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USING AGENT BASED SIMULATION TO EMPIRICALLY EXAMINE COMPLEXITY IN CARBON FOOTPRINT BUSINESS PROCESS

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Abstract

Through the critical analysis of the extant literature, it is observed that Simulation is widely used as a research method in Natural Sciences, Engineering and Social Sciences, in addition to argumentation and formalisation as the third way of carrying out research. Simulation is not so widely used in Business and Management research as it ought to have been, though this is changing for the better with the technological advances in computers and their computational power. These technological advances enhance the capability of theoretical research models, in defining a problem and their use in empirically examining a solution to the problem in simulated reality, like never before. Management journal searches for "Simulation and Complexity Theory" returned nil or zero returns, which explain that this combination is not popular in management research, though they are used individually more often. The major objective of this paper is to analyse some of the conceptual (or theoretical) and methodological (or empirical) contributions that Agent Based Simulation and Complexity Theory can make to the business and management community in their business process related research In view of this, some basic ideas are discussed of using Agent Based Simulation as a method in Business and Management Studies research and how an Agent Based Model can be applied to a business process as complex as Carbon Footprint. It is in this context that the use of Complexity as the base theory to empirically examine a business process is discussed. Throughout this article, our research on complex adaptive systems (e.g., Accounting Information System) in continuously changing organisations managing complex business processes (e.g., Carbon Footprint business process) is considered as the basis for illustrating some of the concepts. Through this article, avenues for further management research using these tools and methodology are suggested.

Keywords: Accounting Information Systems, Agent Based Modelling, Business Process, Carbon Accounting, Carbon Footprint, Carbon Management, Complexity Theory, Green House Gas (GHG) Emissions, Research Method, Simulation

1. INTRODUCTION

It is appreciated that simulation is the third way of doing science besides inductive reasoning (or induction) and deductive reasoning (or deduction) (Macal and North, 2005). This is in sharp contrast to the earlier finding not long ago that "Simulation is rarely used by management researchers, particularly those who study business and other systems as social rather than technical or mechanical entities" (Berends and Romme, 1999). Despite the contradictory nature of these statements, they evidently indicate consistent evolution as well as rapid development of new research methodology and tools involving Simulation in Management research.

In view of the climate change and global warming challenges faced by the populations, the importance of reduction of Green House Gas (GHG) emissions in a cost effective manner is growing enormously. Governments and the international organisations the world over are severally and collectively trying to find a regulatory solution to these challenges. In order for the regulations to be effective and successful, they need to be flexible enough for all the concerned players involved and at the same time, should also suit to the specific circumstances of a particular nation both politically and economically. It is in this context that carbon management through the use of accounting information systems (AIS) is emerging as one of the several approaches, adopted by organisations to achieve reduction of GHG emissions. Carbon Footprint business process, as relevant for this study, relates to the use of accounting principles, practices, standards and units of measure as well as the accounting information systems, by business entities to account for and reduce GHG emissions.

An attempt is made to discuss the idea of engaging complexity theory to empirically examine complexity in the Carbon Footprint business process in continuously changing organisations. Accounting information systems in these organisations represent the complex adaptive systems (CAS) and are aimed at simplification of the complex business processes and therefore providing effective, adaptive and user-friendly solutions.

Simulation modelling is very useful in helping to define a problem and in decision making while solving the problem as a model is used to simulate how a real life environment may behave under varied circumstances. These varied circumstances are built into the model by defining the individual agents, their actions and the impact of these actions on the environment in which the agents operate, through the use of rules. It is important to keep these rules and the model itself as simple as possible and also to maintain detailed documentation, if the model needs to be understood and reused by the wider research community. The literature and the research results available in this area point to the fact that simple models based on simple rules can still achieve complex results. For a research model to be used in a live business scenario, it needs to be flexible, practical and adapted to suit the relevant business needs in helping to define a problem and to solve it.

The thematic objectives of this article are:

- to provide a forum for discussing the ideas to use simulation as an innovative research method in business and management,
- to critically analyse the use of agent based simulation, the popular tools more commonly used by diverse researchers and to examine the factors that make it a better tool,
- to explore the use of complexity as a base theory to empirically examine a complex business process, e.g., Carbon Footprint business process,
- to discuss how simple models, designed and built based on simple rules which are easier to understand and friendlier to use, still achieve the desired complex results, and
- to use our research on complex business processes and complex adaptive systems in continuously changing organisations as the basis for illustrating some of the concepts.

As part of section 2 hereunder, simulation is analysed as a research method in the business and management research and agent based modelling and simulation (ABMS) as a new modelling paradigm. Core capabilities and key uses of the popular tools of agent based simulation are also analysed in this section. Section 3 throws some light on our research into complex adaptive systems handling complex business processes in continuously changing organisations. Section 4 examines Carbon Footprint is examined as a business process and looks into some ideas how organisations use accounting information systems to manage the business process. Factors that make an Agent Based Model successful for the business process and the inherent and underlying assumptions for the model, the process of choosing the right level of the model and validating the model itself are also discussed as part of this section. Section 5 outlines the idea of the use of complexity for theory building in carrying out research and examines the complimentary benefits of combining simulation and complexity in the related research. Section 6 discusses the need for application of rules as simple as possible and therefore building simple models using these simple rules, without however compromising on the complex results that ought to be achieved by the competing and innovative organisations. In the conclusion, it is suggested that avenues and ideas be explored for further management research using these tools and methodology.

2. TOOLS AND METHODOLOGY FOR MANAGEMENT RESEARCH

Research scientists assess, verify and decide what tools and methodologies are appropriate for their own research. The conclusions and the end results of the research very much depend upon this assessment and the decision. In order to explore simulation as an innovative research method in business and management research, it is necessary to analyse the characteristics of agent based simulation along with some examples of its use by the respective researchers in addressing practical problems from sciences as diverse as Anthropology to Sociology.

2.1 Simulation as a Research Method in Business and Management

Simulation is used as a research method by various disciplines as diverse as for example, Anthropology to simulate archaeological data to explain the growth or decline of civilizations; Biology to model bacterial behaviour and interaction; Cognitive Science to develop models on emotion, cognition and social behaviour; Economics to model people's economic behaviour; Physical Sciences to simulate possible emergent structures; Sociology to model social life and interactions among individuals within a particular society; Political Science to understand national identity and state formation (Macal and North, 2005).

More than a decade ago, Simulation is used rarely in Management research though this is changing with the technological advances in computers and their computational power. Berends, P. and Romme, G. (1999) explain the reasons, "The main reasons for the low status of simulation research in management studies are: the emphasis on academic specialization rather than craftsmanship, the complicated systems rather than complex systems viewpoint, and the paradigm of the empirical sciences rather than design sciences which prevails in management studies". The evolution of computer has changed the situation to a large extent and researchers started to use Simulation methods and tools in various disciplines. Among the different approaches of Simulation i.e., Discrete Event Simulation, System Dynamics Simulation and Agent Based Simulation (ABS), ABS is associated with the assumption that the systems are built bottom-up as against top-down approach of Systems Dynamics whereas Discrete Event Simulation is more for the management of events over a period of time. Therefore, ABMS is considered for the modelling and simulation for the purposes of carrying out our research.

2.2 Agent Based Modelling and Simulation

Agent-based Modelling and Simulation (ABMS) is a new modelling paradigm and is one of the most exciting practical developments in modelling since the invention of relational databases (North and Macal). In order to emphasise and further establish this viewpoint, some of the characteristics of Agent Based Simulation (ABS) are highlighted hereunder:

- An agent is an entity, real or virtual, that perceives and acts in its environment (Russell and Norvig, 1995).

- An agent is flexible, and has the ability to learn and adapt its behaviors over time based on experience. This requires some form of memory (Macal and North, 2005).
- Agents can interact with other agents and have a set of rules that guide their behaviour in order to satisfy their goals subject to resources, abilities and perceptions (i.e., autonomous, adapted from Ferber, 1999). These rules can also modify an Agent's own rules of behaviour.
- Agents are diverse and this nature makes ABS more exciting and brings it closer to today's complex systems.
- Its main roots are in modeling human social behavior and individual decision making (Bonabeau 2001).

The above-mentioned characteristics establish ABS as one of the best tools available to replace the other inadequate and inappropriate modelling tools for contemporary management research. The evolution of independent systems of the modern world, e.g., accounting information systems, their inherent complexity and a large number of growing interdependencies among them make our world hugely complex. For example, the effects of globalization and deregulation on the business and industry on one hand and the need for global regulation of GHG emissions on the other.

2.3 Analysis of some tools of Agent Based Simulation

All management scientists may not be familiar with the computer science but they may need to improve these skills in order to catch up with the growing field of simulation tools, agent based modelling techniques and their advantages in management research. There are numerous tools available in the market for using agent based simulation, however, a small illustrative list of the popular tools is provided in table 1. The column one in the table shows the names of simulation tools and the column two describes briefly the environment using which the tool is built and the solution offered by the tool.

Simulation Tool	Brief Description of the Environment and the Solution
Lisp-Stat	Lisp (object oriented) environment – statistical functions and easy to use graphics.
MAML	Provides easy use of the functionality of SWARM without the knowledge its programming language.
NetLogo	Cross-platform, multi-agent programmable modelling environment with built-in graphical interfaces - ease of use and availability of documentation.
SDML	A set of rule bases and databases –construction of declarative models.
SIM-AGENT	An agent-architecture toolkit – allows rapid prototyping, testing and real time response to complex and dynamic domains.
SimBioSys	Similar to SWARM – useful for socio-economic and biological processes.
StarLogo	A programmable modelling environment – useful for Decentralised systems.
SWARM	A set of function libraries, Objective C - Multi-Agent Software platform for the simulation of Complex Adaptive Systems.

Table 1. Some tools of Agent Based Simulation.

Hereunder is the critical discussion on the practical uses of the tools listed in table 1. If we require a multi-agent software platform for the simulation of complex adaptive systems (CAS), SWARM is the tool. In the Swarm system, the basic unit of simulation is the swarm, a collection of agents executing a schedule of actions. It supports hierarchical modelling approaches whereby agents can be composed of swarms of other agents in nested structures. Swarm provides object oriented libraries of reusable components for building models and analyzing, displaying, and controlling experiments on those models. Swarm is available in full, free source code form which is another advantage. Using SWARM, both the memory management and time simulation problems can be avoided. This tool is used in Genetic algorithms (GA), Neural networks, 3-dimensional spaces, Boolean networks, and Date and time management, for example, Patient Flow Simulation in Hospital Management (L.Morenoa and others, 1999).

If the goal is to provide the functionality of Swarm without the need to be familiar with Swarm's underlying low-level language, Objective-C, then the answer is MAML The current version of MAML defines a macro-language for Swarm. This introduces higher level concepts of modelling, and simplifies some constructs already included in Swarm by hiding the technical details needed to program them. The macro-language nature of MAML does not affect the user's access to the whole Swarm machinery. However, SimBioSys, is a general C++ class library for evolutionary simulation. Like Swarm, SimBioSys provides users with a general library aimed at building agent based evolutionary models of socio-economic and biological processes.

Another popular tool available is SIM_AGENT, which is an "agent architecture" toolkit. It allows rapid prototyping and testing of all kinds of agents, from very simple reactive agents to those that can plan and deliberate. It is written in Pop-11 and has been used for experimenting with different kinds of agent architectures that meet a requirement for real-time response in complex and dynamic domains.

A freely available software environment for Agent Based Simulation is NetLogo. The major reason why it is extensively used and supported is because, of its ease of use, most professional in appearance and documentation, it is a cross-platform, multi-agent programmable modelling environment with built-in graphical interfaces. On the other hand, StarLogo, is a programmable modelling environment for exploring the behaviour of decentralised systems (systems that are organised without an organiser, and co-ordinated without a coordinator). StarLogo has been used to model phenomena such as bird flocks, traffic jams, ant colonies and market economies. StarLogo was created for the Macintosh, but a Java version and a PC version are under development (the PC version actually exists, but it is an alpha version).

Lisp-Stat an object oriented environment for statistical computing and dynamic graphics The Lisp language, in particular Common Lisp (Steele 1990), offers many advantages as the basis of a language for data analysis. As a result of many years of refinement the language is powerful yet has a very clean design. However, Lisp has some drawbacks, i.e., it is inherently slow and memory hungry; Lisp syntax is hard to learn; Lisp's popularity has seen a decrease over the past decade (L. Tierney, 2005).

Whereas Strictly Declarative Modelling Language (SDML) is used wherein knowledge is represented in rule-bases and data-bases; all knowledge is declarative; models can be constructed using many interacting agents; complex agents can be composed of simpler ones, Laboratory for Simulation Development (LSD) allows one to create, observe, edit and run micro-founded simulation models. It offers a set of tools that facilitate the most common operations for building and using simulation models, and particularly models with many nested entities as agent based ones usually are.

However, despite the advances in computers and computational power, the gap between the research models and their use in live business environment still exists and therefore, selection of the right tool is crucial for achieving the research objectives.

3. BUSINESS PROCESSES AND COMPLEX ADAPTIVE SYSTEMS

In this section, our research on how complex adaptive systems help the users in managing business processes is examined and how this theme is taken as an example throughout this article to illustrate some of the concepts is also described. Taking Carbon Footprint business process as an example of a complex business process and Accounting Information Systems as an example for complex adaptive systems within the business environment in continuously changing organisations, an attempt is made to summarise our research, approach and methodology in figure 1.

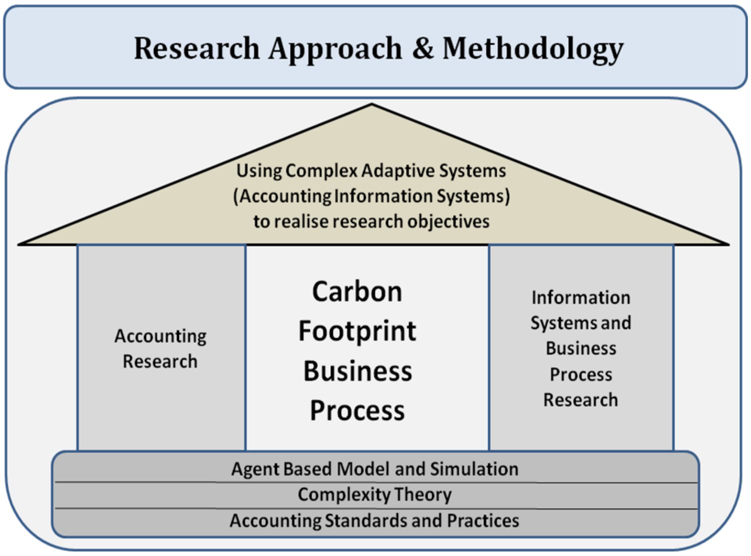

Figure 1. Research Approach & Methodology

Figure 1 depicts accounting research on one hand and the information systems and business process research on the other hand, as the two basic pillars on top of the foundation laid by the accounting standards and practices. Complexity theory as the base theory and agent based model and simulation as the research method as other foundation layers complete the laying of the foundation for our research.

The major objective of our research is shown as the roof of the figure, i.e., how the Accounting Information Systems, being the Complex Adaptive Systems as they are, can help manage accounting and control of GHG emissions.

3.1 Carbon Footprint Business Process

Some greenhouse gases such as carbon dioxide are emitted to the atmosphere through natural processes and human activities. Other greenhouse gases (e.g., fluorinated gases) are created and emitted solely through human activities. For the purpose of this study, the Carbon Footprint business process related to emissions through human activities is only considered. Carbon management policy in an organisation is driven by the business drivers that can be broadly classified into the following areas: regulatory compliance, cost implications, competitive advantages and stakeholder management.

Carbon Trust (2007) defines Carbon Footprint as a methodology and as a technique "… a methodology to estimate the total emission of greenhouse gases (GHG) in carbon equivalents from a product across its life cycle from the production of raw material used in its manufacture, to disposal of the finished product (excluding in-use emissions)" and "… a technique for identifying and measuring the individual greenhouse gas emissions from each activity within a supply chain process step and the framework for attributing these to each output product (we [The Carbon Trust] will refer to this as the product's 'carbon footprint')."

To date carbon footprints have been established for countries and sub-national regions (SEI and WWF 2007), institutions such as schools (GAP et al. 2006), products (Carbon Trust 2006), businesses and investment funds (Trucost 2006). The task of calculating carbon footprints can be approached methodologically from two different directions: bottom-up, based on Process Analysis (PA) or top-down, based on Environmental Input- Output (EIO) analysis. Herein an attempt is made to use the first mentioned approach of the Process Analysis.

With the help of figure 2, Carbon Footprint is depicted as an enterprise level or high level business process along with its sub processes at one level deeper. Figure 2 is also explained using table 2. The numbers of the level 1 or sub processes from 1.1 to 1.9 are only mentioned for illustrative purposes. However, the inter dependencies amongst the sub processes are listed in table 2.

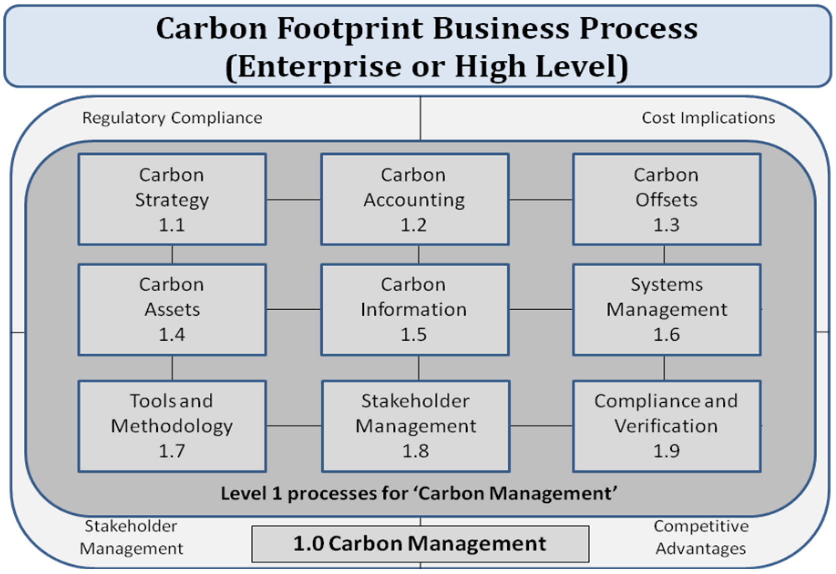

Figure 2. Carbon Footprint Business Process and its Sub Processes

The business drivers which impact the business process are mentioned in the four corners of the figure, i.e., regulatory compliance, cost implications, competitive advantages and stakeholder management.

The degree of relevance of each of the business drivers and the influence thereof in the consequent decisions within this business process and its sub processes depend upon various factors such as the nature of the business of the organisation, its geographical location, enterprise strategy.

3.2 Carbon Footprint Business Process Decomposed

The table 2 is used to list the Level Process names in column number 1, to describe each of the Sub process briefly in column number 2 and also to put together their inter dependencies in the last column.

Level 1 Process	Brief Description of the Sub Process	Inter-dependencies with other processes
1.1 Carbon Strategy	The Strategy of the organisation for the management of GHG emissions.	All the other processes
1.2 Carbon Accounting	Policies, standards and practices for the accounting of emissions, offsets & assets.	1.1, 1.3, 1.4, 1.5, 1.6, 1.7 and 1.9
1.3 Carbon Offsets	Policies and operations of management of offsets.	1.1, 1.2, 1.4, 1.5, 1.6, 1.7 and 1.9
1.4 Carbon Assets	Policies and operations of management of Carbon Assets.	1.1, 1.2, 1.3, 1.5, 1.6, 1.8 and 1.9
1.5 Carbon Information	Policies and operations of collection and dissemination of Carbon information.	All the other processes
1.6 Systems Management	Management of systems related to Carbon Management.	All the other processes
1.7 Tools and Methodology	Management of tools and methodology related to Carbon Management.	1.2, 1.3, 1.5, 1.6 and 1.9
1.8 Stakeholder Management	Stakeholder Management related to Carbon Management.	1.1 and 1.9
1.9 Compliance and Verification	Compliance and verification including Audits related to Carbon Management.	1.2, 1.3, 1.4, 1.5, 1.6, 1.7 and 1.9

Table 2. Level 1 processes or Sub processes of Carbon Footprint business process

All these multiple interdependencies among these level 1 processes reiterate the complex nature of the Carbon Footprint business process.

4 AGENT BASED MODEL FOR A COMPLEX BUSINESS PROCESS

In this section, the focal point of our research, i.e., Agent Based Model for a Complex Business Process, is discussed by:

- examining Carbon Footprint business process and the use of Accounting Information Systems for Carbon Management as an essential part of the business process,
- diving into the requisites that make an Agent Based Model for the business process successful,
- outlining the steps in choosing the right level of the model and arriving at the right assumptions, and
- the process of validating the model itself.

4.1 Pre-requisites to make an Agent Based Model successful

Different designs may be required to address different purposes of simulation. However, every agent design has to be built in such a way that there exist mechanisms for receiving input from the environment, ability to store history of previous inputs and actions, rules for what to do next, for carrying out actions and for distributing outputs. Examples are Artificial Intelligence (AI) approaches, non AI approaches such as neural nets or a hybrid approaches such as MAS (e.g. Kliver, 1998).

Agents are always modelled as operating within some environment consisting of a network of interactions with other agents. The usual assumption is that nearby agents are more likely to interact or are better able to influence each other than those farther agents. Examples are models built using techniques drawn from cellular automata.

If we would like to communicate with others about our model or if we wish other scholars to replicate the results, the model should be documented in detail and if computer programming is used in the model, the code should be properly written and documented along with the instructions how to us the same on different kinds of platforms. Example: use object oriented language.

4.2 Choosing the right level of the Model and the right Assumptions

Macal and North (2005) described that under the following circumstances, it is beneficial to think in terms of agents: when there is a natural representation as agents; when there are decisions and behaviours that can be defined discretely with boundaries; when it is important that agents adapt and change their behaviours; when it is important that agents learn and engage in dynamic strategic behaviours; when it is important that agents have a dynamic relationships with other agents and agent relationships form and dissolve; when it is important that the agents form organisations and adaptation and learning are important at the organisation level; when it is important to have a spatial component to their behaviours and interactions; when the past is no prediction of the future; when scaling up to arbitrary level is important ; when process structural change needs to be a result of the model, rather than a model input. Therefore, choosing the right level of the model and arriving at the right assumptions is the key to the success of the model itself.

Following Axtell & Epstein (1994), we can summarise the levels of agent-based model performance and analysis as follows:

- level 0: the model is a caricature of reality, as established with simple graphical devices (e.g., allowing visualisation of agent motion):
- level 1: the model is in qualitative agreement with empirical macro-structure as established by plotting the distributions of some attributes of the agent population;
- level 2: the model produces quantitative agreement with empirical macrostructure, as established through statistical estimation routines; and
- level 3: the model exhibits quantitative agreement with empirical microstructures, as determined from cross-sectional and longitudinal analysis of the agent population.

Nevertheless, even if we obtain satisfactory results at level 3, a basic question may remain unsolved: the so-called many-to-one or identification problem, i.e. the possibility of obtaining similar results with quite different agent structures. This is, however, a general problem of scientific method, not confined to the methodology of simulation.

4.3 Validation of Agent Based Models and Simulation

The credibility of the model is enhanced through proper validation of the model. Within the Multi-Agent Simulation (MAS) community (Axel, 2000) it is also widely recognized that one weakness of MAS is the impossibility of establishing a mathematical proof of the obtained results. However, the use of several techniques and methods may enhance the credibility of MAS.

As Axelrod (1997a, p. 211) notes, attention to the quality of a simulation model is important throughout the research enterprise. In order to be able to achieve the goals of validation, usability, and extendibility, considerable care must be taken in the entire research enterprise. This includes not just the programming, but also the documentation and data analysis. (...) I have learned the hard way that haste does indeed make waste. Quick results are often unreliable. Good habits slow things down at first, but speed things up in the long run.

Debugging a program is always a difficult task and we can never be sure of producing completely error free code. Nevertheless, we can look for some "alarm" signals that can alert us to the presence of bugs. Srbljinovic, A. and Skunca, O. (2003) gave a special attention to the issues of validation of agent based modelling and simulation. They described validation as assuring external or operational validity which refers to the adequacy and accuracy of the model in matching real world data, where the real world data refer to information gathered through experimental, field, archival or survey analyses of actual human, animal, physical systems, groups or organisations.

Jack P.C. Kleijnen (1998) gives a survey on how to validate simulation models through the application of mathematical statistics. Kleijnen points out the need to evaluate whether the simulation is a success through the validation of the simulation model and surveys the following possibilities about the availability of data for the process of validation: i) If the data is not available, experiments should be guided by the statistical theory on Design of Experiments (DOE); an inferior but popular approach is to change one factor at a time; ii) if only output data is available, real and simulated output data be compared through student t statistic; iii) where both input and output data are available, trace driven simulation is possible. In spite of what Kleijnen says about the non availability of data in i) above, Simulation is not the appropriate method of research under those circumstances where the data is not available because the validation of the model is not possible under those circumstances.

5 THEORY BUILDING

Complexity theory has captured the attention of the scientific community to the extent where its proponents tout it as a dominant scientific trend. Geographers and environmental, human and regional planners have applied the theory to topics ranging from cultural transmissions and economic growth to the braiding of rivers.

It is necessary to move beyond all this, critically examine the nature of complexity research in management studies. Complexity theory research has allowed for new insights into many phenomena and for the development of new manners of discussing issues, regarding management and organisations (M. Lissack, 1999). Henry J. Coleman, Jr. (1999) pointed out that Complexity theory views organisations as “complex adaptive systems” that co-evolve with the environment through the self-organizing behaviour of agents navigating “fitness landscapes” (Kauffman, 1995) of market opportunities and competitive dynamics. Changing external and internal “attractors” influence the process of adaptation by agents (Kauffman, 1995; Morgan, 1996; Stacey, 1996).

5.1 Using Complexity as the Base Theory

Management researchers’ work offers both the theoretical dimensions and empirical knowledge necessary to conduct complexity research. Parkhe (1993) argues that the development of theory should follow a research route which begins with exploratory research.

If we are to apply the science of complexity to continuously changing organisations, we need to have a link between the conceptual framework and development of the theory with that of the empirical model. These research models need to be as close to the real live business scenarios as possible to have the meaningful application of complexity to these organisations.

Manson, S.M. (2000) provides an overview of the evolution of complexity research, establishes a preliminary typology of complexity approaches with their advantages and drawbacks, and identifies areas of further research. Key issues surrounding complexity include: i) the need to understand better the different kinds of complexity theory; ii) provision of data and techniques amenable to complexity research; iii) proper interpretation of complexity theory, especially with regard to human systems; iv) exploration of the ontological and epistemological corollaries of complexity. Manson, S.M. (points out that the value of complexity exists in the eye of its beholder. For some, it is merely a passing fad, for others an interesting complement so accepted conceptual frameworks. Identical findings or phenomena can lead to radically different interpretations. Some of the questions raised and answered by Manson, S.M. bring out the uses of complexity as the base theory for our research, e.g., How far can we extend the epistemological corollaries of algorithmic complexity? Does deterministic complexity allow or prevent prediction and control of complex systems? Does aggregate complexity support the role of individuality and creativity or does it point to biological determinism in human affairs?

5.2 Complexity and Simulation do complement each other

Houchin, K. and MacLean, D. (2005) presented a study on the concepts of complexity theory. The study revealed that although there are different complexity theory interpretations, a number of common concepts are observable. These include the concepts we are using in this study: sensitivity to initial conditions, the presence of disequilibrium and feedback processes, all of which interact to produce novel forms of order. These concepts form the theoretical basis for our study.

Nicholas C. Peroff described Complexity in Management as under: Wilson thinks that the value of both the theory and the concept is, at best, very uncertain. If he is correct, they will contribute little if anything to a consilience of our knowledge about the management of organisations. B. McKelvey (1999) described the complementary uses of complexity and simulation as follows.

Without a program of experimental testing, complexity applications remain metaphorical and are difficult to distinguish from witchcraft. In order for an organisational complexity science to avoid faddism and scientific discredit, it must become model-centred (Michael R. Lissack).

6. KEEP THE MODEL SIMPLE

Some systems are too complex to be modelled let alone to be understood not because the rules are complex and in fact in most cases, simple rules result into complex behaviour of these systems. Following Axtell & Epstein (1994 p.28) the problem of coping with complexity via Agent Based Modelling or Simulation is that the experiments would be of little interest “if we cannot understand these artificial complex systems any better than we understand the real ones.” Therefore, to understand and for others to understand our work, simple but robust guidelines have to be followed in Simulation modelling.

6.1 Simple vs. Complex models

Simulation model is to include rules or programs to maintain history on agents (or data), changes to the data on account of the individual or collective behaviour of the agents (or actions or events) and eventually to distribute the output (or reporting). The biggest advantage of simulation modelling is the possibility to compare the actions of the agent behaviour in the simulated framework with that of these actual agents based on our knowledge about how they behave.

Complex adaptive systems are dynamic systems comprising of independent but integrated modules (or agents) and each module capable of adapting to the constant changes in the environment of the continuously changing organisations. In order to mirror this kind of an environment in a simulation model where both qualitative and quantitative results are expected, we need to adopt more simple and weak criterion.

6.2 Simple Models can still achieve complex results

Macal and North say that perhaps the simplest way to illustrate the basic ideas of Agent Based Model and Simulation is through Cellular Automata, in which the rules are simple and the rules use only local information. Even with the above simple rules, sustainable pattern can emerge in systems that are completely described by simple rules that are based on only local information and the patterns that may develop can be extremely sensitive to the initial conditions. These patterns correspond directly to a wide range of algorithms and logic systems (Wolfram, 2002). Wolfram contends that simple rules can be used to understand much of the complexity observed in the real world.

The Boids Simulation is a good example of how simple rules lead to emergent and seemingly organized system behaviour, reminiscent of schooling or flocking behaviour in fish and birds (Reynolds, 2005). In Boids model, each agent has three rules governing its movement: i) cohesion – each agent steers toward the average position of its nearby “flock-mates”; ii) separation – each agent steers to avoid crowding local flock-mates; and iii) alignment - each agent steers towards the average heading of local flock-mates. Even with these simple rules, the agents’ behaviour begins to appear coordinated and a leaderless flock emerges.

7 CONCLUSION

Carbon Footprint business process is of strategic importance to continuously changing organisations. In order to meet varied expectations of their stakeholders both internally within the organisation and external to the organisation, the business drivers influencing decisions within this process need to be addressed. Complex Adaptive Systems are the help address these issues in business processes, e.g., the use of Accounting Information Systems in Carbon Management. The idea of using of agent based simulation and complexity theory in the research of Carbon Footprint business process provides an opportunity to realise the complementary benefits of Simulation and Complexity Theory as discussed in this article. The evolution of data base management systems, tools and the super computational power are now making it possible to build simulation models that could not even be attempted in the recent past. In view of this, management researchers are encouraged to learn the appropriate computer skills in order to be able to use the computer simulation. However, before taking a decision to use simulation as a research tool to address a particular problem, it is better to undertake a proper analysis of mapping the research needs with the characteristics of the tool in order to ensure that simulation is the appropriate tool for that problem. There may be circumstances where simulation is not an ideal tool, for example, where the problem is too simple to resolve or too complex to understand; or where the cost-benefit analysis for use of Simulation is not favourable; or where it is not possible to validate the model because of non-availability of data or otherwise. Through this article, an attempt is made to provide a forum for discussing Simulation as an innovative research method and Complexity as the base theory for use by the management researchers. More importantly, further research avenues are suggested for use of these tools and methodology in management research.

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