SYSTEM DYNAMICS AND ITS IMPACT ON MANAGERIAL DECISION MAKING

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ABSTRACT

System Dynamics (SD) is a widely used methodology to study complex feedback structures using computer simulation models. However much of its success is attributed to anecdotal evidence. This paper discusses the effect of various SD interventions on dynamic decision making. A series of controlled experiments to test the effect of system interventions is proposed. These effects are analysed by measuring the change in mental models of decision makers (1) as the level of decision aid is increased and (2) as the complexity of the model is increased. The aim of this research is to scientifically test systems-based decision aids thereby resulting in increased confidence of their use.

Keywords: system interventions, decision making, system dynamics, judgment under uncertainty

Introduction

The theory of systems thinking has provided tools and techniques for better understanding of complex systems. Most of these are now well established and have been used since the past forty years. One such technique is “system dynamics” (SD) that was developed at the MIT by J. W. Forrester. With the help of feedback loop analysis and computer simulation, SD focuses on the study of how the structure of a system governs its behaviour. Through its methodology, it aims at improving the mental models of decision makers. SD centres on policy and how policy determines behaviour (Forrester & Senge, 1980). The technique has been successfully applied to many types of dynamic systems since its creation (Richardson, 1999) though much focus remains on business and corporate policy (Scholl, 1995).

The word ‘System’ originates from the Greek word *sunistanai*, which originally meant, “to cause and hang together”. Kauffman (Kauffman, 1980) describes a system to be a collection of parts that interact with each other to function as a whole. We come across systems in our daily life; we ourselves may be part of one or more of them. SD is an offshoot of the broader discipline of “systems thinking” (ST) and there are few fundamental differences between the two. The System Dynamics Society differentiates the two based on the use of computer simulation in the methodology. It notes that “*systems thinking looks at exactly the same kind of systems from the same perspective. It constructs the same causal loop diagrams. But it rarely takes the additional steps of* *constructing and testing a computer simulation model, and testing alternative policies in the model"* (Society, 2005). Though there are difference between the two, what is important to note is that the fundamental concepts of the two remain the same. The ideas put forward in this paper are presented from a SD point of view, however they are equally applicable to systems thinking as a whole. Further research by the author is directed towards the comparison of the impact of systems thinking and system dynamics on managerial decision making.

The methodology of SD is a systematic process that starts with identifying the problem to be solved. Subsequently, a causal-loop diagram based on mental models is developed. This helps in identifying the feedback loops that cause the problematic behaviour. In the next step, this diagram is formally represented in a computer-based software tool. Eventually, a mathematical model is deduced from it and is simulated by using the most likely values of variables. The resulting hypothesis is tested to find various ways to alleviate the problem. These steps help in viewing the system as an interconnected one rather than as isolated parts. There is enough anecdotal evidence of the usefulness of this methodology and some experimental studies conducted recently have verified this (Barros, Werner, & Travassos, 2002; Cavaleri & Sterman, 1997; Doyle, Radzicki, & Trees, 1998; Huz, Andersen, Richarson, & Boothroyd, 1997). However, none so far has performed a controlled experiment in this direction to test the impact of sensitivity analysis and probabilistic SD on decision-making. This research centres on the above-mentioned concept of measuring the mental models of decision makers. The contribution of this paper is to emphasise and test the usage of SD as a decision making aid. The tests discussed here not only test the usefulness of various systems' tools, but also test when are they most useful.

For the purpose of the experiments, the author has chosen to evaluate three levels of decision aid. These are deterministic SD, SD with sensitivity analysis and probabilistic SD. These methods are commonly used in the analysis of complex systems. Each of these methods provides additional information as compared to the previous one. The fourth category for this experiment is a control group which does not use any sort of decision aid.

This paper is divided into six sections. The first is this introduction. The next three sections of the paper are dedicated to discuss the three levels of decision aid, their advantages and drawbacks. The significance of these techniques is argued through a discussion on the effect of complexity in the real-world and the effect of uncertainty in judgment prevalent in dynamic decision-making tasks. Subsequently, the importance of rigorous and reliable scientific testing is put forward and the design of a controlled experiment is discussed. The paper concludes with a note on further research in this direction and the contribution of this study to the field of systems thinking.

Deterministic SD

Most of the systems we come across are so intricate that the inherent complexity of these makes it difficult to capture every detail thus making their mathematical representation complicated. Determining their future state with accuracy is equally hard. In order to resolve these difficulties, complex system modellers often make assumptions that unfortunately change the nature of the system. One such assumption is to describe the individual behaviour of the sub-components of a system by their average (or most likely) interaction parameters; thus ignoring uncertainty and introducing determinism. In the modelling and testing phase, SD models mostly use deterministic values of variables. Hence, each time the model is simulated, it produces exactly the same output for a given set of inputs, thereby reducing the complex system to a mechanical one.

We are aware that "determinism" is untrue for real business settings. This assumption eliminates the effects of luck, noise and randomness in the complex system (P M Allen, 2000). It is a well known fact that deterministic variables only represent average behaviour and fail to represent microscopic diversity (Peter M. Allen, 1988; Bruckner, Ebeling, & Scharnhorst, 1989). Also, various researches in the field of complex systems reveal that these systems are not reducible to a mechanical system and hence the prediction of their future state with 100% accuracy is not possible. Deterministic variables in SD models are unable to capture the true behaviour of a variable as opposed to the ones represented through probability distributions, thereby generating incomplete information. This is a well-known handicap while making decisions in complex problems. Radford (1977) explains that one of the three main effects of limited availability of information is that it makes it impossible for anyone involved to construct a comprehensive model of the decision situation that includes all the relevant parameters and the relationships between them. This occurs due to various reasons - lack of time and resources being the most common ones. SD models have always tried to describe actual decision-making processes. However, with regards to the parameters involved, they have not yet achieved this. Most SD models are deterministic and hence fail to capture the true interactions between entities in a complex system. Moreover, much of this data depends upon measurements that often produce errors, biases, distortions, delays, and other imperfections (Sterman, 2000). This incomplete and inaccurate data eventually leads to incomplete mental models of the decision maker, thus invoking bounded rationality (Simon, 1956).

Furthermore, there is evidence that people do not make optimal decisions in dynamic environments and more so where there is a huge uncertainty attached to key variables (Brehmer, 1989; Sterman, 1989a). The combination of complexity and uncertainty often results in a sub-optimal decision. It is argued that probabilistic SD generates "complete" information thereby improving decision makers' mental models. The experiments designed via this research test the significance of using SD, sensitivity analysis and probabilistic analysis in simple and complex environments, thereby serving the purpose of laying concrete results about the usefulness of system dynamics interventions to decision making. It is hoped that these experiments would be instrumental in producing relevant information that would help decision makers' in making better decisions under uncertainty in complex business environments.

Sensitivity Analysis

As discussed in the prior section, deterministic models are a poor representation of reality. Hence, model validation tests are often conducted on SD models. We discuss one such test that is commonly used - sensitivity analysis. Sensitivity analysis is a procedure to determine the sensitivity of the outcomes of an alternative to changes in its parameters. The process takes into account unprecedented events that are considered one at a time, i.e. in isolation. Forrester and Senge (1980) assert that "*one should attempt to ascertain by comparing different members of the class of systems, whether or not the real system is likewise sensitive to the parameter in question. If it is, the sensitivity parameter may be an important input for policy analysis*". These sensitivity tests are conducted to reveal structural flaws in the model and give a deeper insight on uncertainty intervals and its spread (Ford, 1999). They improve the understanding of the model, help in narrowing down the areas where more data gathering would be useful and help identify pressure points in the model (Moizer, Arthur, & Moffatt, 2001). Furthermore, these tests become more important as the model becomes more important within an organisation (Ford, 1999). The emphasis of testing, verification and validation of SD models has been present since a long time and its importance in SD models has been demonstrated on key variables (Dyner, Franco, Montoya, & Arango, 2000; Huang, Wang, & Jia, 2002) and also on overlooked assumptions (Bayer, 2002). Similar to sensitivity analysis, various other tests could be conducted to improve the confidence level of decision makers. Forrester and Senge (1980) describe a series of seventeen such tests that could be conducted on SD models. These tests help in providing some useful information on the behaviour of the model and policy, which is not produced in case of purely performing a deterministic analysis. However, model validation tests too provide limited insight into the behaviour of a complex system. According to Stover (1980), as sensitivity analysis considers each event in isolation and not as part of the model, the technique has major disadvantages. He stresses that it fails to consider the influences of model variables on event probabilities and neither are the event-to-event interactions captured. Another drawback is that the combined effects of several events occurring in a sequence may be missed by using such techniques. These drawbacks render the technique unsuitable for a comprehensive analysis of the future behaviour of a complex system.

Probabilistic Analysis

The above two sections have discussed the potential advantages and drawbacks of the two techniques - deterministic SD and sensitivity analysis. From this brief discussion, we can infer that a purely deterministic model is incapable of representing true behaviour of a complex system. Some model validation techniques help in reducing this drawback by involving different values of key variables to test their response on model and policy. However, these too do not serve the purpose of representing the system behaviour fully. This lead to the use of probabilistic SD.

Various studies in the past have shown the importance of random variables in complex systems (Mosekilde, Rasmussen et al. 1983; Rahn 1985; Allen 1988). There have been ample studies in the past that focus on predicting the future state of a complex system. Forrester (1961) explains, "*we cannot assume a perfect model in which every relationship in known exactly. Therefore we are committed to models in which every decision function has at least in principle, a noise or uncertainty component*" (p124). He also describes that changing the values of certain variables may affect the system substantially (p268) and proposes that these sensitive variables should be closely controlled or the system be redesigned in order to make it insensitive (p276). These statements show the significance of randomness in complex systems, especially in the SD context. It is evident and well agreed that using purely deterministic variables in modelling does not generate "complete" information for the decision maker and might result in an uninformed decision in most cases. The inclusion of random distributions of uncertain variables to determine event occurrences overcomes these drawbacks. These ideas when applied to traditional SD are referred to as “probabilistic system dynamics”. This technique represents each variable as a probability distribution, thereby producing a distribution as the model outcome, as opposed to a point estimate. This less common form of SD uses sampling methods (like Monte Carlo and Latin Hypercube) on variables and is in tune with various arguments on representing the behaviour of uncertain variables in complex systems, as previously discussed. The method iteratively evaluates a deterministic model using a set of random numbers as input. It helps in analyzing uncertainty propagation where the goal is to determine how random variation, lack of knowledge or error affects the sensitivity, performance or reliability of the system that is being modelled. Probabilistic system dynamics has been used in the past by few system dynamists. The most influential of these studies have been conducted by the Futures Group in mid 1970s (Donahue, 1976; Stover, 1974, 1975). They used the cross-impact analysis to conduct probabilistic system dynamics. Examples in the SD context include the analysis of national development policies (Stover, 1975); studying airfield damage repair (Hagenson, 1990); analysing the uncertainty in Northwest Electric System (Ford, 1990); evaluation of financial-economic performance (Morozowski Filho & Silveira, 2000) and analysis of the Colombian Energy Sector (Dyner, et al., 2000). More recently, the capability of performing PSD has been included in some commercial SD software packages.

Current trend

Given the advantages of using the probabilistic technique, availability of tools to conduct these analysis and examples of successful use, it is surprising that not many people in the SD community use it. Even though the concept of random variables in SD models has been introduced since the beginning of the field, few incorporate these into SD models. Furthermore, many system dynamists do not even conduct sensitivity tests (Kleijnen, 1995). A survey conducted in 1995 (Scholl, 1995) confirmed the same. According to this survey, less than fifty percent of the respondents conducted policy sensitivity tests; just above sixty percent conducted behaviour sensitivity tests and less than sixty percent conducted the “extreme condition” test. These results show the lack of use of validation techniques used by system dynamists and is attributed to various reasons such as lack of time, money and patience (Clemson, Tang, & Unal, 1995; Kirkwood, 1998), as well as the huge number of simulations that need to be conducted for comprehensive testing (Bush, Schneider, Wachtel, & Brimm, 1985; Ford, 1999).

Prior research on dynamic decision-making presents significant results on the error-prone behaviour of decision makers. There is substantial evidence that decision makers misperceive feedback (Sterman, 1989a, 1989b) and their decisions result in chaotic behaviour (Mosekilde & Larsen, 1988). Moreover, the performance in dynamic tasks is strongly affected by feedback delays (Brehmer, 1992) and decision makers are not able to deal with complexity (Doerner, 1980). Furthermore, we are aware that people are not good decision makers where variables are uncertain and hence do not make rational decisions in such circumstances (Kahneman, Slovic, & Tversky, 1982). This is prevalent in those dynamic decision making environments where there is a huge uncertainty attached to key variables. The combination of dynamic complexity and uncertainty is common in real-world business environments and often results in sub-optimal decisions. The above-mentioned studies enhance our understanding about the interaction between the cognitive process of decision-making and complexity in real life. Furthermore, they lay a platform for the usage of techniques that would enable decision makers to make better decisions in such situations of uncertainty and complexity.

Surprisingly, since its introduction, the usefulness of SD has been based only on anecdotal evidence (Cavaleri & Sterman, 1997). According to Doyle (1997), "*important questions about the relationship of systems thinking and basic cognitive processes such as learning, memory, problem solving, decision making, and updating mental models remain unanswered*". Only in the recent past have researchers in SD started to address the issue of testing systems thinking interventions on organizational context and individual decision making (Doyle, 1997). Most of these experiments have not employed basic tools of the scientific method such as control groups, pre and post-tests, random or representative assignment of subjects, standardization of experimental procedures and hence are unreliable (Doyle, 1997). It is surprising that only few researches in the past have paid attention to actually proving if systems thinking interventions had an effect on decision making (Barros, et al., 2002; Doyle, et al., 1998; Huz, et al., 1997). Testing the hypothesis scientifically using a controlled experiment is much needed to counter various criticisms over the years and to provide a sound foundation for the future. Based on the above arguments we formulate the primary hypotheses of this study.

H1. The understanding (mental model) of a complex system is enhanced as the level of decision aid is increased (Figure 1). Specifically,

> **H1.1** The understanding increases when subjects are provided with SD as a decision aid as compared to subjects having no decision aid
>
> **H1.2** The understanding increases when subjects are provided with SD with sensitivity analysis as compared to subjects provided with only SD.
>
> **H1.3** The understanding increases when subjects are provided with SD with probabilistic analysis as compared to subjects provided with SD with sensitivity analysis.

H2. The increase in understanding leads to greater accuracy in decisions.

H3. There is an increase in confidence of the subjects as the amount of relevant information produced by using various decision aids is increased.

H4. Understanding also depends upon the complexity of the model. The usefulness of a decision aid (SD) is directly proportional to the complexity of the model.

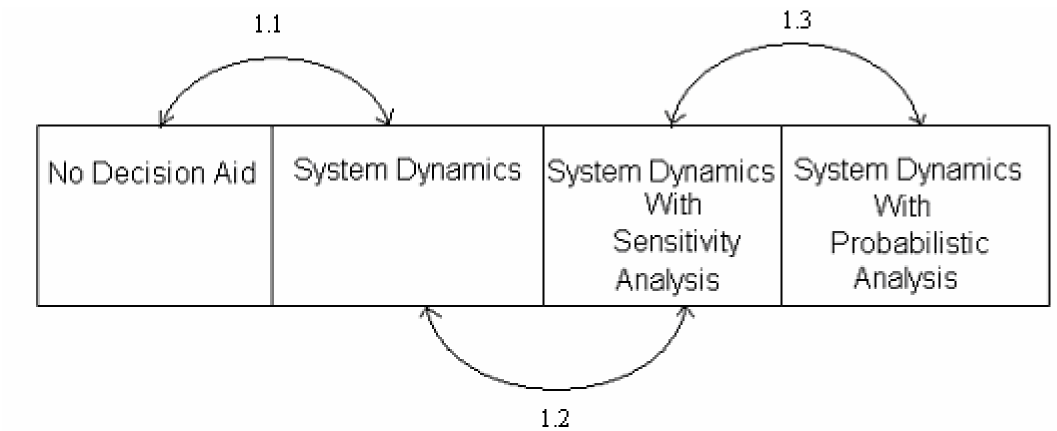

Figure 1: Hypotheses 1

Experiment

There is little evidence that shows its significance in changing the mental models of decision makers in dynamic decision-making task. Anecdotal evidence alone might not be enough to increase the confidence in a technique. Forrester (1993) explains - "*influential system dynamics projects are those that change the way people think about a system*". The only way to test that the technique has an influence on decision-making would be to measure the change in mental models of the decision makers' prior to and after conducting a controlled experiment. This would give an insight on the relationship of dynamic decision-making and additional information generated by various features to the traditional SD methodology.

This experiment is an avenue to test if SD and additional aids (sensitivity analysis and probabilistic analysis) have an effect on managerial decision-making. It follows the eight goals as specified by Doyle (1998).

1. To attain a high degree of experimental control.
2. Separate measurement and improvement.
3. Collect data from individuals in isolation.
4. Collect detailed data from the memory of each individual.
5. Measure change rather than perceived change
6. Obtain quantitative measure of characteristics of mental models
7. Employ a naturalistic task and response format
8. Obtain sufficient statistical power

These requirements are well known in psychology and education literatures and make the results reliable and the approach scientific. The experiment is a typical case study of a project management task where subjects are required to make certain decisions as a project managers. Decisions are made individually. It should be noted that though the experiments are designed by considering a project management scenario, they are equally applicable to any systems application. Graduate students of the School of Business at the University of Sydney are the target group. The subjects are divided into two groups. Each groups consists of at least twenty students. The changes in mental models are assessed as we go from one stage to the other.

The experiment is divided into three stages. Each of these stages is further divided into two phases. Stage 1 is used to analyse the effect of system dynamics on subjects' decision making. Two experiments are conducted - (i) for decisions made in simple environment and (ii) decisions made in a complex environment. Stage 2 analyses the effect of sensitivity analysis in SD on subjects' decision making. Stage 3 analyses the effect of probabilistic SD on decision making. Similar to stage 1, stage 2 and 3 also assess the effect of complexity of the model on decision making.

The model of the experiment is designed in such a way that it solves the purpose of the research and at the same time does not disadvantage subjects. Through this model, we are able to attain the eight goals as specified by Doyle as well as teach the concepts of systems thinking/SD to all students.

The design of stage 1 is briefly explained below
Simple task:

1. Subjects are randomly assigned into two groups – A and B. Each groups consists of 20 subjects.
2. A simple case study is distributed to both groups one day prior to the experiment.
3. At the time of the actual experiment, group A undergoes the pre-test. The pre-test involves open-ended questions about the behaviour of the system. It should be noted that subjects answer these questions based only on their prior experience and knowledge. At this stage they have not been taught any system dynamics.
4. Both the groups undergo a few three-hour sessions on system dynamics. They are taught the basics of field. At the same time group B undergoes some other test which is not relevant to this experiment.
5. Both groups are taught how to use one of the commercial SD tool.
6. Both groups then actively engage themselves in modelling and simulating the same case study.
7. Both groups are then made to answer the same questions again (post-test).

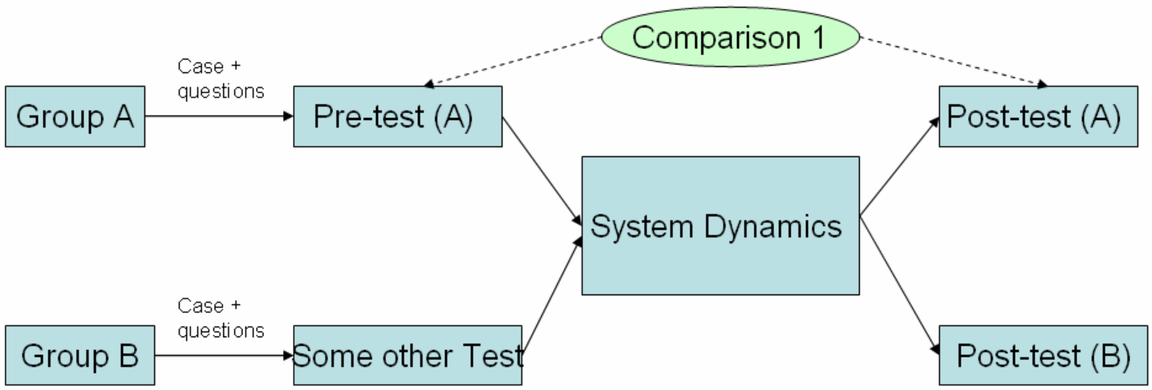

Figure 2: Experimental design for a simple task (phase 1)

Analysis
The pre-test and post-test attempted by group A are compared. Keeping all other effects under control, this analysis helps us to understand the effect of SD on mental models in a simple environment (marked as comparison 1 in figure 2).

Complex Task
A similar experiment is conducted on the same subjects for a complex task. The case presented to the subjects this time in much more complicated than the one presented above. This is conducted after a period of 6 weeks from the first experiment. Subjects continue to be in the same group as before. However, this time group B acts as the control and undergoes the pre-test. Remaining part of the experiment remains exactly the same.
Analysis
The pre-test and post-test attempted by group B are compared. Keeping all other effects under control, this analysis helps us to understand the effect of SD on mental models in a complex environment (marked as comparison 2 in figure 3).

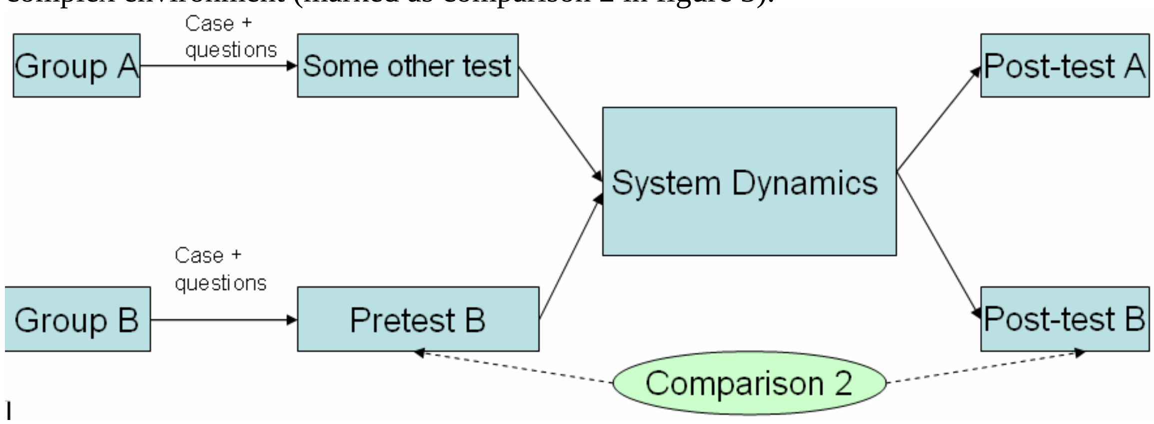

Figure 3: Experimental design for a complex task (phase 1)

Further to the above comparisons, another comparison is made to measure the effect of system interventions on subjects' mental models. Here, post-test of group B from figure 2 is compared with pre-test of group B in figure 3. This allows us to analyse the actual effect of SD on mental models.

In stage 2, we increase the level of decision aid. In addition to the basic SD technique, subjects are taught model validation techniques such as sensitivity analysis. The design for stage 2 of the experiment is a modified version of that of stage 1. Here, subjects' are taught SD prior to the pre-test. The focus of this stage is to test the effect of sensitivity analysis on decision making. The decisions made prior to and after the use of sensitivity analysis are tested in the two settings (simple and complex environment) as shown in figures 4 and 5 below.

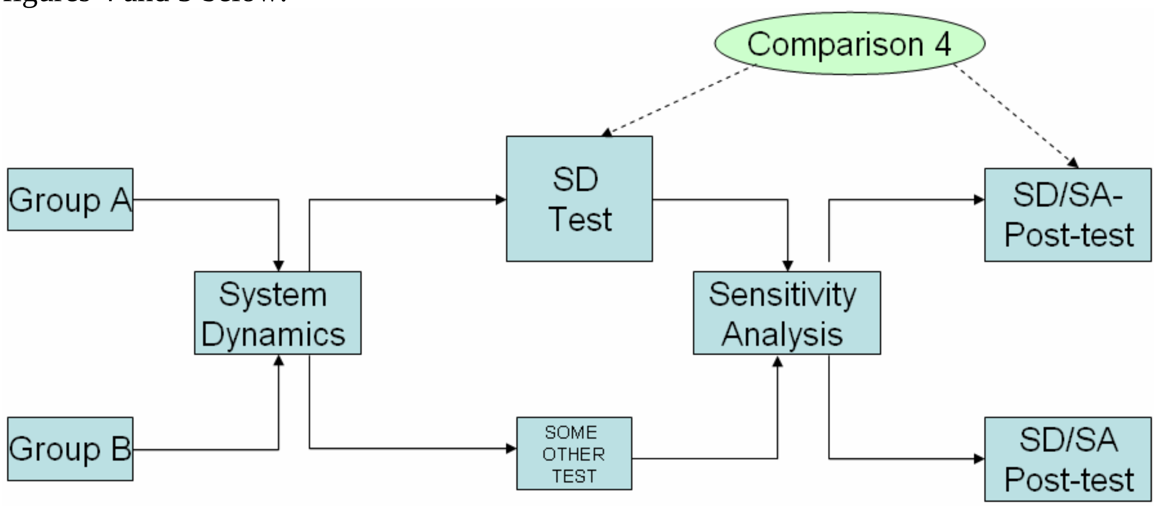

Figure 4: Experimental design for a simple task (phase 2)

Similar to phase 1, the control group now changes to group B.

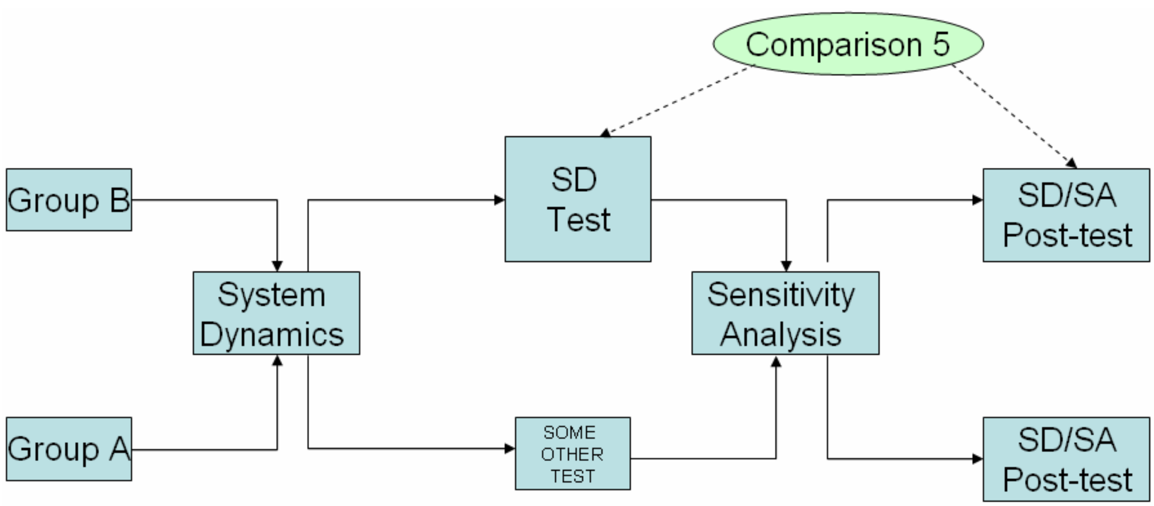

Figure 5: Experimental design for a complex task (phase 2)

The purpose of phase 3 is to test the impact of probabilistic SD on managerial decision making. The control group here is that makes decisions solely on the basis on deterministic SD, whereas the other groups makes use of probabilistic SD. The set-up is similar to the one discussed above and is depicted in figures 6 and 7.

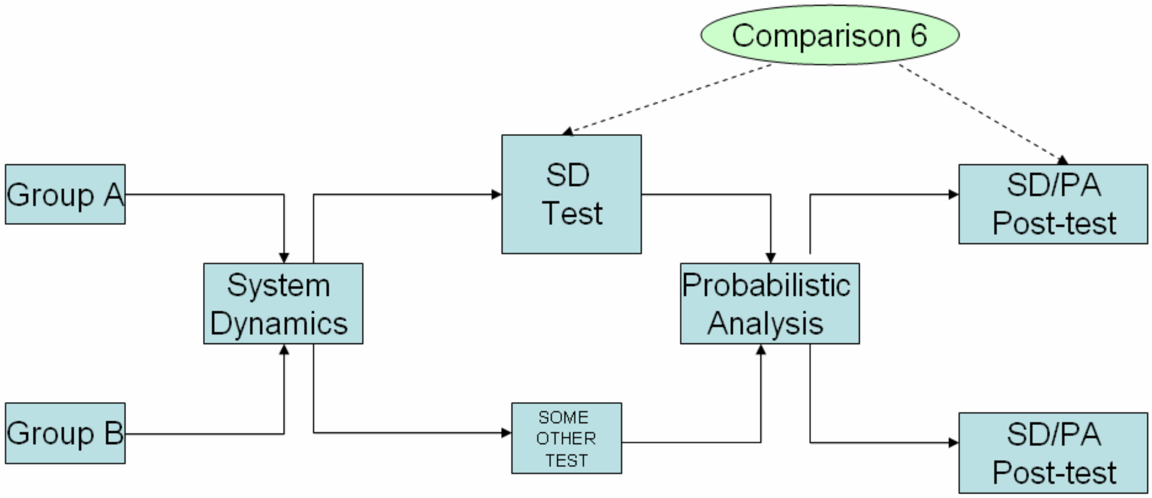

Figure 6: Experimental design for a simple task (phase 3)

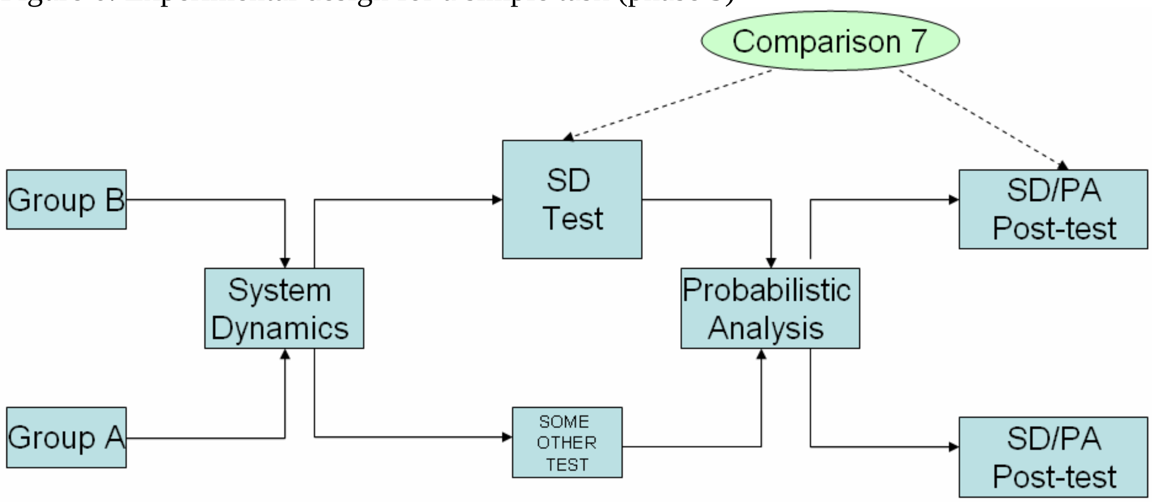

Figure 7: Experimental design for a complex task (phase 3)

The table below summarizes the various experiments that are conducted. Each of these produces significant results.

Potential comparisons for the entire series of tests

1. Effect of SD on decision making (versus no SD) in a simple task.
2. Effect of SD on decision making (versus no SD) in a complex task.
3. Retention of systems concept over a period of time
4. Effect of sensitivity analysis on decision making in SD (versus SD only and no SD) in a simple task
5. Effect of sensitivity analysis on decision making in SD (versus SD only and no SD) in a complex task
6. Effect of probabilistic analysis on decision making in SD (versus SD-SA, SD only and no SD) in a simple task

7. Effect of probabilistic analysis on decision making in SD (versus SD-SA, SD only and no SD) in a simple task
8. Utility of using decision aid as we go from simple to complex model.

Conclusion

Various systems-based decision aids have been successfully used in the past. However, their effect on decision making is yet not fully understood. This paper has made an attempt to design experiments to test the effect of commonly used system dynamics interventions. The tests also focus on appropriate use of these in certain scenarios. The design of a control experiment is discussed which follows rules of a scientific study. The author believes that these are a concrete step in the direction to strengthen the field.

Further researches are aimed at testing the impact of other model validation such as those mentioned by Forrester and Senge (1980). The effect of system dynamics interventions on other aspects of psychology such as memory, analogical transfer and expertise are promising avenues as well. The author has designed a model to test the usefulness of system dynamics when compared to system thinking. This test would be conducted in the near future.

This study takes an example from the project management discipline and applies it to one of the system thinking tools. However, the results are equally useful to other tools and techniques as well, thereby increasing confidence in the use of systems methodologies and making the field more scientific.

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