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Maps and models in system dynamics: a response to Coyle

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Abstract

Geoff Coyle has recently posed the question as to whether or not there may be situations in which computer simulation adds no value beyond that gained from qualitative causal-loop mapping. We argue that simulation nearly always adds value, even in the face of significant uncertainties about data and the formulation of soft variables. This value derives from the fact that simulation models are formally testable, making it possible to draw behavioral and policy inferences reliably through simulation in a way that is rarely possible with maps alone. Even in those cases in which the uncertainties are too great to reach firm conclusions from a model, simulation can provide value by indicating which pieces of information would be required in order to make firm conclusions possible. Though qualitative mapping is useful for describing a problem situation and its possible causes and solutions, the added value of simulation modeling suggests that it should be used for dynamic analysis whenever the stakes are significant and time and budget permit.

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A recent research problem by Geoff Coyle (2000) poses the question, ''How much value does quantified modeling add to qualitative analysis?'' And more pointedly: ''The research issue is whether or not there are circumstances in which the uncertainties of simulation may be so large that the results are seriously misleading to the analyst and the client.'' By uncertainties, Coyle is largely concerned about soft variables, which may be a challenge to formulate as equations and for which numerical data may be lacking. He suggests that an appropriate response in the face of substantial uncertainties is to use causal-loop (influence) diagrams alone, without simulation, to assist in policy analysis. He believes that this approach will remain appropriate at least until better techniques for modeling soft variables have been developed.

This line of reasoning emerges from a stream of work on qualitative analysis, much of it by Coyle and Eric Wolstenholme, that dates back to the early 1980s (see, especially, Wolstenholme and Coyle 1983). Summarizing a major theme of this work, Wolstenholme (1999) states, ''[T]he idea [of using stand-alone causal loop diagrams] was aimed at providing insight into managerial issues by inferring, rather than calculating, the behaviour over time of the system represented.''

Our purpose in this paper is to review the roles of qualitative maps and simulation models in system dynamics, and to argue that simulation—following established system dynamics methodology—can add value beyond mapping

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alone in most cases. This argument rests upon two points that have been demonstrated repeatedly in the laboratory and in real life: first, that one cannot reliably draw inferences from complex causal maps without simulation and, second, that system dynamics is well suited for addressing issues associated with soft variables and incomplete data.

Despite these demonstrations, as George Richardson (1999) has observed, ‘‘We are perceiving a growing tendency to use qualitative mapping approaches by themselves, without quantitative simulation.’’ It may be that some systems practitioners see mapping and modeling as similar, with simulation primarily offering greater numerical precision than mapping, and even that only in some cases. It is just such a blurring of the lines that we wish to argue against here, with the hope that the unique value of simulation may become better appreciated.

Why we map

Causal-loop diagrams have long been used in standard system dynamics practice for two purposes connected with simulation modeling. They were initially employed after simulation, to summarize and communicate model-based feedback insights (see, for example, Forrester 1968). A few years later, they also started to be used prior to simulation analysis, to depict the basic causal mechanisms hypothesized to underlie the reference mode of behavior over time—that is, for articulation of a dynamic hypothesis (Randers 1973; Randers 1980).

The dynamic hypothesis is a cornerstone of good system dynamics modeling practice. It ‘‘explains the dynamics as endogenous consequences of the feedback structure’’ (Sterman 2000), and explicitly states how structure and decision policies generate behavior (Richardson and Pugh 1981). Moreover, ‘‘The inclusion of basic mechanisms from the outset forces the modeler to address a meaningful whole at all stages of model development.’’ (Randers 1973). That is, a dynamic hypothesis is the key to ensuring that the analysis is focused on diagnosing problematic behavior and not on enumerating the unlimited details of a ‘‘system’’.

With the advent of qualitative analysis in the 1980s, the causal-loop diagram started to be used for purposes not necessarily related to simulation modeling, namely, for detailed system description and for stand-alone policy analysis. Wolstenholme (1999) puts the case clearly:

> ‘Causal loop’ qualitative system dynamics enhances linear and ‘laundry list’ thinking by introducing circular causality and providing a medium by which people can externalise mental models and assumptions and enrich these by sharing them. Furthermore, it facilitates inference of modes of behaviour by assisting mental simulation of maps.

We agree that system description can be a useful activity. Systems thinking consultants everywhere can attest to the utility of word-and-arrow diagrams for helping clients to understand the interconnected nature of their problems and the many possible side effects of their decisions. These maps generally go well beyond the conciseness of a dynamic hypothesis, and may often be better described as ''hurricane diagrams'' (Thompson 1999). Their usual intent is to improve the process of thinking about the structure underlying a problem—including feedback loops and perhaps time delays, accumulations, and nonlinear effects—rather than to hypothesize the root causes of reference mode behaviors. For this purpose, it does not much matter whether one uses causal-loop diagrams, or stock-and-flow diagrams, or Wolstenholme and Coyle's modular approach (Wolstenholme and Coyle 1983; Wolstenholme 1990; Coyle 1996), or the ''rich picture'' technique of soft systems methodology (Checkland 1981; Coyle and Alexander 1997) for describing a problem situation.

Although system description has value, it is important to recognize that what is described is structure and not dynamics. When a diagram is built to capture the full complexity of a problem situation, it will invariably include some details not relevant to the generation of reference mode behavior. Indeed, the richer the system description becomes, the more it departs from the concept of a dynamic hypothesis—and the more difficult it becomes to see how structure may be linked to behavior.

Why we model

Even when a causal map is kept relatively simple, its implied behavior may not be so simple or obvious. In fact, causal-loop diagrams are notoriously unreliable tools for behavioral inference (Richardson 1996a). A simulation model corresponding properly to the diagram may fail to behave as expected, even if the causal map contains loops with the polarities and delays one believes are necessary to recreate the reference modes of behavior. This is why we call our initial ideas about causal mechanisms a dynamic *hypothesis* and not an explanatory model. Experimental studies have shown repeatedly that people do a poor job of mental simulation even when they have complete knowledge of system structure and even when that structure is quite simple (Sterman 1994a, 2000).

Simulation modeling provides a tool for formally testing the dynamic hypothesis and determining its adequacy. If the testing is done properly, the flaws in a model will generally make themselves evident when the model's behavior is compared with that of the real world. Often, one finds that a simulation model may reproduce some aspects of reference mode behavior and other pieces of evidence but not all of them. In that case, the model, and perhaps the dynamic hypothesis itself, must be revised and tested again and again until it is found to be fully consistent with available evidence and logical considerations (Homer 1996). Even then, one must be careful not to confuse the model with reality, but always be aware of its limitations, and keep an eye open for additional evidence that may call into doubt some aspect of the model.

Although simulation may not always reveal the shortcomings of a dynamic hypothesis, the risk of leaving the flaws unrecognized is much greater without simulation. As John Sterman (1994b) has said, ‘‘Without modeling, we might think we are learning to think holistically when we are actually learning to jump to conclusions.’’ This is not to say that it is *impossible* to test the inferences drawn from a causal map without computer simulation. One might, for example, gather additional data—new or historical—that could be compared against map-based mental simulations of how the system should behave under specified conditions. Or one might, in some cases, carry out a small-scale, pilot implementation of map-based policy recommendations, to see whether the indicated improvements come to pass. But these empirical approaches to hypothesis testing often have serious drawbacks, including lack of reproducibility, inadequate breadth, and high costs, risks, or time requirements. These are the very drawbacks of traditional social science and policy analysis that simulation modeling is generally able to overcome.

Dynamic analysis without modeling?

Are there instances in which it is appropriate to use a map alone without a simulation model for analyzing dynamic behavior? In theory, the problem may be so straightforward or familiar that dynamic conclusions may be drawn reliably from a causal-loop diagram alone. As George Richardson (1996a) has stated:

> The history [of feedback thought in the social sciences] suggests that [properly] inferring dynamic behavior from word-and-arrow maps involving circular causality comes only in two situations, when the map is a recognized structure previously verified by simulation and when the map is extremely simple.

When might these two situations—a previously-simulated map, such as a generic structure (Paich 1985; Lane and Smart 1996), or a transparently simple one—actually arise in the real world? Infrequently. In both cases, the assumption is that the client has introduced no significant messy details that complicate matters. But problems that have proved so nettlesome as to cause an organization to call in a consultant rarely fit neatly into any straightforward structure. Once one starts to consider the real-world details and the multiple perspectives on a problem, the system description nearly always grows and becomes more elaborate. For this reason, Paich (1985) concludes that ‘‘generic structures are not appropriate for solving specific problems. Rather, generic structures are educational tools for learning about the fundamentals of complex systems.''

Suppose that, despite the messy details and multiple perspectives, somebody persuasive—maybe a member of the client team, maybe the consultant—proposes that a familiar or simple structure, lying at the core of the messiness, really is sufficient to explain the problem and its possible solution. And suppose that the team, after some discussion, unanimously supports this proposal. Is it appropriate to stop at that point and declare the problem solved? Some might say yes, that the team is now ''on the same page'' and can move forward, secure in its new sense of unity and purpose.

Unfortunately, the new insights may be off the mark, no matter how confident the team may feel. Overconfidence is one of the most prevalent and insidious biases in judgment and decision making, while groupthink is a common barrier to learning in the face of complexity (Sterman 1994a, 2000). If the proposed core structure is to be reliably used as the basis for policy analysis, its primacy or dominance over all other loops and pieces of structure that have been described by the team must be demonstrated somehow. Such demonstration is one of the strengths of computer simulation. Just as simulation makes possible the reliable inference of behavior from a given system structure, so too it facilitates the isolation of the core structure underlying a problem behavior.

Dealing with uncertainty

Are there instances, as Coyle suggests, in which the problem description is so rife with uncertainty, and soft variables in particular, that a reliable simulation model cannot be built? Soft variables—hard to measure and often subject to multiple influences—have been a central feature of system dynamics models since Forrester (1961) first described models depicting management decision-making and consumer response. Any reasonably complete text or course on system dynamics should cover principles and guidelines for modeling decision making and human behavior, and for formulating nonlinear relationships, including soft variables. For example, Sterman (2000) devotes entire sections to these subjects (chapters 13, 14, and 15). The ability of system dynamics simulation to handle soft variables has been demonstrated repeatedly, and across a remarkable breadth of applications in the management and social sciences (see, for example, Forrester 1969, 1971; Roberts 1978; Sterman 1985; Levine and Fitzgerald 1992; Richardson 1996b; Oliva and Sterman 2001).

It is true that there may be cases in which insufficient reference mode data or other types of information are available to determine conclusively whether the dynamic hypothesis is adequate to explain the problem behavior, or to assess adequately the various possible implications of policy change. But such cases are less common than one might think, for two reasons. First, even when numerical data are relatively lacking, mental databases are extremely rich and helpful in modeling (Forrester 1980). Second, even when parameter values are uncertain, sensitivity testing often reveals that behavior modes and policy conclusions are not affected by these uncertainties (Forrester 1969; Richardson and Pugh 1981).

Even when there is too little information to reach firm conclusions from a simulation model, it is still not *more* misleading to simulate than to map without simulation. If there is too little information to be able to make reliable inferences about behavior from a simulation model, then certainly the same must be said about a qualitative causal map. One may choose to map simply for the sake of system description and not for behavioral inference; but, in that case, as we have said, one is studying only the structure of a system and not its dynamics.

Moreover, how can one determine that too little information exists to reach firm conclusions *except* through simulation? One generally does not know how powerful a dynamic hypothesis is, or how sensitive to uncertainty, until a simulation model is built and tested. Model testing, including sensitivity analysis, can help to identify which pieces of information would be required in order to determine the adequacy of the dynamic hypothesis or to make firm policy conclusions possible. Consider three examples:

1. In a study of cocaine prevalence in the U.S.A., the behavior of an initial model was found to be sensitive to the strength of assumed causal links from wholesale price to retail price and supply. Extensive analysis of data on undercover cocaine purchases and seizures found little or no strength in these causal links, and led to a thorough reorientation of the dynamic hypothesis and the model (Homer 1996).
2. In a study of automobile leasing strategy by General Motors, sensitivity testing suggested those areas in which further model disaggregation and incorporation of market research data might make a difference to policy conclusions and other areas where it would not (Sterman 2000).
3. In an ongoing study of antibiotic resistance, discrepancies between model behavior and some pieces of empirical evidence have suggested specific areas for further data collection and possible model modification (Homer *et al*. 2000).

Conclusion

The question has been posed as to whether or not there may be situations in which simulation modeling adds no value beyond that of qualitative mapping, or may even be more misleading than mapping by itself. We have argued that simulation nearly always adds value to policy analysis, even in the face of significant uncertainties and soft variables.

Still, we appear to have a situation today in which some systems practitioners may use mapping alone to draw behavioral and policy inferences, without going on to simulation or empirical testing. Some of these analysts may be competent simulation modelers who believe, or whose clients believe, that testing may not add enough value to justify its costs and time requirements. Others may know enough to draw causal-loop diagrams but do not know how to develop proper simulation models.

Such uses of stand-alone mapping are, perhaps in most cases, better than nothing—that is, better than policy discussions that lack feedback thinking. There is clear value in helping a client recognize the existence of delayed responses and self-reinforcing side effects and possible sources of policy resistance that, without a process of mapping, would remain mere unarticulated concerns, vague observations, or simply ignored altogether. Moreover, there probably are certain situations—for example, when a decision must be made quickly or when the stakes are low—in which computer modeling is just too time-consuming or costly to justify its use.

Yet, it remains one thing to explore feedback mechanisms with a client, and quite another to draw conclusions about their dynamic implications. The mechanisms one emphasizes in an untested causal-loop diagram may or may not be the ones the client really ought to be most concerned about. In other words, the map may be misleading, and without simulation or other formal tests of the dynamic hypothesis there is no way to know whether that is so or not.

Consequently, we believe that all systems practitioners should understand and clearly describe to their clients the dangers of inferring too much from causal-loop diagrams, as stimulating as these diagrams may be. Of course, clients should also understand the limitations of simulation models, particularly in the realm of prediction, and the many requirements of proper model testing. But the fundamental distinction remains: Only through formal testing can one solidly bridge the gap from structure to behavior.

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