Chapter 4
Policy Making and Modelling in a Complex World

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Abstract In this chapter, we discuss the consequences of complexity in the real world together with some meaningful ways of understanding and managing such situations. The implications of such complexity are that many social systems are unpredictable by nature, especially when in the presence of structural change (transitions). We shortly discuss the problems arising from a too-narrow focus on quantification in managing complex systems. We criticise some of the approaches that ignore these difficulties and pretend to predict using simplistic models. However, lack of predictability does not automatically imply a lack of managerial possibilities. We will discuss how some insights and tools from "complexity science" can help with such management. Managing a complex system requires a good understanding of the dynamics of the system in question—to know, before they occur, some of the real possibilities that might occur and be ready so they can be reacted to as responsively as possible. Agent-based simulation will be discussed as a tool that is suitable for this task, and its particular strengths and weaknesses for this are discussed.

4.1 Introduction

Some time ago, one of us (WJ) attended a meeting of specialists in the energy sector. A former minister was talking about the energy transition, advocating for directing this transition; I sighed, because I realized that the energy transition, involving a multitude of interdependent actors and many unforeseen developments, would make a planned direction of such a process a fundamental impossibility. Yet I decided not to interfere, since my comment would have required a mini lecture on the management of complex systems, and in the setting of this meeting this would have required too much time. So the speaker went on, and one of the listeners stood up and asked, "But

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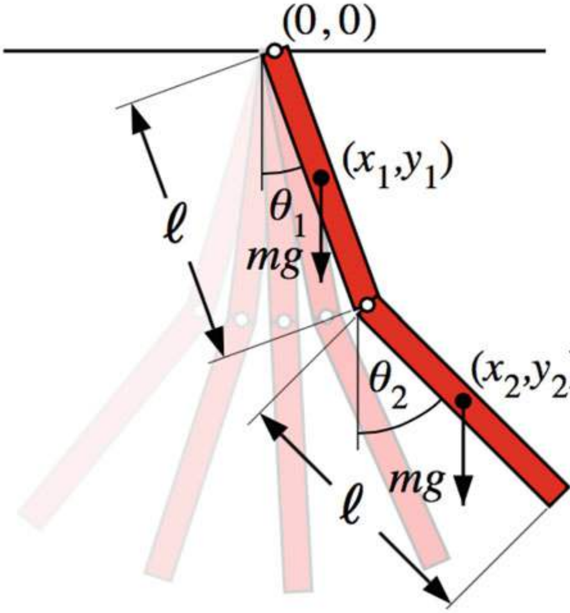

Fig. 4.1 Double pendulum. (Source: Wikipedia)

sir, what if the storage capacity of batteries will drastically improve?" The speakers answered, "this is an uncertainty we cannot include in our models, so in our transition scenarios we don't include such events". This remark made clear that, in many cases, policymakers are not aware of the complexities in the systems they operate in, and are not prepared to deal with surprises in systems. Because the transitional idea is being used very frequently to explain wide-ranging changes related to the transformation of our energy system, and the change towards a sustainable society, it seems relevant to address the issue of complexity in this chapter, and discuss the implications for policy making in complex behaving system. After explaining what complexity is, we will discuss the common mistakes being made in managing complex systems. Following that, we will discuss the use of models in policy making, specifically addressing agent-based models because of their capacity to model social complex systems that are often being addressed by policy.

4.2 What is Complexity?

The word "complexity" can be used to indicate a variety of kinds of difficulties. However, the kind of complexity we are specifically dealing with in this chapter is where a system is composed of multiple interacting elements whose possible behavioural states can combine in ways that are hard to predict or characterise. One of the simplest examples is that of a double pendulum (Fig 4.1).

Although only consisting of a few parts connected by joints, it has complex and unpredictable behaviour when set swinging under gravity. If this pendulum is released, it will move chaotically due to the interactions between the upper (θ_1) and lower (θ_2) joint. Whereas it is possible to formally represent this simple system in detail, e.g. including aspects such as air pressure, friction in the hinge, the exact behaviour of the double pendulum is unpredictable.[1] This is due to the fundamental uncertainty of the precise position of its parts[2]and the unsolvability of the three-body problem as proven by Bruns and Poincaré in 1887. Just after release, its motion is predictable to a considerable degree of accuracy, but then starts to deviate from any prediction until it is moving in a different manner. Whereas the precise motion at these stages is not predictable, we know that after a while, the swinging motion will become less erratic, and ultimately it will hang still (due to friction). This demonstrates that even in very simple physical systems, interactions may give rise to complex behaviour, expressed in different types of behaviour, ranging from very stable to chaotic. Obviously, many physical systems are much more complicated, such as our atmospheric system. As can be expected, biological or social systems also display complex behaviour because they are composed of large numbers of interacting agents. Also, when such systems are described by a simple set of equations, complex behaviour may arise. This is nicely illustrated by the "logistic equation", which was originally introduced as a simple model of biological populations in a situation of limited resources (May 1976). Here the population, x, in the next year (expressed as a proportion of its maximum possible) is determined based on the corresponding value in the last year as $rx(1\text{-}x)$, where r is a parameter (the rate of unrestrained population increase). Again, this apparently simple model leads to some complex behaviour. Figure 4.2 shows the possible long-term values of x for different values of r, showing that increasing r creates more possible long-term states for x. Where on the left hand side ($r < 3.0$) the state of x is fixed, at higher levels the number of possible states increases with the number of states increasing rapidly until, for levels of r above 3.6, almost any state can occur, indicating a chaotic situation. In this case, although the system may be predictable under some circumstances (low r), in others it will not be (higher r).

What is remarkable is that, despite the inherent unpredictability of their environment, organisms have survived and developed intricate webs of interdependence in terms of their ecologies. This is due to the adaptive capacity of organisms, allowing them to self-organise. It is exactly this capacity of organisms to adapt to changing circumstances (learning) that differentiates 'regular' complex systems from 'complex adaptive systems' (CAS). Hence complex adaptive systems have a strong capacity to self-organise, which can be seen in, i.e. plant growth, the structure of ant nests and the organisation of human society. Yet these very systems have been observed to exist in both stable and unstable stages, with notable transitions between these

[1] Obviously predictions can always be made, but it has been proved analytically that the predictive value of models is zero in these cases.

[2] Even if one could measure them with extreme accuracy, there would never be complete accuracy due to the uncertainty theorem of Heisenberg (1927).

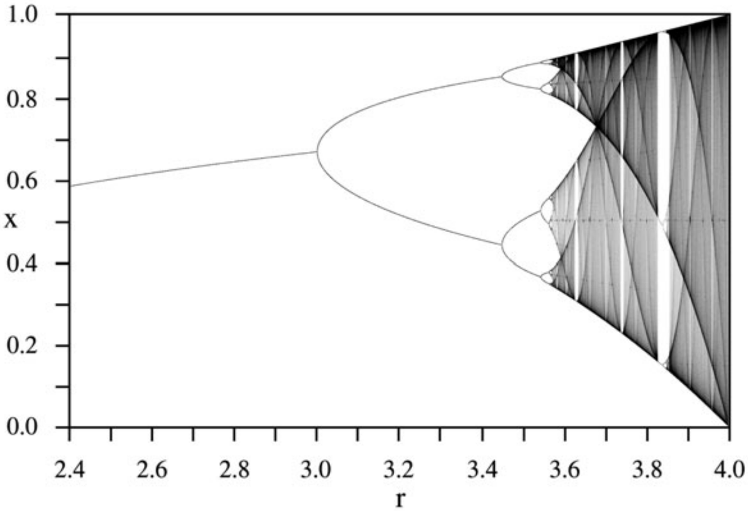

Fig. 4.2 Bifurcation diagram. (Source: Wikipedia)

stages. Ecological science has observed that major transitions in ecological systems towards a different regime (transition) are often preceded by increased variances, slower recovery from small perturbations (critical slowing down) and increased return times (Boettiger and Hastings 2012; Dai and Vorselen et al. 2012; Dakos and Carpenter et al. 2012). A classic example here is that of the transition from a clear lake to a turbid state due to eutrophication. Here an increase in mineral and organic nutrients in the water gives rise to the growth of plants, in particular algae. In the stage preceding to a transition, short periods of increased algal blooms may occur, decreasing visibility and oxygen levels, causing the population of top predating fish hunting on eyesight to decrease, causing a growth in populations of other species, etc. The increased variance (e.g. in population levels of different species in the lake) indicates that a regime shift is near, and that the lake may radically shift from a clear state to a turbid state with a complete different ecosystem, with an attendant loss of local species.

The hope is that for other complex systems, such indicators may also identify the approach of a tipping point and a regime shift or transition (Scheffer et al. 2009). For policy making, this is a relevant perspective, as it helps in understanding what a transition or regime shift is, and has implications for policy development. A transition implies a large-scale restructuring of a system that is composed of many interacting parts. As such, the energy system and our economy at large are examples of complex systems where billions of actors are involved, and a large number of stakeholders such as companies and countries are influencing each other. The transformation from, for example, a fossil fuel-based economy towards a sustainable energy system requires that many actors that depend on each other have to simultaneously change their behaviour. An analogy with the logistic process illustrated in Fig. 4.2 can be made.

Imagine a move from the lower stable situation $x = 0.5$ at $r = 3.3$ to the upper stable situation $x = 0.8$. This could be achieved by increasing the value of r, moving towards the more turbulent regime of the system and then reducing r again, allowing the new state to be settled into. This implies that moving from one stable regime towards another stable regime may require a period of turbulence where the transition can happen. Something like a period of turbulence demarcating regime shifts is what seems to have occurred during many transitions in the history of the world.

4.3 Two Common Mistakes in Managing Complex Systems

Turbulent stages in social systems are usually experienced as gruesome by policy-makers and managers. Most of them prefer to have grip on a situation, and try to develop and communicate a clear perspective on how their actions will affect future outcomes. Especially in communicating the rationale of their decisions to the outside world, the complex nature of social systems is often lost. It is neither possible nor particularly useful to try and list all of the "mistakes" that policymakers might make in the face of complex systems, but two of the ways in which systems are oversimplified are *quantification* and *compartmentalisation*.

Quantification implies that policy is biased towards those attributes of a system that are easy to quantify. Hence, it comes as no surprise that economic outcomes, in terms of money, are often the dominating criteria in evaluating policy. Often, this results in choosing a solution that will result in the best financial economic outcome. Whereas non-quantifiable outcomes are often acknowledged, usually the bottom line is that "we obviously have to select the most economical viable option" because "money can be spent only once". In such a case, many other complex and qualitative outcomes might be undervalued or even ignored since the complex system has been reduced to easily measurable quantities. In many situations, this causes resistance to policies, because the non-quantifiable outcomes often have an important impact on the quality of life of people. An example would be the recent earthquakes in the north of the Netherlands due to the extraction of natural gas, where the policy perspective was mainly focussing on compensating the costs of damage to housing, whereas the population experienced a loss of quality of life due to fear and feelings of unfair treatment by the government, qualities that are hard to quantify and were undervalued in the discussion. The more complex a system is, the more appealing it seems to be to get a grip on the decision context by quantifying the problem, often in economical terms. Hence, in many complex problems, e.g. related to investments in sustainable energy, the discussion revolves around returns on investment, whereas other relevant qualities, whereas being acknowledged, lose importance because they cannot be included in the complicated calculations. Further, the ability to encapsulate and manipulate number-based representations in mathematics may give such exercises an appearance of being scientific and hence reinforce the impression that the situation is under control. However, what has happened here is a conflation of indicators with the overall quality of the goals and outcomes themselves. Indicators may well be useful to help judge goals and outcomes; but in complex situations, it is rare that such a judgement can be reduced to such simple dimensions.

Compartimentalization is a second response of many policymakers in trying to simplify complex social systems. This is a strategy whereby a system or organisation is split into different parts that act (to a large extent) independently of each other as separated entities, with their own goals and internal structures. As a consequence, the policy/management organization will follow the structure of its division into parts. Being responsible for one part of the system implies that a bias emerges towards optimizing the performance of the own part. This is further stimulated by rewarding managers for the performance of the subsystem they are responsible for, independently of the others. However, this approach makes it difficult to account for *spillover effects* towards other parts of the system, particularly when the outcomes in related parts of the system are more difficult to quantify. An example would be the savings on health care concerning psychiatric care. Reducing the number of maximum number of consults being covered by health insurance resulted in a significant financial savings in health care nationally. However, as a result, more people in need of psychiatric help could not afford this help, and, as a consequence, may have contributed to an increase in problems such as street crime, annoyance, and deviant behaviour. Because these developments are often qualitative in nature, hard numbers are not available, and hence these effects are more being debated than actually being included in policy development. Interestingly, due to this compartmentalisation, the direct financial savings due to the reduction of the insurance conditions may be surpassed by the additional costs made in various other parts as the system such as policing, costs of crime, and increased need for crisis intervention. Thus, the problems of quantification and compartmentalisation can exacerbate each other: A quantitative approach may facilitate compartmentalisation since it makes measurement of each compartment easier and if one takes simple indicates *as* one's goals, then it is tempting to reduce institutional structures to separate compartments that can concentrate on these narrow targets. We coin the term "Excellification"—after Microsoft Excel—to express the tendency to use quantitative measurements and compartmentalise systems in getting a grip on systems.

Whereas we are absolutely convinced of the value of using measurements in developing and evaluating policy/management, it is our stance that policy making in complex systems is requiring a deeper level of understanding the processes that guide the developments in the system at hand. When trying to steer policy in the face of a complex and dynamic situation, there are essentially two kinds of strategies being used in developing this understanding: *instrumental* and *representational*. We look at these next, before we discuss how agent-based modelling may contribute to understanding and policy making in complex systems.

4.4 Complexity and Policy Making

An instrumental approach is where one chooses between a set of possible policies and then evaluates them according to some assessment of their past effectiveness.

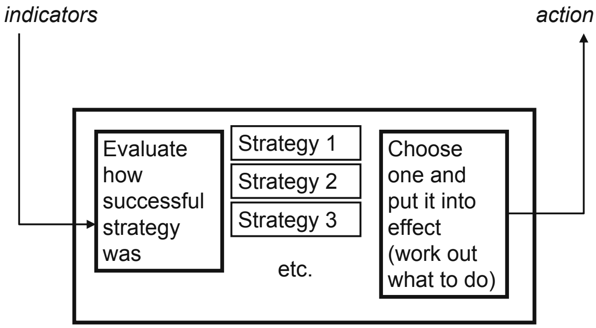

Fig. 4.3 An illustration of the instrumental approach

In future iterations, one then adapts and/or changes the chosen policy in the light of its track record. The idea is illustrated in Fig. 4.3. This can be a highly adaptive approach, reacting rapidly in the light of the current effectiveness of different strategies. No initial knowledge is needed for this approach, but rather the better strategies develop over time, given feedback from the environment. Maybe, the purest form of this is the "blind variation and selective retention" of Campbell (1960), where new variants of strategies are produced (essentially) at random, and those that work badly are eliminated, as in biological evolution. The instrumental approach works better when: there is a sufficient range of strategies to choose between, there is an effective assessment of their efficacy, and the iterative cycle of trial and assessment is rapid and repeated over a substantial period of time. The instrumental approach is often used by practitioners who might develop a sophisticated "menu" of what strategies seem to work under different sets of circumstances.

An example of this might be adjusting the level of some policy instrument such as the level of tolls that are designed to reduce congestion on certain roads. If there is still too much congestion, the toll might be raised; if there is too little usage, the toll might be progressively lowered.

The representational approach is a little more complicated. One has a series of "models" of the environment. The models are assessed by their ability to predict/mirror observed aspects of the environment. The best model is then used to evaluate possible actions in terms of an evaluation of the predicted outcomes from those actions and the one with the best outcome chosen to enact. Thus, there are two "loops" involved: One in terms of working out predictions of the models and seeing which best predicts what is observed, and the second is a loop of evaluating possible actions using the best model to determine which action to deploy. Figure 4.4 illustrates this approach. The task of developing, evaluating, and changing the models is an expensive one, so the predictive power of these models needs to be weighed against this cost. Also, the time taken to develop the models means that this approach is often slower to adapt to changes in the environment than a corresponding instrumental approach. However, one significant advantage of this approach is that, as a result of the models, one might have a good idea of *why* certain things were happening in the environment, and hence know which models might be more helpful,

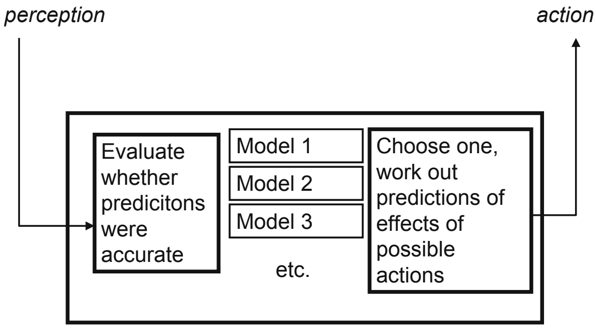

Fig. 4.4 An illustration of the representational approach

as well as allowing for the development of longer term strategies addressing the root causes of such change. The representational approach is the one generally followed by scientists because they are interested in understanding what is happening.

An example of the representational approach might be the use of epidemiological models to predict the spread of an animal disease, given different containment/mitigation strategies to deal with the crisis. The models are used to predict the outcomes of various strategies, which can inform the choice of strategy. This prediction can be useful even if the models are being improved, at the same time, due to the new data coming in because of the events.

Of course, these two approaches are frequently mixed. For example, representational models might be used to constrain which strategies are considered within an otherwise instrumental approach (even if the representational models themselves are not very good at prediction). If a central bank is considering what interest rate to set, there is a certain amount of trial and error: thus, exactly how low one has to drop the interest rates to get an economy going might be impossible to predict, and one just has to progressively lower them until the desired effect achieved. However, some theory will also be useful: thus, one would know that dropping interest rates would not be the way to cool an over-heating economy. Thus, even very rough models with relatively poor predictive ability (such as "raising interest rates tends to reduce the volume of economic activity and lowering them increases it") can be useful.

Complexity theory is useful for the consideration of policy in two different ways. *First*, it can help provide representational models that might be used to constrain the range of strategies under consideration and, *second,* can help inform second-order considerations concerning the ways in which policy might be developed and/or adopted—the policy adaption process itself. In the following section, we first look at the nature and kinds of models so as to inform their best use within the policy modelling, and later look at how second-order considerations may inform *how* we might use such models.

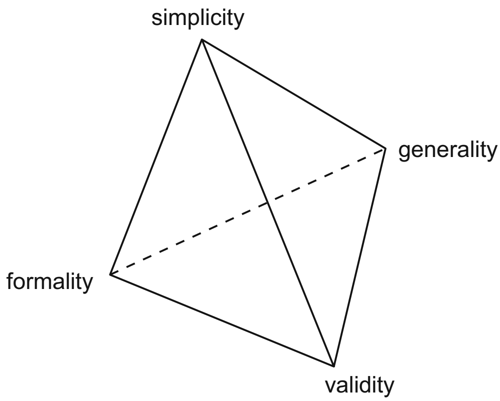

Fig. 4.5 An illustration in some of the opposing desiderata of models

4.4.1 Using Formal Models in Policy Making

The use of models in policy making starts with the question—what the appropriate policy models are? Many models are often available because (1) improving models following the representational approach will yield series of models that further improve the representation of the process in terms of cause–effect relations, and (2) sometimes more extended models are required for explaining a process, whereas often simpler models are used to represent a particular behaviour.

Realising that many models are often available, we still have to keep in mind that any *model* is an abstraction. A *useful model* is necessarily simpler than what it represents, so that much is left out—abstracted away. However, the decision as to what needs to be represented in a model and what can be safely left out is a difficult one. Some models will be useful in some circumstances and useless in others. Also, a model that is useful for one purpose may well be useless for another. Many of the problems associated with the use of models to aid the formulation and steering of policy derive from an assumption that a model will have value per se, independent of context and purpose.

One of the things that affect the uses to which models can be put is the compromise that went into the formulation of the models. Figure 4.5 illustrates some of these tensions in a simple way.

These illustrated desiderata refer to a model that is being used. *Simplicity* is how simple the model is, the extent to which the model itself can be completely understood. Analytically solvable mathematical models, most statistical models, and abstract simulation models are at the relatively simple end of the spectrum. Clearly, a simple model has many advantages in terms of using the model, checking it for bugs and mistakes (Galán et al. 2009), and communicating it. However, when modelling complex systems, such as what policymakers face, such simplicity may not be worth it if gaining it means a loss of other desirable properties. *Generality* is the extent of the model scope: How many different kinds of situations could the model be usefully applied. Clearly, *some* level of generality is desirable; otherwise one could only apply the model in a single situation. However, all policy models will not be completely general—there will always be assumptions used in their construction, which limit their generality. Authors are often rather lax about making the scope of their models clear—often implying a greater level of generality that can be substantiated. Finally, *validity* means the extent to which the model outcomes match what is observed to occur—it is what is established in the process of model validation. This might be as close a match as a point forecast, or as loose as projecting qualitative aspects of possible outcomes.

What policymakers want, above all, is validity, with generality (so they do not have to keep going back to the modellers) and simplicity (so there is an accessible narrative to build support for any associated policy) coming after this. Simplicity and generality are nice if you can get them, but one cannot assume that these are achievable (Edmonds 2013). Validity *should* be an overwhelming priority for modellers; otherwise, they are not doing any sort of empirical science. However, they often put this off into the future, preferring the attractions of the apparent generality offered by analogical models (Edmonds 2001, 2010).

Formality is the degree to which a model is built in a precise language or system. A system of equations or a computer simulation is formal, vague, but intuitive ideas expressed in natural language are informal. It must be remembered that formality for those in the policy world is not a virtue but more of a problem. They may be convinced it is necessary (to provide the backing of "science"), but it means that the model is inevitably somewhat opaque and not entirely under their control. This is the nub of the relationship between modellers and the policy world—if the policy side did not feel any need for the formality, then they would have no need of modellers—they are already skilled at making decisions using informal methods. For the modellers, the situation is reverse. Formality is at the root of modelling, so that they can replicate their results and so that the model can be unambiguously passed to other researchers for examination, critique, and further development (Edmonds 2000). For this reason, we will discuss formality a bit and analyse its nature and consequences.

Two dimensions of formality can be usefully distinguished here, these are:

a. The extent to which the referents of the representation are constrained ("specificity of reference").
b. The extent to which the ways in which instantiations of the representation can be manipulated are constrained ("specificity of manipulation").

For example, an analogy expressed in natural language has a low specificity of reference since, what its parts refer to are reconstructed by each hearer in each situation. For example, the phrase "a tidal wave of crime" implies that concerted and highly coordinated action is needed in order to prevent people being engulfed, but the level of danger and what (if anything) is necessary to do must be determined by each listener. In contrast to this is a detailed description where what it refers to is severely limited by its content, e.g. "Recorded burglaries in London rose by 15 % compared to the previous year". Data are characterised by a high specificity of reference, since what it refers to is very precise, but has a low specificity of manipulation because there are few constraints in what one can do with it.

A system of mathematics or computer code has a high specificity of manipulation since the ways these can be manipulated are determined by precise rules—what one person infers from them can be exactly replicated by another. Thus, all formal models (the ones we are mostly concentrating on here) have a high specificity of manipulation, but not necessarily a high specificity of representation. A piece of natural language that can be used to draw inferences in many different ways, only limited by the manipulators' imagination and linguistic ability, has a low specificity of manipulation. One might get the impression that any "scientific" model expressed in mathematics must be formal in both ways. However, just because a representation has high specificity of manipulation, it does not mean that the meaning of its parts in terms of what it represents is well determined.

Many simulations, for example, do not represent anything we observe directly, but are rather explorations of ideas. We, as intelligent interpreters, may mentally fill in what it might refer to in any particular context but these "mappings" to reality are not well defined. Such models are more in the nature of an analogy, albeit one in formal form—they are not testable in a scientific manner since it is not clear as to precisely what they represent. Whilst it may be obvious when a system of mathematics is very abstract and not directly connected with what is observed, simulations (especially agent-based simulations) can give a false impression of their applicability because they are readily interpretable (but informally). This does not mean they are useless for all purposes. For example, Schelling's abstract simulation of racial segregation did not have any direct referents in terms of anything measurable,[3] but it was an effective counterexample that can show that an assumption that segregation must be caused by strong racial prejudice was unsound. Thus, such "analogical models" (those with low specificity of reference) can give useful insights—they can inform thought, but cannot give reliable forecasts or explanations as to what is observed.

In practice, a variety of models are used by modellers in the consideration of any issue, including: informal analogies or stories that summarise understanding and are used as a rough guide to formal manipulation, data models that abstract and represent the situation being modelled via observation and measurement, the simulation or mathematical model that is used to infer something about outcomes from initial situations, representations of the outcomes in terms of summary measures and graphs, and the interpretations of the results in terms of the target situation. When considering very complex situations, it is inevitable that more models will become involved, abstracting different aspects of the target situation in different ways and "staging" abstraction so that the meaning and reference can be maintained. However, good practice in terms of maintaining "clusters" of highly related models has yet to be established in the modelling community, so that a policymaker might well be bewildered by different models (using different assumptions) giving apparently conflicting results. However, the response to this should not be to reject this variety, and enforce comforting (but ultimately illusory) consistency of outcomes, but accept

[3] Subsequent elaborations of this model have tried to make the relationship to what is observed more direct, but the original model, however visually suggestive, was not related to any data.

that it is useful to have different viewpoints from models as much as it is to have different viewpoints from experts. It is the job of policymakers to use their experience and judgement in assessing and combining these views of reality. Of course, equally it is the job of the modellers to understand and explain why models appear to contradict each other and the significance of this as much as they can.

A model that *looks* scientific (e.g. is composed of equations, hence quantified) might well inspire more confidence than one that does not. In fact, the formality of models is very much a two-edged sword, giving advantages and disadvantages in ways that are not immediately obvious to a nonmodeller. We will start with the disadvantages and then consider the advantages.

Most formal models will be able to output series of numbers composed of measures on the outcomes of the model. However, just because numbers are by their nature precise,[4] does not mean that this precision is representative of the certainty to which these outcomes will map to observed outcomes. Thus, numerical outcomes can give a very false sense of security, and lead those involved in policy to falsely think that prediction of such values is possible. Although many forecasters now will add indications of uncertainty "around" forecasts, this can still be deeply misleading as it still implies that there is a central tendency about which future outcomes will gravitate.[5]

Many modellers are now reluctant to make such predictions because they know how misleading these can be. This is, understandably, frustrating for those involved in policy, whose response might be, "I know its complex, but we do not have the time/money to develop a more sophisticated model so just give me your 'best guess'". This attitude implies that some prediction is better than none, and that the reliability of a prediction is monotonic to the amount of effort one puts in. It seems that many imagine that the reliability of a prediction increases with effort, albeit unevenly—so a prediction with a small amount of effort will be better than none at all. Unfortunately, this is far from the case, and a prediction based on a "quick and dirty" method may be more misleading than helpful and merely give a false sense of security.

One of the consequences of the complexity of social phenomena is that the prediction of policy matters is hard, rare, and only obtained as a result of the most specific and pragmatic kind of modelling developed over relatively long periods of time.[6] It is more likely that a model is appropriate for establishing and understanding candidate explanations of what is happening, which will inform policy making in a less exact manner than prediction, being part of the mix of factors that a policymaker will take into account when deciding action. It is common for policy people to want a prediction of the impact of possible interventions "however rough", rather than settle for some level of understanding of what is happening. However, this can be

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[4] Even if, as in statistics, they are being precise about variation and levels of uncertainty of other numbers.

[5] This apparent central tendency might be merely the result of the way data are extracted from the model and the assumptions built into the model rather than anything that represents the fundamental behaviour being modelled.

[6] For an account of actual forecasting and its reality, see Silver (2012).

illusory—if one really wanted a prediction "however rough", one would settle for a random prediction[7] dressed up as a complicated "black box" model. If we are wiser, we should accept the complexity of what we are dealing and reject models that give us ill-founded predictions.

Maybe a better approach is to use the modelling to inform the researchers about the kinds of process that might emerge from a situation—showing them possible "trajectories" that they would not otherwise have imagined. Using visualisations of these trajectories and the critical indicators clarifies the complex decision context for policymakers. In this way, the burden of uncertainty and decision making remains with the policymakers and not the researchers, but they will be more intelligently informed about the complexity of what is currently happening, allowing them to "drive" decision making better.

As we have discussed above, one feature of complex systems is that they can result in completely unexpected outcomes, where due to the relevant interactions in the system, a new *kind* of process has developed resulting in qualitatively different results. It is for this reason that complex models of these systems do not give probabilities (since these may be meaningless, or worse be downright misleading) but rather trace some (but not all) of the possible outcomes. This is useful as one can then be as prepared as possible for such outcomes, which otherwise would not have been thought of.

On the positive side, the use of formal modelling techniques can be very helpful for *integrating* different kinds of understanding and evidence into a more "well-rounded" assessment of options. The formality of the models means that it can be shared without ambiguity or misunderstanding between experts in different domains. This contrasts with communication using natural language where, inevitably, people have different assumptions, different meanings, and different inferences for key terms and systems. This ability to integrate different kinds of expertise turns out to be especially useful in the technique we will discuss next—agent-based simulation.

4.4.2 The Use of Agent-Based Models to Aid Policy Formation

In recent years, agent-based simulation has gained momentum as a tool allowing the computer to simulate the interactions between a great number of agents. An agent-based simulation implies that individuals can be represented as separate computer models that capture their motives and behaviour. Letting these so-called agents interact though a network, and confront them with changing circumstances, creates an artificial environment where complex and highly dynamic processes can be studied. Because agent-based models address the interactions between many different agents, they offer a very suitable tool to represent and recreate the complexities in social systems. Hence, agent-based modeling has become an influential methodology

[7] Or other null model, such as "what happened last time" or "no change".

to study a variety of social systems, ranging from ant colonies to aspects of human society. In the context of agent-based simulation of human behaviour, one of the challenges is connecting the knowledge from behavioural sciences in agent-based models that can be used to model behaviour in some kind of environment. These modelled environments may differ largely, and may reflect different (inter)disciplinary fields. Examples of environments where agents can operate in are, e.g. financial markets, agricultural settings, the introduction of new technologies in markets, and transportation systems, just to name a few. A key advantage here is that a model creates a common formal language for different disciplines to communicate. This is important, as it allows for speaking the same language in targeting issues that are interdisciplinary by nature. Rather than taking information from social scientists as an interesting qualitative advice, it becomes possible to actually simulate what the behaviour dynamical effects of policies are. This is, in our view, an important step in addressing interdisciplinary policy issues in an effective way. An additional advantage of social simulation is that formalizing theory and empirical data in models requires researchers to be exact in the assumptions, which, in turn, may result in specific research questions for field and/or lab experiments. Hence, social simulation is a tool that both stimulates the interaction between scientific disciplines, and may stimulate theory development/specification within the behavioural sciences.

An increasing number of agent-based models is being used in a policy context. A recent inventory on the SIMSOC mailing list by Nigel Gilbert[8] resulted in a list of modelling projects that in some way were related to actual policy making. Topics included energy systems, littering, water management, crowd dynamics, financial crisis, health management, deforestation, industrial clustering, biogas use, military interventions, diffusion of electric cars, organization of an emergency centre, natural park management, postal service organization, urban design, introduction of renewable technology, and vaccination programmes. Whereas some models were actually being used by policymakers, in most instances, the models were being used to inform policy makers about the complexities in the system they were interacting with. The basic idea is that a better understanding of the complex dynamics of the system contributes to understanding how to manage these systems, even if they are unpredictable by nature. Here, a comparison can be made with sailing as a managerial process.

Sailing can be seen as a managerial challenge in using different forces that constantly change and interact in order to move the ship to a certain destination. In stable and calm weather conditions, it is quite well possible to set the sails in a certain position and fix the rudder, and make an accurate prediction where of the course the boat will follow. The situation becomes different when you enter more turbulent stages in the system, and strong and variable winds, in combination with bigger waves and streams, requiring the sailor to be very adaptive to the circumstances. A small deviation from the course, due to a gush or a wave, may alter the angle of the wind

[8] See mailing list SIMSOC@JISCMAIL.AC.UK. Mail distributed by Nigel Gilbert on December 14, 2013, subject: ABMs in action: second summary.

in the sail, which may give rise to further deviations of the course. This is typically a feedback process, and obviously an experienced sailor is well aware of all these dynamics, and, as a consequence, the sailor responds very adaptive to these small disturbances, yet keeps the long-term outcome—the destination port—also in mind.

The social systems that we are dealing with, in transitions, are way more complex than the sailing example. Yet, the underlying rational is the same: the better we learn to understand the dynamics of change, the better we will be capable of coping with turbulences in the process, whilst keeping the long-term goals in focus. Hence, policy aims such that the transition towards a sustainable energy future provides a reasonably clear picture of the direction we are aiming for, but the turbulences in the process towards this future are not well known. Where the sailor has a deep understanding of the dynamics that govern the behaviour of his boat, for policymakers, this understanding is often limited, as the opening example demonstrated.

Using agent-based models for policy would contribute to a better understanding and management of social complex phenomena. First, agent-based models will be useful in identifying under what conditions a social system will behave relatively stable (predictable) versus turbulent (unpredictable). This is critical for policy making, because in relatively stable situations, predictions can be made concerning the effects of policy, whereas in turbulent regimes, a more adaptive policy is recommended. Adaptive policy implies that the turbulent developments are being followed closely, and that policymakers try to block developments to grow in an undesired direction, and benefit and support beneficial developments. Second, if simulated agents are more realistic in the sense that they are equipped with different utilities/needs/preferences, the simulations will not only show what the possible behavioural developments are but also reveal the impact on a more psychological quality-of-life level. Whereas currently many policy models assess behavioural change from a more financial/economical drivers, agent-based models open a possibility to strengthen policy models by including additional outcomes. Examples would be outcomes relating to the stability and support in social networks, and general satisfaction levels.

Agent-based models, thus, can provide a richer and more complex representation of what may be happening within complex and highly dynamic situations, allowing for some of the real possibilities within the system to be explored. This exploration of possibilities can inform the risk analysis of policy, and help ensure that policymakers are ready for more of what the world may throw at them, for example, by having put in place custom-designed indicators that give them the soonest-possible indication that certain kinds of processes or structural changes are underway.

4.5 Conclusions

The bad news for policymakers is that predictive models perform worst exactly at the moment policymakers need them most—during turbulent stages. Yet, we observe that many policymakers, not being aware of the complex nature of the system they are interfering with, still have a mechanistic worldview, and base their decisions on classical predictions. This may be one of the reasons for scepticism by policymakers of any modelling approaches (see e.g. Waldherr and Wijermans 2013). Even nowadays, when complexity has turned into a buzzword, many policymakers still confuse this concept with "complicatedness", not embracing the essence and meaning of what complexity means for understanding social systems. As a consequence, still many policymakers are "Cartesian[9]" in their demand for better predictive models. On the other side, still many modellers working from a mechanistic perspective (e.g. linear and/or generic models), holding out the false hope of "scientifically" predictive models, look for more resources to incrementally improve their models, e.g. covering more variables. However, whereas it is sometimes justified to argue for the inclusion of more variables in a model, this will not contribute to a better predictive capacity of the model. As Scott Moss reports in his paper (Moss 2002), there are no reported correct real-time forecasts of the volatile clusters or the post-cluster levels in financial market indices or macroeconomic trade cycles, despite their incremental "refinement" over many years. Characteristically, they predict well in periods where nothing much changes, but miss all the "turning points" where structural change occurs.

Even if policymakers have some understanding of the complex nature of the systems they are managing, they still often respond with "I know it is complex, but how else can I decide policy except by using the numbers I have?", indicating that the numbers are often an important justification of decisions, even if people are aware of the uncertainties behind them. The example of the former minister in the introduction is a prototypical example of this decision making.

The challenge, hence, is not in trying to convince policymakers of the value of simulation models, but providing them with a deeper level understanding of complex systems. Here, simulation models can provide an important role by creating learning experiences. But before going to simulation models, it might be important to use a strong metaphor in anchoring the core idea of managing complex systems. Sailing offers an excellent metaphor here, because many people know the basics of sailing, and understand that it deals with the management of a ship in sometimes turbulent circumstances. What is critical in this metaphor is that in more turbulent conditions, the crew should become more adaptive to the developments in the system.

Agent-based simulation is increasingly being used as a modelling tool to explore the possibilities and potential impacts of policy making in complex systems. They are inherently possibilistic rather than probabilistic. However, the models being used are usually not very accessible for policymakers. Also, in the context of education, not many models are available that allow for an easy access to experiencing policy making in complex systems. In Chap. 13 of this book, Jager and Van der Vegt suggest using based gaming as a promising venue to make agent-based models more

[9] Descartes' mechanistic worldview implies that the universe works like a clockwork, and prediction is possible when one has knowledge of all the wheels, gears, and levers of the clockwork. In policy this translates as the viable society.

accessible in education and practical policy settings. A setting where valid games are being used to increase our understanding of the processes in complex management issues is expected to contribute to an improvement of the policy-making process in complex systems.

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