Session 8
Comparing Simulation Methods

SYSTEM DYNAMICS AND DISCRETE EVENT SIMULATION: A META-COMPARISON

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ABSTRACT

System Dynamics (SD) and Discrete Event Simulation (DES) are two established simulation techniques for simulating the dynamics of a system. Both have been widely used in modelling business decisions. This paper presents meta-comparison between the two approaches based on literature survey. Upon reviewing the existing literature it has been identified that existing comparisons could be classified under three main perspectives: Systems perspective, Problems perspective and Methodology perspective. The nature of system and nature of problem have been argued as primary factors for deciding modelling methodology. Therefore SD and DES comparisons have been classified on the basis of systems, problems and inherent aspects and capabilities of both modelling methods. It has been argued that development of sound models need fit between system, problem and methodology.

Keywords: Simulation, System Dynamics, Discrete Event Simulation

1. INTRODUCTION

Simulation has been effectively applied in enterprise decision making. System Dynamic (SD) and Discrete Event Simulation (DES) are two different branches to simulation modelling. SD offers a methodology to assist businesses and government organizations in strategy development, analysis of policy options, and analysis of dynamic processes, where capturing information flow and feedback are important considerations (Sweester, 1999). DES has capabilities that makes it more suitable for detailed analysis of a well defined system. "DES concerns the modelling of a system as it evolves over time by a representation in which the state variable changes instantaneously at separate points in time"(Law and Kelton, 1991).

Both SD and DES being established simulation techniques and widely used in organizational decision making, one would have expected there to be a strong association between the two. However, there seems to be little interaction between the two approaches (Sweester, 1999; Lane, 2000; Brailsford and Hilton, 2000; Morecroft and Robinson, 2006). Both techniques are concerned with modelling behaviour of the system over time, though from different perspectives. Both represent and interpret real systems from different angles (Morecroft and Robinson, 2006). It has been argued in literature that some models are more suitable for certain problems (Pidd, 2004). All these discussions are feeding towards the growing interest in the question of how to decide which modelling technique is better or more appropriate for a particular situation? This question cannot be answered effectively without having a comprehensive understanding of contrasting and overlapping features of both.

There is a lack of comprehensive comparison between the two. Existing comparisons are either based on differences in philosophical aspects or the way SD and DES represent and interpret models or the way they perceive system or their use. "Most of the comparisons are biased as they are carried out either by DES or SD analyst" (Morecroft and Robinson, 2006). A comprehensive meta-comparison of SD and DES based on *the system perspective*, *the problem perspective* and *the methodological perspective* is the main contribution of this paper. It has been previously argued that What (object of the simulation study), Why (purpose of the study) and How (simulation method) are the main criteria for deciding between the methodologies (Lorenz and Jost, 2006). In this context, the importance of the nature of the system and the objectives of the simulation study have also been highlighted by Pidd (2004). However, this paper argues that a combined view of the system, the problem and the methodology maybe necessary to make a decision pertaining to the suitability of SD and DES for modelling specific scenarios.

The paper is structured as follows. The following section provide brief overview of SD and DES. Section 3 presents comparisons and discussion on the outcomes of the findings. Section 4 provides a combined view of comparisons and the last section presents the conclusion.

2. OVERVIEW OF DES AND SD

SD and DES are two simulation techniques widely used in Operational Research. The following sub-sections will provide brief overview of both.

2.1 DISCRETE EVENT SIMULATION

Arguably, DES is the most popularly used OR technique (Brailsford and Hilton, 2000). DES is probably most well known in its use in the manufacturing industry and healthcare systems. Most modelling techniques were developed in order to solve a specific problem. DES is known for problems with queuing characteristics. The model consists of network of queues and entities. The animations and graphics of DES enhanced its visual interactivity. This makes DES an ideal tool for communication with clients. The general principle of model building remains the same regardless of the industry, simulations is applied to. The images and animations provide that tangibility to the factual figures and concepts which help in understanding the system better. e.g. flow of patient depending on severity label. It generates the confidence of the client in the model. The main objectives of these models are prediction, optimisation and analysis of what if scenarios.

As a modelling approach DES model can describe the most complex systems and include stochastic elements, which cannot be described easily by mathematical or analytical models(Venkateshvaran et al., 2005). DES allows one to track the status of individual entities and resources in the facility and estimate numerous performance measures associated with those entities. DES models System as network of queues and activities (Brailsford and Hilton, 2000). Events are the pivot of DES models. Changes in system occur when events happen. Due to this event based focus, changes in system occur at discrete points of time. The activity duration of these events are sampled from probability distributions. DES model building involve identification and representation of resources, entities, logic and flow of entities.

2.2 SYSTEM DYNAMICS

SD is an analytical modelling methodology developed by Jay Forrester (1968) at Massachusetts Institute of Technology. The basic idea was taken from feedback control theory. Engineers have been using modelling of feedback systems via differential equation. Forrester replaced the differential equations with difference equations. The equations tell how to generate the system conditions for a new point in time, given the conditions known from the previous point in time.

SD combines two distinct aspects: qualitative and quantitative, with the aim of enhancing the understanding of a problem and improving the comprehension of the structure of the problem and relationships present between relevant variables (Brailsford and Hilton, 2000). Due to this ability of combining both qualitative and quantitative aspects along with the flexibility of process, SD has been used across many fields such as project management, defence analysis and healthcare etc. It has been only recently that people have started appreciating the benefits of qualitative aspect of SD (Brailsford and Hilton, 2000). The interactions between different constituting units and variable affecting system are represented by influence diagrams. Influence diagrams are highly informative and provide insight into the system being investigated. Along with numerical data, SD models are capable of using descriptive as well as judgemental data. The main objective and advantage of modelling comes from the fact that it helps in formulation and understanding of problem. SD fits into this context very well. It helps in in-depth understanding of problem. Jay Forrester (1968) said that SD models are "learning laboratories".

As a modelling approach SD has three characteristics; concept of feed back loops, computer simulation and need to engage with mental models (Lane, 2000). The most important information about these systems is not documented it is held as mental models. The decisions made by the problem owners are influenced by their mental models. SD as a modelling approach has the ability to engage with mental models (Lane, 2000). Therefore it is highly recommended that modelling work should be done in close proximity with the problem owners, who can see reflection of their mental models in the computer models. Due to its engagement with the problem owner's mental models SD generate confidence in the model and hence has impact on decisions made by the problem owner. Due to their problem structuring ability SD models are more used at strategic level (Coyle, 1985; Sweester, 1999; Lane, 2000; Brailsford and Hilton, 2000).

3. COMPARISON BETWEEN DES AND SD

On extensive literature search, it has been found that literature available on comparison of two techniques is very limited. This could be due to the fact that proponents of two fields have very little appreciation of each other (Sweester, 1999; Lane, 2000). This section compares DES and SD modelling approaches on the basis of existing literature. So far Morecroft and Robinson (2006) paper is the only paper that have compared SD and DES empirically.

SD and DES models have been compared on the basis of technical and philosophical difference in methods, difference in the way they represent and interpret problems and systems and the difference in the way they have been used (Brailsford and Hilton, 2002; Morecroft and Robinson, 2006; Tako and Robinson, 2006; Lane 2000). There is lack of comprehensive comparison which combined all these separate views. The need to fulfil this gap has been further aggravated with the growing interest in finding answer to the question when to apply which methodology (Brailsford and Hilton, 2002; Lorenz and Andreas, 2006; Morecroft and Robinson, 2006)

In an attempt to fill this gap the authors have taken a combined approach and classified existing comparisons under *modelling methodology perspective, systems perspective* and *problem perspective*. Here methodology perspective refers to philosophical assumptions, technical capabilities, limitations and inherent characteristics of modelling method. Problem perspective refers to "Why" the reason behind the modelling exercise and the system refers to real world context under investigation. There are two reasons behind choosing system, problem and methodology as criteria for comparisons, first is that all the existing comparisons can be classified under these three parameters providing a comprehensive comparison. And the second reason is that system, problem and methodology have significant influence in answering the major question, which is better for what? In a way by choosing these three parameters, the authors have tried to kill two birds with one arrow. This comparison not only provides a comprehensive comparison but also leads a way forward for answering the question which is better in which situation.

Pidd (2004) argues that modellers should think about nature of the system and nature of the problem prior to modelling, as some models are better suited for certain problems than others. From his argument it is evident that there needs to be close fit between modelling methodology, system and problem. There are other factors which are related to a successful modelling practice and hence have impact on deciding between modelling techniques, but the systems, problem and capabilities of modelling methodology have come across as primary factors. It is important to note that the boundaries between these perspectives are much diffused with many overlapping features.

3.1 METHODOLOGY PERSPECTIVE

Quite a few comparisons in literature have been found on the basis of capabilities and inherent aspects of both modelling methods such as how the models represent and interpret what are the modelling elements of the models etc. Dominance of comparisons on the basis of inherent capabilities of methods could be attributed to the fact that most of the comparisons are carried out by academics and academics tend to concentrate more on methodological perspective.

Coyle (1985) identified that SD models represent closed, nonlinear processes whereas DES models represent open linear processes. However Morecroft and Robinson (2006) argued that DES can model nonlinear closed processes as well. It has been stated that SD and DES differ in the way they represent and interpret (Morecroft and Robinson, 2006). Differences have been found in their modelling philosophy and underlying mathematics (Coyle, 1985; Mak, 1992; Sweester, 1999; Lane, 2000). David Lane (2000) argued that clients find SD models more transparent and easy to understand, whereas though they find DES models convincing, they do not understand the underlying mechanics of the model. Author agrees with Brailsford and Hilton's argument (2000) that Lane (2000)stance might be applicable to qualitative SD models, however quantitative SD models with their differential equations and mathematical formulae lack this transparency. Models have been compared on the basis of their capabilities (Randers, 1980; Sweester, 1999; Lane, 2000; Usano et al., 1996). They have been also compared on the basis of their output, validity and the way they handle data and time (Randers, 1980; Coyle, 1985; Sweester, 1999; Lane, 2002). It has been argued that SD and DES differ the way they interpret and rep[resent system (Morecroft and Robinson, 2006). David Lane (2000) has argued that both methodologies differs the way they pursue complexity, "dynamic complexity" in case of SD and "detailed complexity" in case of DES. Detailed comparisons on methodological perspective are shown in Table 1.

Table 1: Modelling methodology perspective

MODELLING METHODOLOGY PERSPECTIVE		
CRITERIA	**SD**	**DES**
Modelling Philosophy	Causal structure of the system causes behaviour and model building reveals this	Randomness associated with interconnected variables leads to system behaviour.
Representation	System represented as stocks and flows	System represented as queues and activities, processes
Feedback	Feedback explicit	Feedback Implicit
Relationship	Interested in identification of nonlinear relationships	Relationships can be nonlinear but mostly are linear
Randomness	Randomness is not of direct interest and hence is subsumed into delays	Randomness explicitly modelled
Recurring modelling structures	Standard recurring modelling structures exist e.g. Asset stock management process	Standard modelling structures generally do not exist
	Standard Diagramming format	There is no agreed standard diagramming format.
Interpretation	Feedbacks and delays are vital to system performance over time	Feedback is not that important, randomness leads to system behaviour.
Feedback	Randomness is not important	Randomness is Vital
Interpretation of results	Results are easy to interpret, it does not require in-depth knowledge of stats	Interpretation of results require statistical knowledge
Nature of Results	Qualitative and quantitative results	Quantitative
Data	SD Models are not heavily dependent on numerical data	DES models are highly data dependent
Data Sources	Broadly drawn: Subjective , judgemental data held in the form of mental maps is also crucial	Primarily numerical, tangible data with some informational element
Data	Solution not only requires analysis of numerical data but judgemental subjective data held in the form of mental models is also very crucial	Solution depends on analysis of tangible numerical and informational data.
Complexity	Complexity increases linearly with size	Complexity increases exponentially with size
Type of Model	Qualitative Model/Quantitative	Quantitative Model
Resolution of Models	Homogenised entities, continuous policy pressures and emerging behaviour	Individual entities, attributes, decisions and events
Parameters	SD model's parameters are affected feedbacks loops with in the system	In DES parameters are set after intensive research on historical data but once they are entered in the model they remain unchanged.
Parameter estimation	SD score higher then DES on parameter estimation.	One of the drawbacks of DES is it's weakness in parameter estimation.
Accuracy of the model	System Dynamist are not interested in acute accuracy, As stated that SD models are never more than 40% accurate. They are more interested in the outcome of model as learning laboratories.	DES due to it's heavy reliance on data, produce accurate, statistically valid models.
Flexibility of modelling structures	Modelling structures are more flexible	Modelling structures are less flexible
Point Predictive ability	SD scores less	DES scores high
Formal Correspondence with Data	SD scores less	DES scores high

MODELLING METHODOLOGY PERSPECTIVE		
CRITERIA	**SD**	**DES**
Transparency	client find the model transparent/ fuzzy glass box, nevertheless compelling	Client find the model Opaque/dark grey box, nevertheless convincing
Structure determine performance	SD is based on the concept that Performance of SD model over time is determined by it's structure	DES is based on the concept that Performance of System over time is determined by randomness and by the internal structure of the system. .
Mental Models	SD models generate confidence in clients by engaging with mental models	DES model generate confidence by engaging with data provided by the client
Validity	Validation increases plausibility of the model as a theory for the causal mechanism generating behaviour	Validity proves the model to be true representation of system.
Scope of Validation	Concerned more with model usefulness. SD proponents shy away from holding their model to strict standards of predictive validity.	DES due to its reliability on data have stronger empirical basis
Validation approach	Emphasis on Internal structure approach - white box approach	Emphasis on model outputs - Black box approach
Underlying Mathematics	SD models the behaviour of system using differential equations	DES use statistical distributions to model the increments of simulation clock.
Role of Computer Simulation	Computer Simulation of SD models are used as learning laboratories that allow managers to run SD models in gaming environment	DES models are less used as learning tools for non technical people.
Computer Animation	computer animation is limited to graphs and equations	DES , with its computer animation capabilities where entities can be shown moving across the system help more in visual understanding of process flow

3.2 SYSTEMS PERSPECTIVE

Upon reviewing literature, System's perspective has also been identified as one of the main criteria which was used as the basis for comparisons. The nature of the system being simulated is an important consideration before deciding between the models because "the model needs to be a close fit, a good representation of the system"(Morecroft and Robinson, 2006). SD and DES have been compared on the basis of the nature, representation and view of the systems. It has been argued that SD provides a broader holistic view of the system whereas DES provides narrow, microscopic view focusing on precision and detail (Mak, 1992; Lane, 2000). Sweester (1999) has argued that System Dynamicists are interested in fuzzy ambiguous systems whereas DES modeller focus on clearly defined system. MacDonald (1996) argued that DES is more appropriate for modelling systems where behaviour of the system changes significantly when a specific variable reaches a threshold level, whereas SD is better where the system reacts in a specific way in response to the gradual building up of pressure. Detailed comparison of the two methods with respect to systems perspective is presented in Table 2.

3.3 PROBLEM PERSPECTIVE

The third main perspective which has been identified as criteria for comparison is the Problem Perspective. Again this has been influenced by the relevant literature suggesting that nature, scope and different aspects of the problem has influence on deciding between SD and DES, as both SD and DES are more capable at modelling certain aspects of the problem. It has been argued in literature that SD is more suitable for modelling strategic problems and DES for operational and tactical (Brailsford and Hilton, 2000; Lane, 2000). Problems which are caused by the structure of the system are better analyzed by SD and problems which are caused due to the randomness are better modelled by DES (Sweester, 1999; Morecroft and Robinson, 2006). Detailed comparison of the two methods with respect to problem perspective is presented in Table 3.

Table 2: Systems perspective

SYSTEM'S PERSPECTIVE		
CRITERIA	**SD**	**DES**
System	Holistic view; emphasis on dynamics complexity	Analytic view: emphasis on detailed complexity
Clarity of the system	Fuzzy, ambiguous	clearly defined
Organisational Level	Strategic Level	Operational Tactical Level
Relationships	Nonlinear relations and feedback are under consideration	Linear relations where output has no impact on input
Focus	Wider Focus: general and abstract system at macro level	Narrow focus with microscopic view on detail
Relation to Outside world	Unisolated continuous system with cross boundary interactions	Isolated discrete system with no interactions with the outside world.
processes	focus is on continuous nonlinear processes.	focus is on discrete linear processes.
System Orientation	SD focus more on modelling systems	Des focuses more on modelling processes.

Table 3 : Problem perspective

	SD	DES
Problem perspective	The understanding of the problem lies in analysis of causal feedback effects	Understanding of the problem lies in analysis of randomness associated with interconnected processes and events.
Problem studied	Strategic Level	Operational & tactical Level

4. COMBINED VIEW

There is a growing concern in research in understanding which method is better or more suited for a particular problem. It has been argued that the choice of modelling methodology is dictated by the modeller's expertise (Brailsford and Hilton, 2000, Morecroft and Robinson, 2006). This is a typical example of modifying a nail according to the hammer. Rather than adopting a tool to the problem, analysts try to adapt problem to available tools. However it should be the other way around. This mismatch between problem and methodology could be attributed to the lack of a framework helping decision makers to decide upon methodology.

All modelling techniques are based on certain philosophies and assumptions. Successful choice between methods depends upon understanding the contrasting and overlapping features of modelling methodology. The previous section has given a detailed account on comparisons between SD and DES. It has been argued in this paper that in order to develop sound models, there needs to be strong fit between system, problem and methodology (Fig 1).

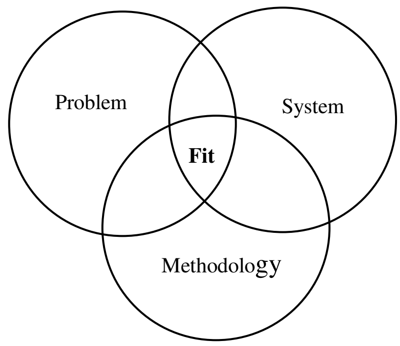

Figure 1: Fit between problem, system and methodology

Upon deciding between SD and DES, it has been argued that the answer to this question of deciding between SD and DES depends more on the purpose of the model rather than the system being modelled (Lorenz and Jost, 2006). On the contrary to that, the authors believe that system is an integral aspect when it comes to deciding between SD and DES. For example there are quite a few models of A&E in literature, where modellers have used analytical methods such as DES to address the A&E problems. These models are result of fit between the purpose and the methodology rather than the fit between purpose, methodology and system. A&E as a system interfaces with many other departments of a hospital. Its internal processes may therefore influence other departments and vice versa. Here consideration of systems perspective along with problem perspective would have definitely contributed more. On the other hand, if cross boundary interactions have zero impact on the internal processes of the system then perhaps the use of DES to optimize the internal functioning would have been the right choice. These cross boundary interactions can only be addressed if the modeller takes into account system perspective as well.

Lane et al (2000) in their study of Accident and Emergency department have highlighted that considering problem perspective alone to measure the effect of bed shortage on A& E waiting time would be misleading. They have emphasised on the point that how a system's perspective along with problem perspective will help in looking at the bigger picture of the problem. The authors agree with Lane et al (2000) that systems perspective will not only represent the connections between the different parts of the system but also highlights how the changes in one part will have ripple effects in other parts of the system.

Lane et al (2000) have argued that reduction in bed will not affect A&E waiting times directly, but it will affect elective waiting times. Because of the increase in elective waiting times the condition of the patients will deteriorate and hence elective patients will present themselves to the system as A&E patients. This will reinforce the problem of A&E waiting times and bed shortage. As A&E patients stay in hospital longer than elective, this will further reduce the availability of beds. As a behavioural consequence of long waiting times for elective patients, GPs will refer more patients to A&E. All these factors will additively affect the A&E waiting times. These factors can not be studied without analysing the problem in system's context.

Similarly, taking system aspect alone for deciding between the suitability of SD and DES can again lead to inefficient/incomplete models. It has been argued that if the system is large SD is better choice because complexity of the DES model increases exponentially with size (Brailsford and Hilton, 2002; Rabello et al., 2004). Brailsford et al (2004) have used system dynamics in their study of accident and emergency department of Nottinghamshire. They have used SD as methodology of their choice and reasoned that the size of the system is large and there are not many reported DES studies of large system as the justification behind their choice. However the authors of this paper do not agree with their reasoning as in the same study they have also used DES to investigate the Government's suggestion that waiting times in A& E can be reduced by the provision of fast track system for minor injuries. Brailsford et al (2004) have argued that this investigation required individual details and SD as a methodology is not capable of capturing this detail. From this it is quite evident that as the systems context in both scenarios is the same the difference lies in the purpose of problem. Hence the use of SD and DES has been governed by the suitability of SD and DES to combined perspective of system and problem. Again authors would like to make a point that size of the system alone without understanding the objectives of the problem is not sufficient for deciding between two.

Like Systems and Problem, using inherent capabilities of methodology on its own for deciding between two can be misleading. For example it has been argued that SD models require less time to develop and DES models require more time and hence SD should be used when there is not enough time (Brailsford and Hilton, 2002) However it has been well proved that quick and dirty models can be developed using DES.. As argued by the authors, choice between SD and DES should be dictated by the problem and the System The combined view is required in order to make better models and hence better decisions. The authors believe that this combined view of comparisons using system methodology and problem (as shown in fig1) will provide a suitable vision for developing a framework for deciding appropriate methodology.

5. CONCLUSIONS

SD and DES are two established simulation methods. They have been compared on the basis of technical and philosophical differences in methods (Brailsford and Hilton, 2000: Lane et al 2000), the way SD and DES represent and interpret problems and systems (Morecroft and Robinson, 2006) and the way they have been used (Tako and Robinson, 2006). There is lack of comprehensive comparison which combines all these separate views. . This paper contributes by providing a comprehensive meta-comparison. This is achieved through three perspectives of methodology, system and problem, perspectives.

Coming back to the question of choosing between the two, it has been argued that what (system), why (problem) and How (modelling methodology) are the main criteria for deciding between methods (Pidd 2004: Lorentz and Jost 2006). The authors have argued that development of sound models require fit between problem, system and methodology. By choosing these three perspectives, this paper has not only provided a comprehensive meta-comparison but has also contributed by providing a vision for the selection of suitable method.

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SELECTION OF SIMULATION TOOLS FOR IMPROVING SUPPLY CHAIN PERFORMANCE

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ABSTRACT:
The performance of the supply chain is a key source of competitive advantage for the firm. Supply chains are becoming ever more complex due to factors such as globalisation and the development of supply networks. Modelling the supply chain is an essential step in the improvement process, and simulation is found to be a good approach in this context of high variation and dynamic behaviour. There are three main approaches to supply chain simulation; System Dynamics (SD), Discrete Event Simulation (DES) and Agent Based Modelling (ABM). At present, choice of technique owes more to custom and practice than suitability. There are no existing frameworks to assist practitioners in selecting the appropriate technique for the supply chain problem under consideration. Establishing this framework will be valuable and will be the subject of further research.

Keywords: Supply Chain, System Dynamics, Discrete Event Simulation, Agent Based Modelling.

1. INTRODUCTION

The performance of the supply chain has become ever more important for the overall competitiveness of firms and indeed can become the focal point for performance improvement (Slone, 2004 and Harrison, 2005). The supply chain has taken over from the individual firm as the focal point of competition and it is considered that it is now supply chains which compete and not companies (Christopher, 2005). This has implications also on how firms choose to improve, moving away from a narrow cost reduction approach towards globally integrated and coordinated sourcing strategies (Trent and Monczka, 2005). In addition to this, globalisation is increasing the complexity of supply chains and it has been found that global supply chains are more difficult to manage than domestic supply chains (Meixell and Gargeya, 2005). There are a number of factors which influence this including geographical distances and different local cultures. Global supply chains also carry significant risks to performance including variability and uncertainty in exchange rates, economic and political instability and changes to the regulatory environment (Meixell and Gargeya, 2005).

Faced with the inherent and increasing complexity of the supply chain and decision making within it there is a growing need for modelling methodologies that allow firms to understand current performance and to evaluate the likely performance of alternatives (Biswas and Narahari, 2003). It is suggested that the first step in performing a supply chain study should be to determine the type of modelling approach to be used (Harrison, 2005). Modelling is also considered a key precursor to the effective integration of processes in the supply chain (Vernadat, 1996; Fleisch and Osterle, 2000).

Supply chain modelling approaches typically fall into three main areas, namely optimization, simulation and heuristics (Harrison, 2005). Although optimization has often been used, it has significant limitations, in particular; optimization has no way to handle forecast error or inaccuracy; optimization does not help when the business objectives change over time and some problems are too complex for optimization (Ingalls, 1998). Heuristics are limited in that they result in a solution with unknown quality (Harrison, 2005). Simulation has strengths as an approach in dealing with the key features of the supply chain. For example, simulation is good for modelling the impact of variation, for example, forecast error, supplier reliability and quality variance (Biswas and Narahari, 2003). Time phased and dynamic behaviour is important in supply chains. Examples of this are process delays and lead times of information and material conversion and transfer. A classical example of the consequences of these factors is the amplification of the demand signal, otherwise known as the 'Bullwhip effect', first described by Forrester (1961). Simulation has been found to be a good technique for modelling these dynamic features. Simulation has also been found to be useful in modelling business processes and their features such as abstract representation, information and physical flows, randomness and time-based effects (Ball et al, 2004). Simulation is the only approach that can holistically model the supply chain (Tang et al, 2004).

The objective of this paper is to describe the three main approaches to supply chain simulation, namely System Dynamics (SD), Discrete Event Simulation (DES) and Agent Based Modelling (ABM); to demonstrate that these techniques have different strengths and weaknesses in application, and that a framework to assist practitioners in selecting the appropriate technique would be valuable. The paper is structured as follows. The next section presents an overview of the three techniques. Section 3 discusses the literature which compares the three techniques. Section 4 discusses some of the strengths and weaknesses of the three techniques in application, demonstrates the need for a framework and leads to Section 5 which sets out the further work which will be necessary to develop the framework.

2. SD, DES AND ABM IN SUPPLY CHAIN MODELLING

2.1 SYSTEM DYNAMICS (SD)

The origins of System Dynamics date back to 1958 and Jay Forrester (Forrester, 1958) who applied the principles of control engineering to the solution of management problems and developed a new approach. This caused some controversy at the time and the approach was criticised for lacking supportive evidence for its validity, among other things (Ansoff and Slevin, 1968; Forrester, 1968). Since then there has been a rich tradition of applying the System Dynamics approach to a range of supply chain problems including supply chain re-engineering (Berry, 1994; Towill, 1996a), demand amplification (Ge et al, 2003; Sterman, 2000; Towill and Del Vecchio , 1994); information sharing (Ovalle and Marquez, 2003) and facility allocation (Akkermans and Voss, 1996). Towill (1996b) reports that system dynamics can be used to model supply chains and achieve significant performance improvement and that the approach is holistic and can accommodate the real world. A detailed summary of the work done in this field is given by Angerhofer and Angelides (2000). More recently, Akkermans and Dellaert (2005) suggest that system dynamics 'has never been so relevant for the field of Supply Chain Management (SCM) than today'. They propose that the field of SCM can learn from SD and vice versa. They also propose more cross learning between SD and other approaches.

2.2 DISCRETE EVENT SIMULATION (DES)

Discrete Event Simulation began in the 1950s with the development of early computers. Early advances in simulation methodology, such as the three-phase simulation approach (Tocher, 1963) also took place around this time. The real boom in the use of simulation coincided with the computer revolution in the 1980's, the arrival of powerful micro-computers and PC's. This enabled the development of software packages on which users could build useful models much more efficiently (Robinson, 2005). DES as a methodology differs from SD in a number of ways, the most fundamental being the treatment of time, which is continuous in SD and discrete in DES. Cavalieri and Terzi (2004) provide a comprehensive literature review of the application of DES to the supply chain context. They describe its application across a range of objectives including supply network design, strategic decision support and analysis of supply chain processes. They classify articles according to three criteria i.e. the scope and objectives of the application, the simulation paradigm and technology and the development stage. One key conclusion they reach is that the use of DES in this context can be divided into two approaches namely local simulation and parallel and distributed simulation (PDS). They suggest that distributed simulation offers a fruitful area of research because it allows firms in a network to retain their data integrity whilst still taking part in a simulation programme. The methodology of DES in application is not as well defined as SD (Morecroft and Robinson, 2005; Robinson, 2005), although there are good descriptions of the overall approach (Law and Kelton, 2000; Pidd, 2004).

2.3 AGENT BASED MODELLING (ABM)

The use of agents in the design of simulation models has its origins in complexity science (Phelan, 2001) and game theory (Axelrod, 1997). Agent based modelling lacks a consistent set of definitions for key concepts such as what an agent actually is, as well as a philosophy of application (Schieritz and Milling, 2003; Borshchev and Fillipov, 2004). This may reflect the relative immaturity of this field when compared with SD and DES. A key feature of the agent based modelling approach is the concept of emergence. What this means is that a group of agents are defined which follow a set of rules. In their interaction, whilst following these rules the behaviour of the system emerges (Phelan, 2001). Another feature of this method is that the structure of the system, rather than being set in advance, is also a function of the interaction of the individual agents. Agent based modelling allows the modeller to give the individual agents rules for its interaction with other agents. This means that this approach can be used to model the behaviour of individual entities in systems. These features of agent based modelling are exciting interest among researchers and ABM is starting to be used to investigate the supply chain. Particular interest seems to be in areas where the behaviour of individual system entities in relation to each other is a significant feature, for example when studying the dynamics of supply chain competition (Akkermans, 2001; Allwood and Lee, 2005).

3. SELECTING THE SIMULATION APPROACH

When faced with a supply chain simulation challenge, then, the modeller has three modelling approaches to choose from, or indeed may decide to use a hybrid approach combining two or more of the techniques. At present, it would appear that the choice of which modelling approach to use in a given situation owes much to the background of the modeller and the techniques they are more familiar with (Morecroft and Robinson, 2005; Lane, 2000). The significant investment in learning a particular modelling paradigm means that it is rarer to find modellers who are skilled in more than one approach. As a consequence, there appears to have been little dialogue between the various schools of thought and little comparison work done. There are frameworks for selecting simulation systems but not techniques, the assumption being that the modeller will be from one 'school' or the other. In addition to this, the pattern of use of the techniques suggests that there is not a framework for technique selection other than custom and practice. Modellers will choose the technique they apply based either on their own background and experience or on what has become the accepted norm. Moreover, the structure of academic groups and conferences is focused on technique, not problem domain. Therefore, this tends to focus on one of the three approaches, rather than on the comparison and selection of the most appropriate tool for the problem being tackled.

There have been a few studies which compare SD with DES (Brailsford and Hilton, 2000; Morecroft and Robinson, 2005; Sweeter, 1999) as well as a number which compare ABM with SD (Parunak et al, 1998; Rahmandad, 2004; Scholl, 2001; Schieritz and Milling, 2003). There are some studies which have compared all three approaches (Borshchev and Fillipov, 2004; Lorenz and Jost, 2006). Tako and Robinson (2006) set out an interesting approach to empirically compare SD and DES in the supply chain domain in terms of model building, modelling philosophy, applications and use. Their aim is to test empirically whether differences identified in the literature are confirmed in practice. Their focus is on the application of the tool i.e. how it is applied, and how differences emerge at this stage. This differs from the focus of the research described here which is more on the application domain i.e. how do the techniques compare in terms of their relative strengths and weaknesses in helping to address a given supply chain challenge. In relation to this, it should be noted that there is no detailed analysis from first principles of these techniques, so as to identify their relative strengths and weaknesses. In relation to the theoretical analysis, Lorenz and Jost (2006) point the direction in their work comparing all three techniques, but in their conclusion they admit "…it must be admitted that there is still a way to go in order to provide the wanted orientation framework that can be applied by modelling practitioners independently".

4. THE NEED FOR A FRAMEWORK

The three techniques have different strengths and weaknesses in application. They are not the same in the way that they model the problem nor indeed in the way they are used by practitioners. One technique may be more suitable or effective in modelling a particular aspect of the supply chain than another. The problem at present is that, because there is no guide for selection, an inappropriate choice can be made and thus the modelling process can be less effective, potentially ineffective or misleading. The following examples are areas where there are differences in the way that the three techniques model a particular aspect of the supply chain and demonstrate that in some cases one technique seems to be more suitable than the others.

4.1 MODELLING STRATEGIC DECISION MAKING

The three approaches are not equally suited to the modelling of strategic decision making in the supply chain context. System Dynamics is an established approach in this area and there has been extensive work on the use of SD as a tool for facilitating management decision making through management games and 'management flight simulators' (Sterman, 1992). Rabelo et al (2005) consider that when it comes to the strategic and aggregate levels then SD has some distinct advantages over DES. They argue that DES is a data hungry technique. This is not a problem for modelling manufacturing activities where the data exists, but is much more of a problem when trying to model business level decisions where data may not exist or only as rough estimates and approximations. This makes DES inappropriate for investigating many business decisions or the interactions between business and production branches of the enterprise (Rabelo et al, 2005). Baines and Harrison (1999) consider that the qualitative and continuous nature of many top management parameters, also creates challenges to the use of DES at these levels. Agent Based Modelling shows some promise in this area, due to its inherent ability to model rules at the agent level.

4.2 APTLY MODELLING THE PROCESSES

Another good example of where the approaches differ is in the modelling of supply chain processes.

4.2.1 Modelling the Detail

DES has some inherent strengths in this area because individual entities and detailed processes can be represented. Discrete event simulation is able to represent detailed transactions (Ball et al, 2004). SD is more limited in this respect as building more detailed models of processes and in particular representing individual transactions is extremely difficult and this technique is therefore appropriate to more abstract analysis (Ball et al, 2004).

An example of this is given by Bilczo et al (2003) who are modelling and investigating the Boeing supply chain. Their overall objective was to better plan their supply chain so as to improve the supply of specific raw material alloys which seem to go through periods of severe shortage, thus disrupting aircraft production. SD is initially used to model the supply chain, and insights are achieved on the causes of demand amplification. A specific example of this is the delay in suppliers increasing their capacity in response to demand increases, due to the costly need for capital investment. Suppliers wait until they are sure the demand increase is for real. What they found as the investigation unfolded, was that the insight they needed was in understanding the lowest levels of the supply chain, the processing houses and machine shops. For this purpose they found DES to be a more suitable tool.

4.2.2 Discrete Versus Continuous

As Lee and Kim (2002) point out, the nature of the supply chain system is neither completely discrete nor continuous and both aspects must be considered together in developing a supply chain model. They also suggest that the supply chain activities can be considered to exist in three levels, namely operational, tactical and strategic. They propose that a purely DES model will have the following problems :

- Reflecting the continuous nature of the process is not possible;
- Representing the interaction that occurs among those levels is not possible;
- There is too much simplification for small scaled models.

This implies that when modelling supply chain problems the practitioner may need to apply different techniques to different areas of the supply chain system. This suggests the need for a framework in matching the technique to the area of analysis.

Their solution to this is to propose a hybrid model which uses continuous modelling and discrete modelling together to suit the characteristics of the aspect being modelled.

4.2.3 Modelling Variation and Dynamic Behaviour

It has already been established (1.4) that simulation is an approach that is suited to modelling sources of variation as well as the dynamic aspects of the supply chain. With DES, variation in inputs to the system can be modelled as different distributions which can approximate the behaviour of the real world. Other sources of variation can be modelled in the logic of the individual entities and processes. With SD, randomness in inputs can be modelled as noise to the continuous inputs. With ABM, randomness can be programmed into the logic of the individual agents. These differences in the way that the variation is represented in the three approaches may well mean that they are more or less suited to modelling specific types of variation and stochastic behaviour. SD has traditionally been strong in modelling dynamic behaviour because of its strong links to control theory and the use of feedback loops as a fundamental feature of the approach. As has been described in section 2.1, SD has been used to study classical dynamic effects such as demand amplification. SD thus has strengths in this area which may not be present in the other two approaches.

4.3 A FRAMEWORK FOR SIMULATION TOOL SELECTION

Building simulation models is expensive because it requires a significant investment in time, and scarce skills. This has led to interest in developing reusable model elements (Albores, 2007; Swaminathan, 1998) in order to reduce costs and improve model building efficiency.

Without doubt, because of the issues outlined above, it is possible to use the wrong modelling approach to model a supply chain problem. For example, Lee et al (2002) found that when DES was used alone to model a supply chain, excess levels of inventory were recommended when compared with a combined continuous and discrete model, although they do not go into a detailed explanation as to why. This demonstrates the risks of using an inappropriate approach. Therefore, we need a framework to assist supply chain practitioners in matching problem types with modelling approaches. This would improve the success rate of modelling projects and improve the return on investment for businesses using these techniques.

5. SUGGESTED FRAMEWORK

Development of a framework will require investigating both the problem types that practitioners are trying to solve, along with the features of the technique they are using to analyse them. This matching of problem type to the feature of the technique will form the core of the work. The approach to developing this framework is described in the following sections. In addition, the initial structure of the analysis of the techniques is presented, along with some examples of how they might be classified.

5.1 IDENTIFICATION OF A TAXONOMY OF SUPPLY CHAIN PROBLEMS

Through a review of the literature, a taxonomy of supply chain problem types will be identified. Additional research in the practitioner community will be carried out to add depth and triangulate the findings of the literature review. This will create the problem types which can be analysed using these simulation approaches.

5.2 THEORETICAL ANALYSIS OF THE THREE TECHNIQUES

A key aspect of the research, and an area which has not been examined rigorously to date, is to perform a theoretical analysis of the techniques. The purpose of the review will be to identify the features of the three techniques in relation to key fundamental simulation concepts. This analysis will provide guidance as to how the different techniques are likely to perform in relation to each other.

So far the following simulation aspects have been defined (see Table 1 below). To illustrate how this comparison will work, five of the aspects are explored in more detail in Table 2.

5.3 DEVELOPMENT OF A FRAMEWORK

The purpose of the framework will be to create a linkage between the supply chain problem types and the relative utility of the simulation approaches being used. This will be achieved through identifying and mapping the relationship between the problem types, the features of these problem types, and the types of simulation challenges they present. These features will then be linked to the fundamental theoretical aspects of the tools, and this will be used to assist in the selection of the appropriate approach to modelling that particular problem. The utility of the approach will be defined, and will be a combination of factors including ease of model building (speed and cost), ability of the technique to model the problem characteristics (informed by the theoretical work), speed of model running and ease in interpreting model results.

5.4 EXPERIMENTAL DESIGN

It is anticipated that there may be areas where the three approaches demonstrate clear strengths and weaknesses compared to each other in relation to modelling certain problem types. However, there may also be areas where their relative utility is unclear. In these cases, experiments will be designed to test the findings through modelling the same problem type using the different approaches to establish whether this can be clarified empirically. These experiments will provide further insights on the use of the tools in practice.

5.5 TESTING THE FRAMEWORK WITH PRACTITIONERS

The purpose of this phase will be to test the framework with simulation modelling practitioners both in the business and academic communities. This will involve selecting supply chain improvement or analysis opportunities and using the framework to see how effective it is in application. Feedback will be sought on how useful the framework is and how it might be improved.

6. CONCLUSION

In this paper, it has been demonstrated that simulation is well suited to improving supply chain performance. The literature on the three main approaches has been reviewed and it has been proposed that a framework for assisting practitioners in selecting the appropriate techniques for their challenge would be valuable, since they have different strengths and weaknesses in the supply chain domain. The approach to developing this framework has been outlined. The key finding so far is that there is no framework in existence which matches the simulation approach, and its theoretical underpinnings, with the supply chain problem under consideration.

Table 1 – Simulation Aspects

Aspect	Description
Model Elements	What are the basic building blocks used to represent the system?
Individual Entities	How are individual entities represented?
Treatment of Time	How is time represented in the model?
System Structure	How is the system structure represented in the model?
Spatial Relationships	How are distances between individual entities represented?
Delays	How are delays modelled?
Feedback	Can feedback be shown in the model and if so how?
Decision Making	How is decision making modelled?
Randomness and Uncertainty	How is randomness of inputs and processes represented?
State Changes	What is the approach to modelling state changes?
Human Agents	How are human agents represented and modelled?
Adaptation	How does the technique model the process of adaptation?
Mathematical Formulation	What is the underlying mathematics and logic of the technique?

Table 2 – Initial Comparison of Simulation Techniques

Modelling Aspect	System Dynamics	Discrete Event	Agent Based Modelling	Modelling Implications
Model Elements	Stocks, flows, causal loops, delays	Entities, resources, flow charts	Agents, rules, state charts	**SD** - if structure is known, but dynamic response of structure is aim of the investigation. **DES**- requires knowledge of structure, how things are related to each other. Requires definition of entities, resources. **ABM** - key is to define agents and the rules for their interaction. Key modelling feature is the agent. Does not require structure to be defined.
Individual entities	Aggregated and represented as stocks and flows	Can be represented as entities	Can be represented as agents	**SD -** systems being modelled need to consist of reasonably homogenous entities (is there a limit to this? If so, what is it?) Possibly more efficient at systems consisting of large numbers of entities (populations) rather than small groups or individual entities. SD also suited to modelling continuous phenomena such as liquids and processes rather than physically distinct phenomena. **DES -** Individual entities can be represented, with resources treating them differently depending on what they are. Able to model heterogeneous groups of entities. Maybe more efficient at modelling from small groups to large groups (the middle ground?). **ABM -** Individual entities can be represented with their own rules for how they interact. So perhaps inherently more suited to modelling individuals / small groups / heterogeneous populations.
Spatial relationship between entities	Is not represented in the model explicitly because entities are aggregated.	No reason why distance between entities in the model cannot be calculated and used in logic to drive system logic.	Can be calculated and can be a key driver in model. For example, in Anylogic Bass Diffusion model, distance between entities is used as a factor in calculating likelihood of user adoption.	**SD -** if the spatial relationship between entities is important then SD will not be the best modelling approach. **DES -** Can take account of distance between entities and resources. **ABM -** this is a strength of ABM. Individual agent behaviour can be influenced by spatial relationship.

Modelling Aspect	System Dynamics	Discrete Event	Agent Based Modelling	Modelling Implications
Delays	Modelled and central to model behaviour	Modelled for entities	Modelled as part of statechart	**SD -** delays are treated as being the same for all entities in the flow, so again SD assumes homogenous behaviour on the part of system entities. So SD will be suited to systems where this assumption holds true. **DES -** The delay experienced can be varied dependant on the individual characteristics of the entity. So if it is important for some reason to model very different entity delays, DES would be more suitable than SD. **ABM -** The delay experienced by the agent can be modelled as a function of the decision logic of the agent in interaction with other agents in the system. So if the level of detail or granularity needed to be understood is key, then ABM will be suitable.
Feedback	Explicitly modelled through causal loops.	Can be intrinsically modelled through flow chart.	Intrinsically modelled through agent behaviour (state chart)	**SD -** If the intent of the modelling exercise is to understand the impact of feedback in the system, SD is a good fit, **DES -** Limited feedback of entities can be modelled, but taking a systems view is more difficult, **ABM -** Feedback is not modelled 'overtly' but is a function of the interaction and behaviour of the agents. Better suited for open, investigative modelling exercises where very little is known or understood about system behaviour?

Identifying aspects and the initial modelling implications have been informed by Brailsford and Hilton (2000), Borshchev and Fillipov (2004), Lane (2000), Law and Kelton (2000), Lorenz and Jost (2006), Morecroft and Robinson (2005), Pidd (2004) and Schieritz and Milling (2003).

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COMPARISON OF MODEL BUILDING IN DISCRETE-EVENT SIMULATION AND SYSTEM DYNAMICS

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ABSTRACT:
This paper presents an empirical study on the comparison of the model building process in Discrete-Event Simulation (DES) and System Dynamics (SD). In the research presented we use Verbal Protocol Analysis (VPA), a qualitative research method derived from psychology. We observed 4 modellers (2 DES and 2 SD modellers) as they think aloud, while they create simulation models of a prison population case study. The transcripts were coded based on the context that modellers talk about as part of the stages followed in a simulation project: problem structuring, conceptual model, data inputs, model coding, experimentation, implementation and validation & verification. From the analysis of the transcripts, we notice that even though DES and SD modellers follow similar stages while building a simulation model, modellers take a different approach to modelling in each specific stage. The differences in each modelling stage are presented.

Keywords: Discrete-Event Simulation, System Dynamics, model building, comparison, Verbal Protocol Analysis.

1. INTRODUCTION

Discrete-Event Simulation (DES) and System Dynamics (SD) are two simulation approaches, which are widely used in OR. However they exist as two separate streams, with not much communication between each-other. There are a few studies on the comparison of DES and SD, but work is scarce and usually represents the authors' personal opinions (Brailsford and Hilton, 2001; Morecroft and Robinson, 2005). Therefore, this paper presents an unbiased and empirical study on the comparison of DES and SD model building approach. The comparison deals with the modelling process, simulation modellers follow when building simulation models. We acknowledge that key fundamental differences exist between DES and SD simulation models and the respective software used. However, this is not the scope of the current paper. The objective of this paper is to provide empirical evidence on the differences and similarities of DES and SD model building process.

The current consists of a pilot study, which provides a preliminary qualitative study of the modelling process followed by DES and SD modellers. Conclusions are drawn based on the unbiased account of modellers undertaking a simulation modelling exercise. The aim of this study is to provide preliminary results on the comparison of the modelling process of DES and SD modellers. Our study brings closer the two fields of simulation, with a view to creating a common basis of understanding. The paper is outlined as follows. It starts with a review of the existing literature on the comparison of DES and SD, followed by a description of the study undertaken, where the case study and the research method used, Verbal Protocol Analysis (VPA), are described. We then present the preliminary results of the study, based on observations from 4 modelling sessions. Finally, we discuss the limitations and the insights gained from the current study and the scope of future work.

2. EXISTING WORK ON THE COMPARISON OF DES AND SD

In this section, the existing literature on the comparison of two simulation techniques DES and SD is reviewed. We focus mainly on the comparison of the model building process. At the end, we finalise our thoughts and explain our incentives for the current work.

The literature on the comparison of DES and SD is scarce. As a general comment, work on the comparison of the two simulation techniques consists mostly of generally accepted statements based on the authors' personal opinions. Comparisons tend to be biased towards either the DES or SD approach (Brailsford and Hilton, 2001). Morecroft and Robinson (2005) argue that the modelling approaches should be considered as complementary to each other. Furthermore, little dialogue exists between the two modelling communities (Sweetser, 1999; Lane, 2000; Morecroft and Robinson, 2005) and the need for mutual communication has been pointed out (Lane, 2000).

Discrete-Event Simulation models systems as a network of queues and activities, where state changes occur at discrete points of time (Brailsford and Hilton, 2001). Whereas System Dynamics models consist of a system of stocks and flows where continuous state changes occur over time. In DES the objects are individually represented, which can be tracked through the system. Specific attributes are assigned to each individual and determine what happens to them throughout the simulation. On the other hand, in SD the entities are presented as a continuous quantity. In DES state changes occur at discrete points of time, while in SD state changes happen continuously at small segments of time (Δt). Specific entities cannot be followed throughout the system. DES models are stochastic in nature with randomness incorporated with the use of statistical distributions. SD models are generally deterministic and variables usually represent average values. Despite the differences listed, it is claimed that both simulation approaches are used to understand how systems behave over time and to compare their performance under different conditions (Sweetser, 1999).

First, Coyle (1985) comes into the discussion from a SD perspective, while considering ways to model discrete events in a SD environment. His comparison focuses on two aspects: randomness existing in DES modelling and the model structure, where it is claimed that open-loop vs. closed loop systems are represented in SD and DES respectively.

In her doctoral thesis, Mak (1993) studies how DES activity cycle diagrams can be converted into SD stock and flow diagrams. Mak also presents a list of fundamental differences between DES and SD modelling.

Coming from a consultancy background, Sweetser (1999) provides a comparison based on the established modelling practice and the conceptual views of modellers in each area. He ends by comparing DES and SD conceptual models of a production process.

Brailsford & Hilton (2001) studied the comparison of DES and SD, applied in health care modelling. The authors compare the main characteristics and the application of the two approaches, based on two specific health-care studies presented (one in SD and the other in DES) and on their own experience as modellers. They conclude with a presentation of the technical differences between the two approaches, providing a list of criteria when each approach is more appropriate.

Lane (2000) gives a thorough comparison between DES and SD, focusing on the conceptual differences. His discussion is again based on his personal experience as a system dynamicist. Lane considers three modes of discourse, where it is argued that DES and SD can be presented as different or similar based on the position taken (the mode of discourse). At the end, Lane provides a list of conceptual differences, taking a mutual approach. However, Morecroft and Robinson (2005), disagree with some of the statements made. Theirs is the first study where the comparison is based on empirical work, a common fishery model. The authors built a step-by-step simulation model, using SD (Morecroft) and DES (Robinson) modelling. However, one could claim the existence of bias, as the two modellers were aware of each other's views on modelling.

An empirical study on the comparison of DES and SD from the users' point of view was carried out by Tako and Robinson (Forthcoming). The authors found that users did not find many significant differences when using two simple DES and SD models. So far, we have not yet identified comparison work providing unbiased, empirical evidence supporting the statements made in the literature about the comparison of DES and SD. Furthermore, there is no study which provides a self-contained and independent account of the DES and SD model building process. Therefore, the objective of this paper is to present an empirical study on the comparison of DES and SD model building process and to provide insights for both areas of simulation.

3. THE STUDY

The current study consists of an empirical research comparing DES and SD involving simulation modellers. We compare the DES and SD model building process, with the help of Verbal Protocol Analysis (VPA), a qualitative research method. For the application of the empirical work, we use a case study on the prison population.

3.1 THE CASE STUDY

A suitable case study for the purposes of this research needs to be sufficiently simple to enable the development of a model, which can be built in a short period of time (1-1.5 hrs). In addition a suitable case study had to accommodate models from both simulation techniques, so that the specific features of each technique (randomness in DES vs. deterministic models in SD, the aggregated presentation of entities in SD vs. the individual representation of entities in DES, etc.) would be present in the models built. Among others, we were interested in how the same aspects of the problem would be represented with each simulation approach (e.g. feedback). After considering a number of possible contexts, the prison population problem was selected. The prison population case study, where prisoners enter prison initially as first time offenders and then return back to prison as recidivists can be represented by simple simulation models, using both DES and SD. Furthermore, the prison population has already been modelled using each simulation approach. DES models of the prison population have been developed by Kwak et al. (1984), Cox et al. (1978), Korporaal et al. (2000), and a SD model has been developed in Bard (1978). Therefore, we consider the UK prison population case study as suitable for this research.

The UK prison population case study used in this research is based on Grove et al. (1998). The case study starts with a brief introduction to the prison population problem with particular attention to the issue of overcrowded prisons. Following, were descriptions of the reasons for, and impacts of, the problem. The figures and facts used in the case study are mostly based on reality, but slightly adapted for the purposes of the research.

In the case study two types of prisoners are involved, petty and serious offenders. There is already an initial number of prisoners in the system (76,000). Offenders enter the system as first time offenders and receive a sentence depending on the type of offence. Petty offenders enter the system at a higher rate, on average 3,000 people/year vs. 650 people/year for serious offenders, but receive a shorter sentence length, on average 5 years vs. 20 years for serious offenders. After serving time in prison the offenders are released. A proportion of the released prisoners re-offend and go back to jail (recidivists) after on average 2 years. Petty prisoners are more likely to re-offend. However, these numbers were intentionally not given to the modellers, who were expected to either make their own assumptions or ask for further data.

In order to solve the situation two possible scenarios are considered, either to increase the current prison capacity and so facilitate the introduction of stiffer rules, or the alternative of reducing the size of the prison population by introducing alternatives to jail and/or enhancing the social support provided to prisoners. The task for participating modellers was to create a simulation model, which would be used as a decision-making tool by policy makers.

3.2 VERBAL PROTOCOL ANALYSIS

In the modelling sessions we use Verbal Protocol Analysis (VPA), a qualitative research method, which was originally derived from psychology (Ericsson and Simon, 1984). Willemain (1994; 1995) was the first to use VPA in Operational Research (OR) to document the thought processes of OR experts during model formulation. Building on Willemain's initial work, Powell and Willemain (2007) and Willemain and Powell (2007) used VPA to study the model formulation processes followed by novice modellers in OR, with the view to gain insights about the best way to teach OR to students. VPA requires the subjects to 'think aloud' when making decisions or judgements. The main objective is to understand in detail the mechanisms and internal structure of cognitive processes that produce these relations, based on the verbal reports of participants (Ericsson and Simon, 1984).

VPA is considered to be an effective method for the comparison of the DES and SD model building process. It is useful because of the richness of information and the live account it provides on the experts' modelling process. Another option would have been to observe real-life simulation projects, using DES and SD, throughout the modelling process. However, observing real life projects was not suitable for the timescales of this research. Evidence suggests that simulation projects can take between one and three months, for a typical project, or even longer (Robinson, 2004). In addition, for a valid comparison it was necessary to have comparable modelling situations. We also considered running interviews with modellers from SD and DES area. However, we believe that modellers' reports would not represent the full picture of model building. Also modellers' reflections may not correctly reflect the processes they follow during the model building process. Whereas using VPA it is possible to capture modellers' thoughts, as part of a controlled experiment, using a common stimulus – case study.

Protocol analysis as a technique has its own limitations. The verbal reports may omit important data (Willemain, 1995) because the experts being under observation may not behave as they normally would. The modellers are asked to work alone and this way of modelling may not reflect their usual practice of model building, where they would interact with the client, colleagues, etc. In addition, there is the risk that participants do not 'verbalise' their actual thoughts, but are only 'explaining'. To overcome this and to ensure that the experts speak their thoughts loudly, short verbalisation exercises, based on Ericsson and Simon (1984) were run at the beginning of the sessions.

The subjects involved in this case were provided with the prison population case study and were asked to build simulation models based on it using their preferred simulation approach. During the modelling process experts were asked to speak their thoughts - to 'think aloud' as they model. The researcher (Tako) sat in the same room, but social interaction with the subjects was limited and she only intervened in the case that participants stopped talking for more than 20 seconds to tell them to "keep talking". The researcher was also answering explanatory questions and provided participants with additional data inputs (if they asked for) and also prompted them to build a model on the computer in the case when they did not do so by their own initiative. The modelling sessions were held in an office environment with each individual participant. The sessions lasted approximately 1-1.5 hours. The participants had access to writing paper and a computer with relevant simulation software (e.g. Simul8, Vensim, Witness, Powersim, etc.). The protocols were recorded on audio tape and then transcribed.

3.3 THE SUBJECTS

The subjects involved in the modelling sessions were 4 simulation (DES and SD) modellers, 2 in each approach. Subject 1 and 4 (called SD1 and SD2 in the paper), came from a SD background, while Subject 2 and 3 (called DES1 and DES2 in this paper), came from a DES background. The sample size of 4 participants is considered reasonable, although a larger sample would be better. According to Todd and Benbasat (1987), due to the richness of data found in one protocol, VPA samples tend to be small, between two to twenty.

For reasons of confidentiality participants' names are not revealed. All participants use simulation modelling (DES and SD) as part of their work and have at least 2-3 years of experience in modelling. Our sample consisted of two lecturers and a doctoral student from Warwick Business School and a Research Fellow from the University of Warwick. The four modelling sessions presented in this paper were part of a pilot study. Future research will involve 10 expert[1] modellers (DES and SD), 5 in each area.

3.4 CODING THE TRANSCRIPTS

A coding scheme was designed in order to identify what the modellers were thinking about. The coding scheme was devised following the steps of a simulation project, based on Robinson (2004). We devised the following modelling topics and their definitions:

1. Problem structuring: What the problem is about? What are the objectives of the project?
2. Conceptual modelling: What are the parts of the model? What should be included in the model? How to represent people? How are variables defined?
3. Data inputs: How modellers refer to data inputs? How are the already provided data used? Are modellers interested in randomness? How are data derived?
4. Model coding: How is the model code created? How is the initial condition of the system modelled? What sort of units (time or measuring) is used? Does the modeller refer to documentation? How to model the user interface?
5. Experimentation: What are the results of the model? What sort of results the modeller is interested in? What sort of scenarios to run?
6. Implementation: How will the findings be used? What learning is achieved?
7. Validation/ Verification: What has gone wrong? Why the model is not working? Are the results correct?
8. Other

Based on the codes presented above, we divided the transcripts into episodes and classified each episode into one of the 8 categories/codes created. We coded the transcripts manually. Automatic coding was not considered appropriate. We based our coding on the context that the participants were talking about, so subjectivity in the interpretation of the scripts was unavoidable. In order to deal with subjectivity, we recoded the transcripts after a period of 3 months after the first coding. Overall, there was 93% agreement between the two sets of coding, which we considered acceptable. In the cases where the coding did not agree, we re-examined the episodes and arrived at consensus coding.

[1] The term "experts" refers to practitioners of DES or SD simulation modelling, who have at least 4 years of experience in modelling and who use simulation modelling as part of their work.

4. OBSERVATIONS FROM THE VERBAL PROTOCOLS

In this section we present our observations based on the modelling sessions run with the 4 simulation modellers (2 DES and 2 SD modellers). The transcripts were coded using the coding scheme created based on the stages followed in a simulation project. We then analyse modellers' thought processes and compare the approach taken by the DES and SD modellers in each stage. The analysis presented here is mainly of a qualitative nature, commenting on the quotes received for each category of codes.

We begin here with some general comments about the modelling sessions observed. Overall, all modellers needed some prompting to build a model on the computer. Only 3 out of the 4 modellers did so, apart from one of the SD modellers, who objected to creating a model, due to limited time and also due to the lack of data inputs. In addition, we observed that DES and SD modellers followed a similar sequence of steps. The differences lay mainly in the approach taken or the time spent in each stage. Another general observation made, was related to the fact that none of the modellers considered any other alternative modelling approach before modelling. In one instance, one of the DES modellers mentioned SD modelling, as an alternative modelling approach. However, he/she did not try to build a SD model him/herself. This shows that modellers choose to use the simulation approach they are familiar with rather than using the approach they think is most appropriate.

4.1 PROBLEM STRUCTURING

We define problem structuring, based on Robinson (2004), as the process of understanding the problem situation and determining the modelling objectives. From the sessions organised with the 4 subjects, (2 DES and 2 SD modellers) we identified that the DES and SD modellers, had different views with respect to problem structuring. Overall, we observed that SD modellers took a holistic approach while identifying what the problem is. For DES modellers the problem was perceived as well-defined and they spent limited time in defining the problem. Meanwhile the SD modellers showed an interest in looking into the further issues that cause prison overcrowding.

More specifically, during the modelling sessions, SD modellers (SD1 and SD2) took a more holistic approach towards the problem. Their approach to the problem was not limited to the projection of the prison population and the problem of prison overcrowding. For example, SD1 concentrated on the financial aspect, the money that society spends on the prison system. For SD2, a model that only projects the prison population is not sufficient.

SD2: What it [the mode] represents is the prison population, but in itself it doesn't mean anything.

He or she considers that the problem and objective of the modelling exercise is related to spending efficiently the money paid by society.

SD2: the problem is what happens to the society, which is better for the society.

DES modellers concentrated in creating a model that projects the total number of the prison population. DES2 refers to the model as a policy tool, a "what if" model, where the main output is the projected prison population. Whereas DES1, did not mention the objectives of the model at all because the ones already provided in the case study were considered sufficient.

4.2 CONCEPTUAL MODELLING

The actual process of designing the conceptual model was classified as "Conceptual Modelling". The main topics discussed in the protocols were:

- Model contents
- Variables (definition of variables)
- People (representation of people)

DES modellers spent less time in considering the contents of the model, compared to SD modellers. DES modellers referred to the contents of the model once (DES1) and 3 times (DES2), compared to 7 (SD1) and 4 quotes (SD2) made by SD modellers. Both SD modellers took a systems view approach, i.e. SD1 argues that the modellers should be able to set the boundaries to the system. This is considered important in order to make a judgement about what to include and what not to include in the model. This is clear evidence of a systems thinking approach. In addition SD1 considered extending the existing conceptual model, by adding additional factors (i.e. death sentence) to the already existing conceptual model. So did, SD2, who had a totally different view of the system, compared to the other participants. SD2 decomposed the model into 7 populations and suggested analyzing the effects of the different populations and sentence types. On the other hand, DES modellers accepted the already given conceptual model. For example, DES2 *"would normally start with a conceptual model"*, but in this case he or she did not consider it necessary as it was already provided.

Both SD modellers paid more attention to the definition of variables, compared to DES modellers. They often mentioned the words: variable or parameter, when defining variables. A possible reason for this could be that in SD software, variables (constant or auxiliary variables) are an integrated part of the model. They created two types of variables: quantitative and qualitative. Both SD modellers, SD1 and SD2, created qualitative or soft variables, e.g. type of punishment, quality of life in prison, psychological impact on society, etc. These are anecdotal data, which the modellers define based on their own experiences and understanding of the real world. SD1 described soft variables as "aggregate", which the modeller defined by setting up the factors they consist of. SD1 also mentioned that these variables are "*elusive*" and "*vague*" and need to be well-defined to avoid misinterpretations. While defining or talking about variables, SD2 often used the verbs "influence" or "have an impact on", evidence of the SD thinking process, where modellers think about the effects that factors have on other factors or parts of the model (i.e. the effects on the overall society).

As expected, we observed a difference in the way that the population is observed by DES and SD modellers. SD modellers consider the population as an integral part of the model, where either "petty offenders" or "serious offenders" are considered to share the same characteristics as part of the group they belong to. Specific individuals were not considered and no issues were raised regarding the large population size. While DES modellers made comments about the big population size, which is either difficult to fit in the queues, or it affects the speed of the model run. They tended to deal with the large population by using the high volume option in Simul8 or batches, where one entity in the system would represent a batch of 100 or 200 prisoners ("Grouping Entities", Robinson (2004)). While using batches, DES modellers were not happy with giving common characteristics to a batch of petty or serious offenders. Still, specific characteristics were given to each batch, with the use of labels.

4.3 DATA INPUTS

Under this heading, quotes referring to entering and quantifying the variables introduced during the "Conceptual Modelling" stage, are considered. Contrary to our expectations, both, DES and SD modellers, required to be provided with data before building the model. The difference lay in their perception of and the type of data required.

All modellers, DES and SD, referred to data collection in one way or another. There was an obvious interest in getting the right data by SD modellers, be it tangible or intangible variables. SD modellers in particular, considered data collection as an important step before building the model itself. SD1 did not agree to build a model without first having the data. SD2 also emphasised the need for research/ data mining before building the model. Providing SD modellers with some basic numbers was not considered sufficient, they clearly pointed out the need for research.

> SD1: *if you …collect sufficient data you should be able to do it [meaning model] …*
>
> SD2: *… what I need is the numbers, and once I have the numbers, then I can actually model this.*

Furthermore, the need to set up the structure of the model (conceptual model) first and then enter the data into the model, was suggested by one of the SD modellers.

> SD2: *OK, so now what I've done is I've got all the flows in and now I'm ready to put in the numbers.*

Both, SD and DES modellers, asked for tangible, concrete data. For example, SD1 suggested the need for thorough research, regarding concrete data, such as costs, by saying: *"This data is already available and it should be researched"*. Examples of tangible data asked for by DES modellers are data regarding the arrival of people in the system. Even though, fixed numbers were given (averages), DES modellers preferred to include randomness with the use of statistical distributions. In order to represent the arrivals of people in the system, they tended to choose between the Exponential and Poisson distribution. Due to the fact that a fixed number was given for arrivals in the system, i.e. 3000 petty and 650 serious enter prison annually, DES modellers tended to prefer Poisson. Regarding the other distributions, DES modellers preferred to make an informed decision. Even after suggesting the type of distribution to use, they tended to ask for detailed information regarding the parameters of the distributions, i.e. k for the Erlang distribution. DES1 mentioned that they would choose a distribution based on the data available.

> DES1: *if I could see what the data was, when I plotted the times and the frequencies …; I would go to the data; there should be data about this [the distribution of time that recidivists take to re-offend] somewhere.*

DES modellers were not prepared to make assumptions about the kind of distributions to use. They preferred to either have the real data handy or to be given the relevant distributions that represent the behaviour of variables in the real system. This is equivalent to the tendency of the SD modellers' behaviour asking for data that represent the effects of variables on each other. Even though SD modellers accepted the average (fixed) numbers given by the researchers representing the arrival of prisoners in the system, they required to have in-depth data in order to model the effects of variables on other variables. For example, while setting up the relationships between variables, i.e. effects of one variable to the other, SD2 mentioned the use of algebraic functions, utilising the law of diminishing returns and the need for research to back up the numbers was mentioned again.

> SD2: *what you may find is maybe you can easily take the first 10 persons to come this route without spending too much money, but if you want 90% of them to come this way [rehabilitate], maybe it will cost huge amounts of money, so that's the research you have to do to figure out how much it costs to have one person to go this way [rehabilitate] instead of going this way [re-offend].*

Another aspect of data inputs in SD modelling are soft variables and how they are quantified. For example, SD1 defines the quality of life in prison by introducing a scale from 1 to 10, where 1 is very low and 10 very high. According to this approach, the data are defined by the factors included, and based on that, a number is chosen from the scale. SD2 also asked for data to quantify the soft variables identified while designing the conceptual model.

Overall, SD modellers mainly asked for data backed by research, based on the variables they introduced. DES modellers had a different perception of the data and their conception. They concentrated on the data as provided. When asking for data, they would refer to tangible data, which are already available or can be collected from Home Office statistics. There is a clear distinction in the perception of the data inputs by SD and DES modellers. SD modellers actively create the data they use in their simulation models, which gives a feeling that they drive the data, as compared to DES modellers who are driven by the already existing data.

4.4 MODEL CODING

Under the heading "Model coding", quotes related to the coding of the simulation model on the computer were considered. It was observed that the researcher (Tako) needed to prompt both SD and DES modellers in order to create a model on the computer. SD modellers did not consider model coding as an important task. SD2 for example mentioned that the coding of the model is a mechanical task that did not involve any clever connotations about the model. While SD1, due to time restrictions and unavailability of the data requested, did not agree to build a simulation model on the computer.

In the case of SD modelling, model coding involved the creation of a stock & flow system and linking them together. In the case of DES modelling, model coding revolved around creating a system of queues and activities, and joining them up. However, DES modellers spent a longer time with this step, compared to the SD modellers. In addition, DES modellers were faced with issues such as modelling the initial conditions of the system, finding ways of coding the large population, etc. Due to their attention to these issues model coding for DES modellers took a longer time.

In setting up the initial conditions in the model, DES2 used the warm-up time, which is letting the model run for a long time up to the point when it gets to the conditions we are interested in. DES1 created two dummy work entry points, with very large inter-arrival times, which would bring in the model a designated batch according to the data given. He or she used "First at start time", an option available in Simul8 and also chose Priority as a routing out discipline. With regards to the large population, the DES modellers duplicated the activity centres (Imprisonment and Release activities), so that prisoners would enter and leave prison without affecting other prisoners who might be due to go in or out at the same time. Both DES modellers modelled people in batches, where one entity represented 10 or 100 entities. DES modellers were not familiar with dealing with large numbers, so their choices were decisions made on the spot. During model coding, it was mentioned that if they had a longer time, they could have considered different options to model the large population.

4.5 EXPERIMENTATION

As part of the experimentation stage, we observed modellers as they were thinking about the results and the scenarios to be built into the model. Overall, it can be claimed that leading from their different views about the problem, DES and SD modellers acquired a different approach to experimentation. While, SD modellers take a holistic approach by considering the cost paid by society, DES modellers look at the total number of prisoners as the end result. For example SD2, was interested in getting a figure for the total cost, i.e. the money spent by the society, which is considered to be driving overcrowding and also the number of people in prison.

Only the two SD modellers considered creating scenarios. Having spent most of their time coding the model, the DES modellers spent limited time on the model results and scenarios. SD1, considered building a game simulator, where the user has access to a set of control buttons and graphs and can observe the effect of varying the different parameters. SD2 talked about creating a set of policies, which are compared based on the total cost (economical and psychological) paid by society. Furthermore, SD modellers considered building a user-friendly environment, whereas DES modellers mentioned the end-user sparingly.

4.6 IMPLEMENTATION

There was no reference regarding implementation made by any of the participating DES and SD modellers. This is not surprising as this was not a real world exercise and it concentrated mostly on model building.

4.7 VALIDATION & VERIFICATION

We also observed modellers performing validation and verification (V&V) tasks. Only 3 out of the 4 modellers went through this stage. SD1 did not verify or validate the model, mainly because he/she did not build a model. For SD2, V&V consisted of verifying the model and more specifically checking the code and the model against the conceptual model. In SD modelling, the main focus of verification was on representing the correct structure of the model. No effort was made in checking that the model is running correctly. SD modellers did not show an interest in entering the numbers and therefore they did not pay any attention in validating the results of the model.

On the other hand, DES modellers (DES1 and DES2) spent more time in checking that the code is working as intended. The main way of verifying the model was running visual checks and checking the code. During the verification stage modellers would normally find mistakes and correct the model. DES2 expressed also the intention of collecting the desired statistics and validating the outputs of the model, however, due to lack of time he/she did not implement this procedure.

4.8 OTHER

In this category, quotes which did not relate to any of the codes above were included. For example, we observed that SD1 was concerned in creating a model which can be re-used in the future. SD1 expressed the need for a generalisable model, which can be applied to any prison system (Welsh, European, etc.). This again is evidence of SD modellers taking a systems view. DES modellers did not tend to plan ahead when modelling complicated issues of the model. DES2 mentioned that he/she preferred to use a "trial & error" approach in order to figure out the best way of modelling the problems encountered during model building. Another issue mentioned by DES modellers was related to the speed of the simulation run. Both DES modellers in this case used Simul8 to build their simulation models, however this is a problem expected to be present in the case of any DES simulation software. However the speed of running the model was not a problem in the case of SD software.

5. DISCUSSION

In this paper, we present a qualitative analysis of 4 modelling sessions with simulation modellers, as part of a pilot study. From the analysis of the verbal protocols with the DES and SD modellers we observed differences in the thought processes followed. The sample used in this study consisted mainly of academics. As a continuation to the work presented here, the authors are already studying simulation modelling with 10 expert modellers from the two areas of simulation. Practitioners, expert modellers might follow a different approach to modelling, compared to the modellers "observed" in the current study. Differences in the results are not ruled out. In the modelling sessions presented in this paper, there were aspects of modelling which do not occur in the protocols, such as implementation or scenario building in the case of DES modelling, but this might not be the case with experienced modellers.

The study presented in this paper is part of a pilot study. The preliminary results presented are based on a small sample size with 4 modellers only. This, of course, limits the scope of the findings. A future study involving 10 expert modellers is expected to provide a more representative picture of each simulation field.

Apart from providing some preliminary results, the pilot study gave the researchers valuable insights about VPA. Regarding the coding scheme, we tested and changed the initial codes a few times before arriving at those finally used. We also practiced running the real VPA sessions. As a result, the main learning points from running VPA consisted of the following:

- From this study we found out that it is necessary to intervene in order to remind the modellers to keep talking, in the case that they remained silent for more than 20 seconds. Especially during the time that modellers build the model on the computer, they tend to concentrate on the technical side and long pauses can result if the researcher does not intervene.
- The study suggests that it is important to ensure that the case study material is unbiased towards the DES or the SD approach. This is a sensitive issue because it is expected that DES and SD modellers need different types of information when modelling. For this reason it is important to ensure that the information given in the case study material is generic and that it does not lead the modellers towards DES or SD. Therefore, additional information, i.e. specific data, is provided to the modellers as they ask for it, during the modelling sessions.
- In addition we observed that modellers do not tend to build a model on the computer when asked to build a simulation model; they tend to work only on the conceptual model. Prompting is needed so that they build a model using the relevant simulation software on the computer.

6. CONCLUSIONS

From the research conducted, it can be concluded that DES and SD modelling are quite different, from the perspective of the model building process. From the observations of modelling sessions with DES and SD modellers, we found that SD modellers gave more emphasis on the first stages of the modelling process: Problem structuring, Conceptual modelling and Data Inputs, Meanwhile the DES modellers spent more time with Model coding and the verification of the model built. Overall, SD modellers took a wider view of the problem situation and looked into other factors that affect the problem, while the DES modellers considered as adequate the definition of the problem already given in the case study. Contrary to what was expected, we found that both DES and SD modellers are dependent on data inputs. However, differences lie in their conception of data inputs. It was difficult to satisfy both groups of modellers with the same type of data. While DES modellers were happy to receive suggestions about some preliminary data, SD modellers were not prepared to accept data that were not supported from research. SD modellers emphasised the need for customised research based on the variables created. Differences were also found regarding the verification approach taken. While SD modellers were more concerned with building the right structure of the model, DES modellers focused more on coding correctly and ensuring that the model was working as intended.

To the best of our knowledge this is the only empirical study comparing DES and SD based on the model building process of simulation modellers. The findings presented here are based on a preliminary study involving a small sample size. The authors intend to extend the current work by studying the model development process with 10 expert modellers. We also intend to perform a quantitative analysis on the verbal protocols of expert modellers, which will provide evidence about the amount of attention modellers give on each stage of the simulation model building.

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