMA and CAVES modellers at municipal, village or catchment level. If one were to look for qualtiative analyses involving larger scales, the obvious example is Foresight processes such as are used by the Intergovernmental Panel on Climate Change (Nakicenovic and Swart, 2000). Foresight processes are used to generate largely qualitative scenarios that might be constrained by physical models and are certainly constrained by sets of assumptions about general attitudes and institutional properties. In the IPCC emissions scenario case, there is a hierarchy (storylines and scenario families) of alternative assumptions about attitudes and institutions. These are used to explore issues rather than to offer predictions and so are, in that regard, rather like qualitative research and policy modelling.

The purpose of these storylines and scenario families is to provide a priori constraints on scenario generation exercises just as agent based computational economists use economic theories to constrain their model designs or



(a) Deep stakeholder engagement (b) Independent policy analysts

Figure 1: Ideal-types of analyst role in modelling

econophysicists constrain their model designs by the requirements of physical modelling techniques. Perhaps policy analysts prefer such constraints to be imposed by scientists as an alternative to their own engagement in the design and validation process. There is clearly an important set of issues here relating to the relationhip between policy analysts and policy modellers.

There are two ideal-types of modeller-analyst relationship. One is typified by companion modelling with its iterations between stakeholder engagement and, in particular, role-playing games for purposes of knowledge elicitation and model evaluation. An alternative ideal-type is for the policy analysts (the stakeholders for whom the models are being developed) to stand outside the modelling process and to receive the model outputs without prior engagement in the model development process. In the latter case, some objective or perhaps independent validation of the model will be required. Where standard statistical models are concerned, reports of the results of standard hypothesis testing procedures may (and usually do) suffice for the model users. Models that represent individual behaviour qualitatively and capture dense social interaction in ways that give rise to unpredictable bursts of volatility do not necessarily satisfy the conditions of application of standard hypothesis testing procedures. In these cases, independence of the model users from the modelling process requires a different approach to validation.

Though the phases of model and policy development are unlikely to be as clearly differentiated as indicated in figure 1, the broad differences between the approaches with deep stakeholder participation and with stakeholders as clients are clearly distinguished. In many cases, there will be an element of independent validation alongside stakeholder participation or there will be some revision of models and re-validation in response to client-analysts use and user evaluation of the model. The archetypical model captured by figure 1b is statistical or econometric. In developing such models, statistical data is acquired and regression or clustering[7] algorithms applied to the data.

[7]For example, principle components or cluster analyses based on correlation matrices.

Several formulations of the statistical model are likely to be tried and the best fitting model then chosen. The objective evaluation takes the form of standard hypothesis testing so that the model and test results can be presented to the clients (the policy analysts). In some cases, such as with respect to macroeconometric models, there is an *a priori* conceptual model based on experience and judgement used to constrain the computational (in this case, statistical) model.

Not just companion modelling but also a model based Foresight procedure typifies the process captured by figure 1a. The core idea here is to engage the stakeholders as domain experts or sometimes as intermediaries between modellers and experts to formulate the conceptual model. In companion modelling exercises, role playing games are typically used to engage stakeholders in the formation of the conceptual model and the validation of the computational model. Another approach is to engage stakeholders in generating narrative scenarios which are used to formulate conceptual models. The formalisation of the conceptual models as computational models underlies simulation experiments that produce more formal, though still a type of narrative, scenario. The virtue of these more formal scenarios is that they lend a degree of precision that cannot be captured informally. They also automate scenario generation so that the resulting scenarios can suggest previously unconsidered possible outcomes of a policy initiative.

Experience shows that policy analysts frequently find independence more attractive than participation. Pahl Wostl and Hare (2004) reported that stakeholders involved in the development of water management policies in Zurich occasionally became impatient with the process because they could not see clearly where it was going. Pahl Wostl and Hare suggested that this was partly the fault of the researchers since, in the nature of research, they were themselves learning about the process and were therefore unable clearly to describe the outcome. This reported experience and the author's own experience confirm the obvious: the stakeholders (including policy analysts) and the modellers must have a clear and clearly shared interest in the outcome from the qualitative research process. The success of qualitative research in a business setting shows that such a shared interest can be generated. However, even a shared interest and enjoyment of role playing games has its limits.

Additionally, an advantage for policy analysts of independence from conventional modelling is the claim that such models offer predictions or, at least, distributions of probable outcomes. Reliance on such predictions and model generated probabilities must relieve the policy analysts of some responsibility for failure of policy initiatives predicated upon those predictions and probabilities.

6 Conclusion

The promise and prospects for policy modelling include the advantages of linking up with the qualitative research community, the much generality of policy models because they can capture elements of complexity that cannot be captured by statistical or equilibrium models and the ability to capture a wide range of qualitative as well as statistical evidence that is denied to even computational models constrained by unrealistic theories. The problem facing policy modellers in gaining acceptance for their approach is that policy analysts will have to change their expectations of what models can do for them and they (or their surrogates) will have to participate more fully in the design and evaluation of the models and in the exploration of model outputs. The latter in particular is a much more expensive procedure in terms of time than is the use of quantitative models. Another problem will be to overcome the suspicion of qualitative researchers.

I confess that I do not know how to solve these problems. But unless we do solve them, it is hard to see how the benefits of agent based social simulation can be realised.

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