Applying a Fuzzy-Morphological approach to Complexity within management decision-making

Amir M. Sharif[1] and **Zahir Irani**
Information Systems Evaluation and Integration Group (ISEing)
School of Information Systems, Computing and Mathematics,
Brunel University, UK

Purpose: Noting the scarcity of complexity techniques applied to modelling social systems, this paper attempts to formulate a conceptual model of decision-making behaviour within the Information Systems Evaluation (ISE) task, against the backdrop of complexity theory.

Methodology/Approach: Complexity Theory places an emphasis on addressing how dynamic non-linear systems can be represented and modelled utilising computational tools and techniques to draw out inherent system dynamics. In doing so, the use of Fuzzy Cognitive Mapping (FCM) and Morphological Analysis (MA) (hence a Fuzzy-Morphological approach), is applied to empirical case study data, to elucidate the inherent behavioural and systems issues involved in ISE decision-making within a British manufacturing organisation.

Findings: The paper presents results of applying a combined Fuzzy Cognitive Mapping and Morphological Analysis approach to modelling complexity within management decision-making in the ISE task: both in terms of a cognitive map of the key decision criteria; a matrix of constraint criteria; and a synthesised model that provides an indication of the linkages between technology management factors and organisational imperatives and goals. These findings show the usefulness of viewing the topic in complexity science terms (emergent behaviour, non-linearity and chaotic response).

Research limitations/implications: This research is limited in applying the given technique to a single case study organisation in the UK manufacturing sector, where the sample size is limited. Since this is the first time known to the authors that such a combined MA-FCM technique has been used in this field, future research needs to validate and explore the implications of this approach in a wider context (multiple organisations and viewpoints).

Practical implications: The paper highlights the need for those involved in analysing managerial decision-making to include aspects of complexity theory in their evaluations – namely uncovering inherent inter-relationships that may exist between stakeholders, processes and systems. In doing so, expanding the manager's understanding of how to achieve congruence between driving forces and factors, which may exhibit non-linear, chaotic or feedback behaviour.

Originality/value: The given research brings together both artificial intelligence and operational research techniques, applied in the socio-technical milieu of information systems evaluation, within the context of complexity theory, in order to describe the rich detail within the ISE decision-making task.

Keywords: Complexity Theory, Systems Dynamics, Management, Information Systems Evaluation, Fuzzy Cognitive Mapping, Morphological Analysis

Paper Type: Research paper

Dr. Amir M. Sharif is a Visiting Research Fellow at the School of Information Systems, Computing and Mathematics at Brunel University. Amir obtained his PhD in Knowledge Management and has a BEng in Aeronautical Engineering, with research interests in Enterprise Information Systems, Application Integration and Artificial Intelligence. Amir has also worked with many multinational organisations both as a consultant and as an MIS researcher, and is a collegiate member of several UK research grant governing bodies. He is currently working as a Business Analyst for JPMorgan Chase and Co., in London.

Professor Zahir Irani is the Head of Information Systems and Computing and a member of Senate at Brunel University. Professor Irani leads a multi-disciplinary group of International PhD students that research information systems evaluation and application integration. He is the Hooker Distinguished Professor at McMaster University (Canada) as well as being a Visiting Professor at the Arab Academy of Science and Technology (Egypt) and at Ahlia University (Bahrain). He is the editor-in-chief of the established Journal of Enterprise Information Management and European Editor of the Business Process Management Journal. He has co-authored teaching text-books and written almost 200 internationally refereed papers and received ANBAR citations of research excellence. He has spoken at conferences and guest seminars world wide, and is internationally known for his scholarly work in the area of information systems evaluation and application integration.

[1] Corresponding author, email: ams@amir.demon.co.uk

INTRODUCTION

It is well known within management science that the behaviour of leaders and managers greatly affects the outcome of those aspects of the enterprise that they are connected with. The infamous studies by Vroom and Yetton (1973), and Bass and Avolio (1995) highlighted the endemic characteristics and traits within managerial decision-making, where aspects of corporate culture, competency, change / transformation, trust and experience all have a bearing on the realisation of organisational objectives (Connell *et al.*, 2002). It is also understood that many managers seek to quantify and qualify their actions by becoming involved in management interventions, in a transformational (leadership) or transactional (managerial) sense, as highlighted by Farey (1993). One such organisational scenario that is routinely affected by such interventions is that of investment in Information Technology (IT) projects, and the resulting Information Systems Evaluation (ISE) process (Farbey *et al.*, 1993; Remenyi *et al.*, 2000). The latter task involves a lengthy, expensive and complex process of investigation and analysis into the benefits, costs and risks of IT/IS (Small and Chen, 1995). Techniques such as Return on Investment (RoI), Internal Rate of Return (IRR) and Net Present Value (NPV), typically set project costs against quantifiable benefits to be achieved. It may be difficult for management to understand the implications of choosing a particular ISE approach due to the multitude of approaches available (Farbey *et al.,*1993). However, in order for senior management to commit to any expenditure, they need to be convinced of the business justification of such investments via formal justification proposals (Butler, 1997; Farbey, Land and Target, 1993; Primrose, 1991; Willcocks, 1994). The extensive time and money invested in IT/IS is frequently not perceived to be delivering the business benefits that were initially intended (Irani, Ezingeard, Grieve and Race, 1999; Remenyi *et al.*, 2000). This is since typical ISE requires the involvement of key stakeholders impacted by the investment process (senior management, project managers, users and support staff such as IT), and also the existence of a formal IT justification process against which project objectives can be measured (Hochstrasser 1992; Remenyi, Money, Sherwood-Smith and Irani, 2000).

Indeed as has been noted by Irani *et al.* (1999) and Bennett (1998), managerial behaviours within this process can sometimes appear to be ad-hoc, and even chaotic, lacking consistency. Against this backdrop this paper attempts to investigate, in an exploratory sense, facets of management behaviour within the Information Systems Evaluation (ISE) decision-making task in a manufacturing organisation, using a Case Study-based research methodology (Yin, 1994). Noting the contingent character of organisations as non-linear, dynamic systems, the author draws upon notions of Complexity Theory (as a basis for understanding such a process); Artificial Intelligence (in the form of a Fuzzy Cognitive Mapping, FCM); and Operational Research (in the form of Morphological Analysis, MA) in order to develop a model of decision-making behaviour. Through mapping technology management factors and choices within a given ISE scenario using a combination of FCM as well as MA-FCM techniques, the authors thereby synthesise those aspects of behaviour that can be classified against characteristics of Complexity Theory, by comparing the dynamic phase responses of the ISE task in both of these cases. In doing so, the paper concludes with providing a general model of decision-making as applied to the ISE task within the manufacturing industry. Thus, this combined technique provides a useful method for expanding the understanding of organisational decisions, across workforce stakeholders, against the backdrop of social and process (IT/IS) factors which underpin the way in which a firm works.

COMPLEXITY THEORY, FUZZINESS AND MORPHOLOGY: A COMPLIMENTARY APPROACH

The field of Complexity Science, or Complexity Theory as it is otherwise known, is a relatively recent approach to modelling and dealing with complex, adaptive and non-linear systems. As Phelan (2001) notes, Complexity Theory ultimately concerns itself with studying regularities and irregularities within dynamic systems, and thenceforth, providing “simple” causes or models, for “complex” effects (as in the fields of meteorology, physics, artificial life, biological systems and economics). Multiple definitions of systems which exhibit complex behaviour have been given – the most notable of which have been defined in Gallagher and Appenzeller (1999): systems which rely on some form of network of associations or structures which have many dependent and interdependent parts; systems which show structure with variation; systems which are highly sensitive to initial conditions or where the number of interacting components is large and exhibit evolutionary change or growth; or systems which by design or function are both difficult to understand and verify. Such a world-view however, has been largely based upon the field of non-linear dynamics and the modelling of chaotic systems: systems which behave in a non-deterministic manner, which have a high sensitivity to external stimuli and initial conditions (Gleick, 1992). The study of weather patterns by Edward Lorenz – the so-called ‘butterfly effect’ exhibited by the well-known Lorenz Attractor; and the self-similar, infinitely repeating geometrical structures found by Benoit Mandelbrot - fractals – are two of the more well known manifestations of such systems.

Thus, Complexity Theory aims to represent systems or structures which are inherently difficult to model through other means and which tend to exhibit varying, unpredictable, or irreversible behaviour as a matter of course, under a wide range of conditions (Coveney and Highfield, 1995; Green and Newth, 2001; Standish, 2001). It has as its root, 4 key concepts: Self Organisation (the ability to create / recreate structure of form or representation); Non-Linearity (behaviour and response which is non-deterministic, and dependent upon feedback loops, exhibiting hysteresis); Order / Chaos Dynamic (possessing an implicit capability to exhibit linear or non-linear behaviour as a function of stimulus response); and Emergent Behaviour (the ability to show evidence of complex patterns of behaviour as a result of non-linear, self-organising or chaotic interactions within the system). Bergmann *et al.* (2003) note, that whilst there has been much work carried out in the fields of environmental science, electronics, and long-range planning there has been relatively little work in the field of modelling social systems with a large human content, using complexity theory. This is most probably due to the fact that there is a problem of dimensionality (breadth and range) and difficulty (closure and computation) in representing human-focussed behaviours, where the coupling between deterministic and non-deterministic outcomes is very difficult to ascertain. Maani and Li (2004), have shown that it is useful and perhaps necessary to model complex decision-making behaviour, such as in the case of management interventions. Lyons (2004) notes similar reasons also, for employing simulation modelling approaches for the representation of Complex Adaptive Systems (CAS) in management and organisational contexts, by structuring and then applying a diverse range of inputs and stimuli in order to characterise corporate responses such as organisational learning. However, the vagaries of human (ir)rational behaviour and psychology are difficult to quantify and predict, even if a combination of “hard” and “soft” modelling approaches are used.

Improving our understanding of management decision-making

Reichel (2004) notes, that without providing a general social science and systems dynamics theory to link ontological views of the world with models for social model structuring, it is difficult to understand and apply decision-making tools to managerial problems. Mittelstaedt (2004) also raises this issue and suggest that organisations tend to be at the mercy of a chain of managerial or leadership interventions, which lead to failure or in the worst cases, disaster. Mittelstaedt notes that those organisations which tend to fail, have an inherent and implicit propensity to do so as a result of administrative and organisational characteristics, in terms of: Myopia (at best short-sightedness, at worst, blindness and obliviousness to events that are occurring); Hubris (at best over-confidence, at worst, over-bearing arrogance, displaying a form of myopic self-reliance upon existing capabilities and abilities); and finally, Egocentricity (at best, charismatic leadership, at worst, dogmatic stricture). All of these observations point to the fact that managerial and social behaviours are in some sense complex amalgams of individual choice, external choice, internal conflict, personality, motivation, and the desire to achieve goals and objectives. This interconnectedness of managerial / leadership associations therefore represents what could be construed to be a complex system, one comprising of many parts, evolving and responding to stimuli in a variety of ways, with little or no discernible pattern.

Hence the principal aim of the given research, is to extend the boundaries of understanding those factors which impinge upon management decision-making, by applying a structured approach to recognising the complex aspects of linking management behaviours with organisational imperatives and goals. In addition, by attempting to delineate those drives of information systems evaluation within a case organisation, the authors seek to provide a mapping between such criteria and technology management (i.e. equivalent "hygiene") factors. The basis for this is to try to provide a deeper understanding of where and how decision points overlap with and stimulate human behaviour, with given known and unknown information. Although this may appear to be a difficult, and ad-hoc approach to modelling decision-making behaviour, the focus of the work is to provide an overall context for targetting future research into the overlap between the interaction and relationship between human behaviour and organisational systems.

Complimentarities of existing techniques

Algorithmic techniques which are based upon equivalent natural phenomena such as the human brain (Neural Networks) or evolutionary biology (Genetic Algorithms, Cellular Automata), are amenable to displaying characteristics of componentisation, interconnection and interdependent behaviour. These methods have been shown to be useful corollaries to natural processes of decision-making in terms of optimisation, selection and classification in this regard (Golderg, 1989; Simpson, 1990). In fact any method which exhibits qualities of self-regulation and organisation, and which allows implicit, often hidden, characteristic patterns to emerge via enumeration of system variables, such as these is useful. However, it is useful to note the words of the father of Fuzzy Logic, Lotfi Zadeh, as noted by Sowell (2005):

> *"As the complexity of a system increases, it becomes more difficult and eventually impossible to make a precise statement about its behaviour, eventually arriving at a point of complexity where the fuzzy logic method born in humans is the only way to get at the problem."*

Zadeh proposed that in order to model uncertainty or vagueness in this context, required the ability to cover all intermediate states of a system in a non-deterministic, "fuzzy" manner (Zadeh, 1965). The basis of Fuzzy Logic is built on the notion of variable(s) existing/belonging to a set of numerical values to some degree or not. Membership of variables to a certain set can be both associative and distributive (Kosko, 1990; Zadeh, 1965). By extending this view further, fuzzy logic allows the membership of more than 1 set of concepts and consequently allows sets of statements to overlap and merge with one another. Thus, although various artificial intelligence techniques as mentioned above have attempted to represent such intricate systems, the application of Fuzzy Logic has not been used explicitly within the field of complexity science. The detailed work of Majumder and Majumdar (2004) is the most recent evidence of fuzzy approaches being applied to complex systems modelling, wherein the researchers have attempted to rationalise fuzzy, probability and complexity science theories for the modelling of carcinogenetic and bio-cybernetic systems. Extending this concept along the lines of elucidating the interrelationships between components of social, economic, technical or other systems using the concept of cognitive or causal mapping (Ackermann and Eden, 2004; Axelrod, 1976; Montezemi and Conrath, 1986), has given rise to the technique of Fuzzy Cognitive Mapping (FCM) in this regard (Kosko, 1990; Kosko, 1991).

FCMs represent variables of a dynamic system graphically, by links that signify cause and effect relationships, being augmented with fuzzy or multivalent weights, quantified via numbers, or words (Kosko, 1991). Essentially, an FCM is a non-hierarchic digraph from which changes to each statement, hence fuzzy concept (i.e. *node*), are governed by a series of causal increases or decreases in fuzzy weight values (i.e. *links* between nodes). The advantage of modelling dynamic systems via an FCM, is that even if the initial mapping of the problem concepts is incomplete or incorrect, further additions to the map can be included, and the response of new parameters on the map can be quickly seen (thus providing a holistic picture of the scenario being modelled). Causality is inferred by positive (+) and negative (-) signs on each nodal link also. An FCM is therefore read by noting which concept is linked together with another one, using *causal modifiers* to provide a causal relationship between each node or concept. Such mappings have proved useful in analyzing non-linear systems such as those found in agriculture, clinical diagnosis, business planning, ecology and conservation, electrical engineering and legal negotiation (Aguilar, 2005), and also have been applied successfully in the area of ISE by the authors also (Irani *et al.*, 1999; Sharif and Irani, 2005; Sharif and Irani, 2006).

A complimentary technique which has only seen limited use within the field of Operational Research (OR), is that of Morphological Analysis (MA) developed by Zwicky (1969). This is a problem-solving technique, which seeks to quantify, though not reduce, a systems' known parameters by reducing the solution space of the combined outcomes of all possible combinations of parameters which define a given system. Typically, this approach is used when causal modelling cannot succinctly satisfy all system parameters, and where there are so-called "genuine uncertainties" as to either the meaning or outcome of system parameters. As such, the MA approach is used to define a structure of form (hence a *morphology*) of the system being analysed, so that it may be solvable. By solvable it is meant that other techniques such as those found in the systems sciences (forecasting, scenario planning, heuristics, simulation etc), can be applied to the given variables.

The MA technique consists of defining all the variables of the system to be modelled (i.e. the morphological *dimensions*), and then listing all the known outcomes or *conditions* for each variable – hence creating a *morphological field*, or matrix of the state of all conditions in the system. All potential known outcomes and responses for the system or problem being modelled should therefore, theoretically, fall within this matrix, i.e. these are the number of *configurations* (for which the product of *n* parameters x *n* conditions will exist). By filtering out those conditions which are vague, ill-defined or contradictory to each other,(i.e. by enforcing *consistency* of all the known variables), a reduced set of parameters is produced. This is not a reductionist philosophy in the sense that the form of the system is not inherently unchanged (i.e. the guiding parameters), merely the *set of solutions* (conditions) that pertain to them. A number of different “what if?” scenarios can then be played out by then defining a number of fixed conditions under a known parameter, carrying out a “walkthrough” of all other known parameters to achieve a solution, built up of acceptable conditions (albeit subjectively). Rhynne (1995) called the latter approach, *Field Anomaly Relaxation* (FAR), which “relaxes” or simplifies ambiguity (the anomalies) within the morphological field, through combining a series of parameter configurations as described. Such a technique has been found useful in the application to scenario planning, strategy formulation and forecasting in the fields of defence studies, economics and policy development (Coyle *et al.*, 1994; Ritchey, 1997), where a multitude of causes and effects exist within the same context to be considered. Hence, noting these two useful techniques for problem-solving, Table 1 shows a comparison of both the FCM and MA techniques with regards to complexity theory concepts.

Take in Table 1

As can be seen, the fuzzy method has many similarities, principally based upon that of providing an interconnected, networked representation of a system’s components (although the boundaries are fixed by the static connectivities defined for the map). Similarly the MA approach is also well suited to modelling or addressing complexity, although once again there is no means for emergent behaviour to become visibly manifest as the morphological field is reliant upon the overall parameters. There is also no concept of feedback or growth, as this technique is a structural device used to convey a multiplicity of associations amongst system variables. As such, it can be argued that the usage of an FCM approach satisfies the modelling of complex systems across each of the four key root concepts of complexity theory: through the iterative approach of an enumeration of state variables which interact amongst themselves to reach fixed point, limit or chaotic cycles (thereby satisfying notions of self-organisation, non-linearity, order/chaos dynamic and emergent behaviour). The MA technique also provides us with a complimentary technique which allows the researcher to address situations where a complex system cannot be simplified further; non-reducible complexity and where causal modelling requires support. This is in terms of reducing the *solution space*, as opposed to the reductionist ideal of limiting the number of *variables* that make up a system, as noted by Gallagher and Appenzeller (1999). Hence, because of the strength of MA to reduce the solution space (i.e. the potential range or number of combinations of inter-relationships between variables) as well as the ability of FCMs to model such interconnections graphically, the authors feel that by using a combination of FCM and MA techniques, a useful and novel insight into modelling complexity within management decision-making can be provided. In particular by applying an MA approach to evaluating key decision-making criteria, extraneous or anomalous parameters which may engender divergence from inherent behaviour can be carried out using FAR on a morphological field of (expert) knowledge.

Derivation of a suggested Fuzzy and Fuzzy-Morphological approach

The authors therefore propose that by using a combination of FCM and MA (FAR), bounds of complexity within the modelling of real world organisational scenarios can be achieved. The approach to be used is shown in Figure 1.

Take in Figure 1

This shows how these complimentary tools and techniques can be used to understand management behaviour and in turn to place this in the context of organisational imperatives and goals to be achieved. In this paper, we will focus on the decision making task of ISE, but other scenarios in the business world could easily be modelled in this vein also, such as those other business processes shown in the top half of the diagram. In the above conceptual model, the authors propose that each tool combined together can be used in order to build up a dynamic picture or model of management responses. This assumes that in order to model management behaviour requires an understanding of the organisational imperatives as well as knowledge used by managers in their decision-making tasks. This can be achieved by applying a FAR approach to the range of decision-making scenarios that they are involved with. The standard MA approach can then be applied, whereby a series of walkthroughs of a matrix of possibilities is carried out, either by an individual expert in the area, or in concert with and facilitated by a researcher and a group of interested parties (e.g. organisational stakeholders). Consensus on each of the combinations of decision-making parameters can then be achieved within a workshop setting.

Once a combination of walkthrough situations are recognised and agreed upon, this information can then summarily be coded into key / critical nodes which will form the basis of an FCM. The natural question which arises is which or how many nodes will constitute the FCM as a result of the preceding MA step? A trivial solution to this may be to simply take the core MA parameters identified (i.e. the key boundaries of the decision-making task), as being the FCM nodes; whilst this may provide a rapid approach to formulating a system mapping it is still relatively "coarse" in terms of representation. Such an FCM would therefore provide an *indication* of the interactions between each parameter, and would not be indicative of those particular and specific explanations which detail each component part of the system being modelled. However, the purpose of such modelling efforts is not to achieve accuracy but to stimulate thought and discussion on the behaviours represented and their albeit simplified responses.

Once an FCM is created in this way, the mapping can be enumerated via an algorithmic fuzzy protocol, whereupon fuzzy weightings and connectivities are defined with appropriate connectivities between concept nodes (i.e. a matrix of node-to-node connection relationships). The FCM can then be run as a discrete simulation and the results plotted. The output of each node's response will immediately highlight if any linear/non-linear response and self-organisation characteristic exists; and upon plotting the dynamic behaviour of each node interaction on the polar plane in terms of a phase plot (in either 2- or 3-dimensional phase space), will likewise uncover any order/chaos relationship and emergent behaviour properties. This is through analysing the trajectory motion of each system parameter as it converges / diverges from stable, deterministic behaviour to unstable, non-deterministic plateaus. Finally, upon creating such results, this information can therefore potentially lead to an understanding of the situational behaviour within the problem being modelled – the resultant effects thenceforth being amenable to classification with respect to complexity theory characteristics.

Management context and relevance

The approaches outlined above, are essentially what Checkland and Holwell (2004) would call a complimentary view of both "hard" and "soft" systems thinking. In such a way engineering a view of the real world, in understand it better. As such, it may appear that the combined techniques of MA and FCM are somewhat of an intellectual curiosity which has very little bearing on the day to day operational understanding of a working organisation. However, the raising of this question belies its own answer, in that by attempting to highlight as many of the known conditions which affect and drive human decision-making behaviour, we can begin to learn and have an appreciation of those factors which exist "under the surface", as it were. Although the basis for the combined technique outlined in this paper may be technical and academic in nature, the actual application and process of clarifying decision-making processes was seen as being revelatory to those involved. This was in the sense of bringing a different conceptual view to bear on a well known problem, which in itself, allows a fresh approach to extending our experience and knowledge of a real-world problem.

For managers and practitioners, the procedure of applying MA-FCM can best be summed up as another useful “what-if?” scenario tool, which provides not only an intellectual disection of organisational processes, expectations, biases, a-priori knowledge and heuristics, but also provides a very visual method for composing multiple stakeholder views of the world in a structured way. Furthermore, by placing such a technique within the context of complexity theory, also accentuates the idea that man-made systems and processes are very much natural and open-ended systems, which may or may not be under control at any given time. In an operational, tactical and strategic sense, this ultimately can provide a manager with an alternative, holistic appraisal of risk – which can easily supplement lead/lag metrics as can be found via scorecarding or even other hierarchical ranking methods. The application for these techniques is seen by the authors to be amenable within both general management practice and also more specifically within IT/IS management, in this regard. Given these views, the following sections now detail an example to show how such a combined method works, through the use of a case study example within a British manufacturing company.

CASE RESEARCH METHODOLOGY AND DETAIL

For the purposes of this and the following sections, the ISE task within a previously investigated company (Sharif and Irani, 2005) will be used as the basis for analysing and assessing the proposed Fuzzy-Morphological (i.e. MA-FCM) approach shown in Figure 1 and in the preceding section. The methodology chosen to do accomplish this, was based upon the empirical, interpretivist approach favoured by Walsham (1993) and Yin (1994), in the guise of Case Study research. This approach has been chosen since case study approaches, whilst common within the fields of Management Information Systems (MIS), Operational Research (OR) and Management Science (MS), are not frequently used within the field of systems dynamics, and can offer a useful and alternative view of complex systems (Laws and McLeod, 2004).

The overall research design involved the definition of suitable research objectives and rationale; gathering of extant literature and background material; the development of an appropriate field data protocol employing primary data gathered from semi-structured interviews, participant observation (with senior management encompassing the Managing Director, Production Director and Purchasing Director), as well as secondary data gathered form company archival documents, memos and reports; the application of a Fuzzy and Morphological Analysis methods to the case data; the use of an exploratory, descriptive analysis approach, driven by narrative discourse (in the vein of “systems stories”, Modjahedzadeh and Andersen, 2001); and finally, a synthesis phase which placed the case data and analysis results against the background of complexity theory, in order to formulate a general model of management decision-making behaviour within ISE. As such, the case company investigated observed the managerial decision-making behaviour of the managing director and senior board of directors of a bespoke British manufacturing and engineering organisation, which was involved in evaluating and implementing an Enterprise Resource Planning (ERP) system (Sharif and Irani, 2005; Sharif and Irani, 2006). Management viewed the investment in an ERP system as being strategic in nature, inherently providing realizable benefits via achieving competitive advantage. The appraisal perspectives taken by the firm were categorised in terms of Innovation (i.e. Strategic), Maintenance (i.e. Tactical) and Support (i.e. Operational) factors; and whilst these were not formalized by the company, they were seen to be an accurate reflection of the very much informal and ad-hoc decision-making process employed. Project justification was perceived to be a “hurdle that had to be overcome”, and was not seen as a technique for evaluating the project's worth as compared to traditional orthodox financial frameworks.

This had significant implications, as during the preparation of the ERP project’s proposal, managers spent much time and effort investigating its technical and financial aspects (in a strategic sense), rather than risk and benefit aspects (in a tactical / operational sense). Hence, the managing director of the firm became committed to the belief that the project was essential. The underlying company culture amongst the shop floor workers was meanwhile hesitant to change, a fact bourne out by the managing director’s desire to have a qualified, skilled and experienced manufacturing workforce. As a result, the remaining project team members tried to address the given implementation and human resource risks, against estimated cost implications. The management team identified pertinent technology management factors that influenced their ISE decision:

- Identify and implement a resource planning system that will be useful for current and future organisational scenarios (training / development of staff skills, productivity and process improvements, lean working and manufacturing), denoting a level of *Acceptability* of an ERP system;
- Increase throughput to meet production internal as well as external (customer order-driven) goals via a “one team” based ethic, denoting *Productivity*;
- Execute a strategy to realise benefits and efficiency gains via an inclusive workable business plan, denoting *Efficiency*;
- Increase competitive advantage and market share by introduction of new technology using a skilled and educated workforce, denoting *Benefits*;
- Provide capital expenditure on plant, resources and equipment necessary to achieve strategic goals, denoting *Direct Costs*;
- Identify maintenance, training and resource costs to keep business running and profitable, denoting *Indirect Costs*;
- Understand market share and competitor risk, providing planning and training across business initiatives, denoting *Risks*;
- Apply an IS evaluation approach over time horizons relevant to the business (short, medium and long term) , denoting an appropriate *Evaluation Mode*.

So, whilst there was a desire to invest and implement in technology, there were, in a sense, opposing views of the justification process, and how the ERP should be implemented. The resulting outcome of the whole initiative led to a stoppage in the IS rollout as issues of training and education, ERP module applicability, company culture and managerial differences of opinion surfaced. Although these setbacks delayed the original execution of the firm’s manufacturing technology strategy, the organisation overcame these obstacles by addressing the aforementioned issues through a change of ISE approach, involvement of all system stakeholders and a re-organisation of manager /leader responsibilities (between the managing director and the production director). Hence, although the firm transformed failure into success in the long term, it is not known what other implicit or inherent organisational factors contributed to the combination of managerial hubris, egocentricity and myopia (in the sense of Mittelstaedt, 2004).

APPLICATION OF FCM TO MODELLING COMPLEXITY

The authors now present the codification of the managerial decision-making process involved within the case company, through the application of a standard FCM and MA-FCM approaches. In doing so, the capability of both of these techniques to address issues of handling complexity within this scenario will be presented in terms of simulation results of both of these computational models. This will attempt to show an analysis of the decision-making and technology management factors in the case organisation and potentially uncover further reasons for what happened. To carry out the resulting simulations, involves an enumeration of each node or concept (in this case management decision criterion), with its requisite fuzzy causal weighting. Since an FCM is a series of interconnected concepts which define a directed graph, the propagation of a set of initial node criteria allows a response from each node in the map to be ascertained – much like the response that can be achieved from a set of neural nodes. Hence, given an FCM with a number of nodes, C_i where i = 1… n exists, the value of each node in an iteration, can be computed from the values of the nodes in the preceding state, using the following equation:

$$C_i^{t+1} = f\left(\sum_{j=1}^{n} W_{ij}\, C_i^t \right) + C_i^{t-1} \tag{1}$$

where C_i^{t+1} is the value of the node at the t + 1 iteration, C_i^{t-1} is the value of the node at the t - 1 iteration, f is a given threshold or transformation function, W_{ij} is a corresponding fuzzy weight between two given nodes, i and j, and C_i^t the value of the interconnected fuzzy node at step t (Kosko, 1991). The threshold function, $f\,(\mathrm{x})$, can be constructed as being bivalent (x = 0 or 1); trivalent (x = -1, 0 or 1); hyperbolic (usually $\tanh$ (x)); or the sigmoidal / step function (x = 1 / 1 + e^{-cx}, where c is a constant). In order to simulate the dynamic behaviour of the FCM, therefore requires the additional definition of the fuzzy weights, W_{ij}, within a connection matrix, W, and the initial or starting input vector at time t, C^t. As such, the latter is a 1 x n row vector with the values of all concepts, C_1, C_2,…, C_n for n concepts or nodes in the FCM, whilst the former is a n x n matrix of weights between any two fuzzy nodes, w_{ij}. If there is no direct relationship between the i[th] and j[th] nodes, then the value of the connection strength is zero. As such, the connection / influence matrix, W, can be written as:

$$W = \begin{bmatrix} \cdots & \cdots & \cdots \\ \cdots & w_{ij} & \cdots \\ \cdots & \cdots & \cdots \end{bmatrix} \tag{2}$$

Whilst the initial row vector can be represented as:

$$C^0 = \left(w_{i,j}^1, \ldots, w_{i+1,j+1}^n \right) \tag{3}$$

for n nodes in the FCM. The values within this vector signify the activation level of a node in the FCM. Hence each $w_{i,j}^n$ value defines an initial static state of the FCM, for which each node is set to an “on”, “off” or other intermediary position. The simulation proceeds by computing C_i^{t+1} based upon this initial starting vector, and the given threshold function in f, as well as the causal connection strengths in the n x n matrix, *W*. Each subsequent $t + 1$ iteration then uses the values of the preceding $t - 1$ row vector in C^0. By calculating each subsequent value of equation (1), the FCM simulates the dynamical system being modelled. Each corresponding linked node within the mapping responds to its respective inputs – the state of each, defining any underlying modality or "hidden pattern of inference". As such, the input influence matrix in equation (2) is essentially a set of training data, and thus the iterative application of equation (1) describes a machine learning process (similar to a supervised neural net).

By applying equations (1 – 3), a "simulation" of how the FCM responds can be carried out, the details of which are described for each FCM in the following sections. The threshold function, *f*, for advancing both FCM simulations as given in equation (1), was set to be the hyperbolic function, $f(x) = \tanh(x)$. The goal or objective ISE task situation was defined to reflect that used by senior management within the company, in relation to the investment decision: a Strategic-driven view which assumes assuming Financial considerations are always inherently a part of any investment justification. The causal modifiers are likewise also given in Table 2.

Take in Table 2

Based upon these, the initial FCM conditions, or starting row vector C^0, was set accordingly as:

$$[1.000\ 0.333\ 1.000\ 0.000\ 1.000\ 0.333\ 1.000\ {-0.333}] \qquad (4)$$

In other words, Acceptability, Efficiency, Direct Costs, and Risk were viewed as being always a constituent part of an investment decision (i.e. a fuzzy value of 1); Productivity and Indirect costs were viewed as being occasionally of importance (i.e. a fuzzy value of 0.333); Benefits were viewed as being unknown or neutral (i.e. a value of 0); and the evaluation – ISE – mode was viewed as being possibly beneficial to the decision used (i.e. the value of –0.3333). The application of the preceding equations and method is now shown in terms of both a standardised FCM and a MA-based FCM also, which are now detailed in the next section.

Standard FCM

In order to create this FCM, the authors chose the key ISE criteria that were mooted by management, as the nodes of the map. This is shown in Figure 2.

Take in Figure 2

This FCM shows a combined view of the case study company's ISE approach (Irani *et al.*, 2001), in terms of Strategic, Tactical, Operational and Financial as well as functional project risks, benefits and costs view based upon team member responses. In the diagram, AC are Acceptability criteria; PR are Productivity criteria; EF are Efficiency criteria; BE are Benefits; DC are Direct costs; RI are Risks; EM are Evaluation Modes; and IC are indirect costs. The associated fuzzy connectivity matrix is given in equation (5):

$$W = \begin{bmatrix} -1.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 \\ 1.000 & 0.000 & 0.667 & 1.000 & -1.000 & 1.000 & 0.000 & 0.000 \\ 1.000 & 0.667 & 0.000 & 0.333 & 0.000 & -1.000 & 0.000 & -0.333 \\ 0.667 & 0.000 & 0.000 & 0.000 & -0.333 & 1.000 & 1.000 & 1.000 \\ 1.000 & 0.000 & 0.000 & 1.000 & 1.000 & -0.333 & 0.333 & 0.000 \\ 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & -0.333 & 0.667 \\ 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 \\ -0.333 & 0.000 & 0.000 & -0.333 & 0.000 & 1.000 & -0.333 & 0.000 \end{bmatrix} \quad (5)$$

By applying the hyperbolic threshold function along with the initial FCM condition from equation (4), allowed the FCM response shown in Figure 3 to be generated.

Take in Figure 3

This graph shows the result for the standard FCM, which shows a convergence to a steady state within 45 iterations for all factors except of the Acceptance criteria (which continues oscillating). In itself, this is an interesting reaction to the given initial row vector of the cognitive map, and may well denote acceptance of an IT/IS investment is intrinsically linked to the Evaluation mode chosen (i.e. the IS appraisal method itself). Familiarity with a given evaluation approach thereby confers stability with regards to the acceptance of that approach (as can be seen in the closely linked behaviour of both of these curves between iterations 4 through to 8). Likewise there is an inherent relationship with the level of risk – in this case, the risk curve is out of phase with the evaluation mode curve, denoting that ambiguity or uncertainty relating to the application of an ISE approach, which implies all intangible factors are adversely affected. In other words, from this graph, intangible factors are those that predominantly dominate the lower, negative, half of the y-axis (such as Indirect costs and risk factors); whilst those more tangible factors dominate the upper, positive, half of the y-axis (such as evaluation mode, benefits, acceptance, efficiency and productivity). Productivity and efficiency gains are almost inextricably linked, achieving fixed point convergence within 11 iterations. The relationship between direct and indirect costs is also worthy to note, as the response given highlights that indirect costs only stabilize or as subsumed within the investment, once benefits start to be realized (i.e. once an up-front investment in "visible" and physical products or services occurs, seen as the stabilizing effect of direct costs on benefits from iteration 8 onwards).

MA-based FCM (MA-FCM)

In the case of this MA-FCM, the nodes of the FCM generated were generated as a result of relaxing, i.e. carrying out a consistency check across all morphological conditions, and then finding an analogous set of statements that matched the standard FCM C^0 vector (i.e. the strategic driven view). The MA matrix shown in Table 3 was generated and defined as a result of filtering and consolidating responses from the management team within the case organisation, in terms of the key technology management factors. This shows a field with a 79,380 configurations (3x3x6x5x2x3x7x7 conditions).

Take in Table 3

That is, the product of all available conditions in the system. Ritchey (1997) notes that for mildly complex systems with approximately 5 or 6 key parameters, this product can be in the range of 11 – 20,000 configurations. Our case is approximately six times that empirical figure, although this should not imply that this system being modelled is almost approximately 8 times as difficult. This merely means that the solution space is quite vast, based upon the decision criteria stated by management within the case company. In order to address the decision-making goal as defined in equation (4), an equivalent set of conditions were set and a FAR approach of cross-checking consistencies, where duplicate, ambiguous or erroneous conditions were removed. The resulting FAR matrix is thus given in Table 4. This shows a reduction in the solution space to 5,184 configurations (3x2x2x3x2x2x6x6 configurations) - a reduction of 93.47% on the initial case. Again, this does not imply that the resulting explanation for the dynamics of this system will be 6.53% of the complexity of the original morphological field. Rather this is an indication of the level of redundancy in the decision-making parameter which define the system.

Take in Table 4

As such, in the table the dark shaded cells denote the goal condition to be reached, whilst the light shaded cells highlight those conditions which best meet the given strategic aim. Hence the conditions "Investment Integrated in Business Plan" and "Tangible" were set as goal parameters with the conditions "Company Culture", "Implementation team and functional teams", "Continuous Project Evaluation", "Educated Decision", "Time Horizon" and "Competitive Risk", "Stakeholder Analysis" being identified by the researchers to satisfy these criteria. This relaxed field was generated by removing the duplicate / contradictory and ambiguous conditions of "Workforce Educated and Trained" (as this was seen as a Benefit condition); "Management Educated and Trained" (as management are inherently part of the workforce); "Strategic, Tactical and Operational", "Short/Medium term" and "Long term" (as these fall under a general condition of "Time Horizon"); and finally, "Monthly Management Review Meetings", "Formal Documentation Process" and "Ad-hoc documentation process" (as these can all be subsumed under the guise of the "Continuous Project Evaluation" condition). The authors have then used these highlighted cells as the basis of the nodes of an FCM to be simulated – the resulting MA-FCM model – which is shown in Figure 4. In this diagram, CC is "Company Culture"; IF is "Implementation / Functional Teams"; CP is "Continuous Project Evaluation"; WT is "Workforce Trained and Educated"; TB is "Tangible Benefits"; FP is "Formal Project Management"; CR is "Competitive Risk"; MT is "Management Team"; ED is Educated Decision; and TH is "Time Horizon".

Take in Figure 4

Once again, the associated fuzzy connectivity matrix is given in equation (6):

$$W = \begin{bmatrix} 0.000 & 0.667 & 0.333 & 0.333 & -0.333 & 0.000 & 0.000 & -0.333 & -1.000 & 0.000 \\ 0.333 & 0.000 & 0.667 & 0.333 & 1.000 & 1.000 & 0.000 & 0.333 & 0.333 & 0.000 \\ -1.000 & -0.667 & 0.000 & 0.000 & -0.333 & -0.333 & 0.000 & 0.333 & 0.667 & 0.333 \\ 0.333 & 0.000 & 0.000 & 0.000 & 1.000 & 0.000 & 0.000 & 0.333 & 0.000 & -0.333 \\ 1.000 & 0.333 & 0.333 & 0.000 & 0.000 & 0.000 & 1.000 & 1.000 & 1.000 & -1.000 \\ 0.333 & 1.000 & 1.000 & 0.000 & -0.333 & 0.000 & -0.667 & 0.333 & 0.333 & 0.667 \\ 1.000 & 0.000 & 0.000 & 0.000 & 0.333 & 0.000 & 0.000 & 0.667 & -0.333 & 0.000 \\ -0.333 & -0.333 & 0.667 & 0.000 & 0.000 & 0.333 & 0.000 & 0.000 & -0.333 & 0.000 \\ -0.667 & 1.000 & 0.000 & 0.000 & 0.333 & 0.000 & 0.333 & -0.333 & 0.000 & 0.000 \\ 0.000 & 0.000 & 0.000 & 0.667 & 1.000 & 1.000 & 0.000 & 1.000 & 0.000 & 0.000 \end{bmatrix} \tag{6}$$

Thenceforth, the initial stimulus vector for approaching a strategic, financially-driven goal was set as follows in equation (7):

$$[0.000\ 1.000\ 1.000\ 1.000\ 1.000\ 1.000\ 0.6667\ 1.000\ 1.000\ 0.000] \tag{7}$$

The hyperbolic threshold function was once again used for the algorithmic simulation as in the previous FCM case, for which the resultant nodal response calculated via equation (4), is shown in Figure 5.

Take in Figure 5

The key observation that can be made from the MA-FCM is that the response for the initial stimulus given in Figure 5, does not converge to a fixed point but results in cyclical behaviour well beyond 48 iterations. In fact, it has been noted that this behaviour commences at approximately iteration 45, and has a recurring period of 7 iterations, with all nodes responding together. This therefore highlights a limit point, though non-chaotic, behaviour. However, initially beyond iteration 12 the interaction of nodal responses flips the system response into the cyclical behaviour exhibited, without any apparent cause, being a deviation from the initial response. Up to that point of divergent behaviour, there is heavy interaction and “communication” between each node, wherein the primary driver of response is related to “Time Horizon”, which leads “Implementation / Functional teams”, “Workforce Trained and Educated”, “Company Culture” and lastly “Formal Project Management”. A number of interesting interactions can be seen however. It can be seen that “Company Culture”, “Implementation / Functional Teams” and “Time Horizon” (and to a lesser extent, “Formal Project Management”), tend to react and respond in the same manner from iteration 2 to iteration 12. That is to say that these are similar in some respects to each other. However, “Educated Decision”, “Management Team”, “Competitive Risk” (and also to a lesser extent, “Continuous Project Evaluation”) tend to stabilise to a positive causal state (i.e. a value of 1), denoting that these factors are inherent to achieving the strategically focussed financial ISE goal. As would be expected perhaps, a focus on management practice as viewed by management could provide a bias to these results in some respects.

However, an interesting response arises in the form of “Tangible Benefits” which initially seem to be converging to a positive causal stability also, but then at iteration 15 onwards, begin to oscillate between positive and negative causality, leading to a limit cycle being reached. This response appears to lag the effects of “Workforce Trained and Educated” and “Implementation / functional Teams” and possibly an inflection occurs due the negative causality formed by “Formal Project Management”, “Time Horizon” and “Company Culture”, at that point. This implies that some implicit relationship appears to be stronger between tangible benefits and the method by which projects are implemented and adopted in this firm. On this point, the effect of a heavy positive causality of management responses noted earlier, belies the causal response suggested by the “Company Culture” plot. As such, this factor can also be seen to be an influence on the response of “Implementation / Functional Teams” and therefore indirectly, “Workforce Trained and Educated” too. Ultimately in this case, this means that the success / failure of the ISE task may be dependent upon company culture, in a causal sense, a fact which may not have been taken into account in the initial ISE process.

COMPARISON OF THE FCM AND MA-FCM APPROACHES: A GENERAL FUZZY-MORPHOLOGICAL MODEL

Perhaps the most crucial aspect of the modelling exercise detailed in this paper is to ask the question about the complexity of the decision-making scenario being modelled: in effect, is this a complex system and does it display characteristics of complexity? By plotting the 2-dimensional phase space plots for each node of each FCM, the trajectories or behaviour of each concept can be plotted to show any oscillatory or hidden system dynamics of each nodal parameter, as it responds and interacts with other nodes to the initial stimuli. This can be achieved by plotting the behaviour of each node within the fuzzy range [-1, 1] by producing a polar plot (measured in radians), of each node's response, according to the transformations:

$$x = C_i^t \cos(C_i^t).\frac{\pi}{180} \tag{7}$$

$$y = C_i^t \sin(C_i^t).\frac{\pi}{180} \tag{8}$$

Hence for the standard FCM of Figure 3, Figures 6a – 6h The behaviour of each node varies widely across each of these plots, although it can be seen that there are similarities in response between Acceptance and Risk (Figure 6a and 6f); Productivity and Efficiency (Figure 6b and 6c).

Take in Figure 6a – h

Both sets of phase responses have broadly equivalent phase trajectories also. In each case what can be said is that there is some level of low-dimensional harmonic response wherein an oscillating pattern begins to emerge; but at some stage, some factor triggers a deviation from the given pattern and leads to a new fixed point state. In each case, the trigger point occurs at values of –1 on the x-axis and approximately 1 on the y axis for all the given node phase space responses. That is to say, when each nodal parameter, hence concept reaches a negative causal limit, the immediate response of the system and nodes is to "flip" to a positive causal state. Thus suggesting that the system being modelled, wishes to achieve the strategic goal as defined in equation (4), possibly even indicating a tendency towards the largely positive causal aspects of managerial intervention. As Guneralp (2004) notes with regards to visualising phase space responses using eigenvector analysis, as well as Castiaux (2004) who reports on the application of Lotka-Volterra (hunter-prey) equations to organisational relationships, positive causal loops tend to exhibit "run-away" behaviour which appear to be goal-seeking in nature. However, and as confirmed by the experiments of Kauffman (1995) on feedback within boolean-based closed networks, this appears to be only valid for certain initial conditions, which in some cases results in systems bordering on the "edge of chaos" (i.e. being in a state between fixed point, limit and / or cyclical behaviour). Therefore, these results can only be properly put in context when compared to the MA-based, non-reductionist approach also.

Phase plots of the MA-FCM are also presented in Figures 7a – j and undoubtedly show, in the best auspices of non-linear visualisation, "closed form" behaviour of the MA-FCM representation of the case company ISE system. This is in the sense that no fixed point is reached and the system continues to swing from one response to another and back again (showing a high level of hysteresis) – and hence indicate complex system behaviours. Unlike the phase response of the standard FCM (in

Figures 6a – h), all the conditions shown here, share a similar “criss-cross” effect, showing the nodal response trajectory moving across the fuzzy range [1, -1]. The responses which are most similar to each other in these terms include the “Implementation / Functional Teams”, “Tangible Benefits”, and “Formal Project Management” plots: indicating a close coupling between these variables in the FCM. However, end states (hence a fixed point) are reached for “Workforce Trained and Educated”, “Competitive Risk”, “Educated Decision” and “Time Horizon” plots.

Take in Figure 7a – j

Thus, Table 5 shows an empirical grouping of those factors which, from the results, appear to respond to each other, independently of direct fuzzy connectivities and associations previously defined in the given connectivity matrices. This table is generated as a result of interpreting and synthesising the nodal and phase responses given within Figures 3, 5, 6 and 7. From the given matrix of associations in Table 5, the authors suggest that an underlying decision-making behaviour can be formulated which provides an *indication* of managerial tendencies within the ISE scenario investigated.

Take in Table 5

The factors Efficiency (EF), Productivity (PR), Indirect Costs (IC), RI (Risks), Benefits (BE), and Evaluation Mode (EM) have all been noted to have close inter-relationships from the analysis of the results. For the relationship between EF and PR (denoted as EF-PR), it is understood that such a causal relationship should exist as this was originally defined as a positive causal link in the setup of the FCM to begin with. Similarly, the association between IC-BE was also defined as being a negative causal, within the fuzzy connectivity matrix in equation (5) but in terms of the results generated turned out to show a close relationship that may indicate a positive causal relationship instead. More interestingly, the relationship RI-AC and EM-AC was noted as existing in the nodal response in Figure 3, was never described as a causal link in the FCM. Furthermore, this relationship is an underlying connection found from the analysis of the results, and as such may signify a level of emergent behaviour (and indirectly, through the evolution of the FCM time history itself, a form of self-organisation), whereby a link in terms of an inferred relationship has materialised. That is to say, the consideration of indirect costs (IC), benefits (BE), risks (RI), acceptability / satisfaction of IS requirements (AC), and an evaluation mode (EM) are intrinsic factors which govern this particular model of the ISE task.

Similarly, looking at the results for the MA-FCM, we can see that the conditions of Corporate Culture (CC), Implementation / Functional Teams (IF), Continuous Project Evaluation (CP), Management Team (MT), Tangible Benefits (TB), Formal Project Management (FP), Competitive Risk (CR), Workforce Trained and Educated (WT), Educated Decision (ED) and Time Horizon (TH) all have close inter-relationships. Again, looking at the fuzzy connectivity matrix for the MA-FCM in equation (7) shows that all relationships as shown in Table 5 for CC, IF, CP, MT, and between TH-WT were defined in *W* already. Hence, it should be of no surprise that these same relationships have been found as a result of plotting the nodal responses. The only emergent relationships that have been found are those between TB-MT, FP-CC, FP-TB, CR-WT, and ED-WT for which no defined causal relationships were stated in the initial MA-FCM associativity matrix. Once again, this highlights an emergence of interrelationships, in this case having a shared commonality between Tangible Benefits (TB), Formal Project Management (FP) and Workforce Trained and Educated (WT).

That is to say, that factors relating to management (MT), corporate culture (CC), risk (CR), and decision-making (ED) are all in some way inextricably linked together with these underlying causes and drive one another in this model of the ISE task within the case firm. In both cases of the standard FCM and MA-FCM, it can therefore be stated that issues of benefit realisation (i.e. BE and TB), risk management (i.e. RI and CR) and method of IS evaluation (i.e. EM and ED) are fundamental components of the system being studied. What is interesting to note is that the additional factors of IC, AC, MT, CC, FP and WT have no equivalent relationship across both FCMs. Tacit relationships have thenceforth been found between these factors in both types of FCM: relating to benefits, risks and evaluation mode in the first case; and corporate culture, formal project management, workforce trained and educated in the second case. These findings can then be grouped into a number of emergent relationship clusters in terms of managerial control and intervention (MT, EM/ED), IS project assessment (RI, CR, CP, FP, BE/TB, IC), and consideration of stakeholder issues (AC, WT). It is interesting to note that Direct Costs (DC), Efficiency (EF), Productivity (PR), Implementation / Functional Teams (IF), and Time Horizon (TH) all have a lesser role to play in the dynamics of this system – although they may have been at the forefront of management's decision-making criteria to begin with. Based upon this analysis, a general model of how fuzzy cognitive mapping and morphological analysis can now be formulated, taking concepts of complexity theory and system dynamics into account. This is shown in Figure 8.

Take in Figure 8

The given model can essentially be used to run through a series of scenarios to highlight cases which exhibit (good or bad) risk in an *a-priori* or *post-hoc* manner (i.e. in either a forecasting or evaluative mode). By doing so, it can lead to understanding decision-making, and hence management behaviour "in the large". This can be achieved by first of all choosing or selecting a particular organisational imperative or goal (in this case, ISE), detailing the need via highlighting specific technology management factors. Following on from this, the relationships between each of these factors can then be modelled, either using FCM, or an MA-FCM approach. The results of these simulations can then be gathered and a "scaled response" or overall outcome to the goal required can be formulated thereby providing an indication of the underlying factors that drive the decision-making task – belying inherent and implicit system behaviour. As noted above, issues relating to managerial governance and control, project assessment and stakeholder involvement can further be broken down into specific business process tasks that can be aligned to a-priori and post-hoc worldviews as appropriate. Hence, managerial interventions may need to involve the execution of scenario planning, risk analysis and performance measurement in the first instance (in order to align appropriate IS evaluation techniques with realistic operational project management approaches); and the application of programme management, stakeholder analysis and post-evaluation in the second instance (in order to provide an insight into how benefits, costs and risks were realised and managed). This resulting system behaviour then in itself, feeds back into the definition of the self-same goals and imperatives initially defined, leading to an adaptive organism of sorts, highlighting McElroy's claims that "complex systems are, by any other definition, learning organisations" (McElroy, 2000). This is shown as the dotted line going back to the organisational imperatives, in terms of an organisational learning component. However, in applying this method of mapping to this situation highlights the fact that such a forensic approach to attempting to understand organisational and individual behaviours confers a *post-hoc* rationalisation (Ackermann and Eden, 2004, p.139). The application of a research methodology which would include the ability to verify and validate the modelled system would therefore be a requisite check on the efficacy of such a mapping approach taken.

CONCLUSIONS

This paper has attempted to investigate and report on the applicability of fuzzy and morphological approaches to modelling complexity within information systems evaluation (ISE) decision-making, within a British manufacturing company case setting. In doing so, the authors have highlighted and developed a fuzzy-morphological technique which is based upon Fuzzy Cognitive Mapping (FCM) and Morphological Analysis (MA) techniques. As such, the aim of the paper was an attempt to model a perceived complex system using a computational tool (the FCM) – both in a "standard" sense, as well as using the technique of Field Anomaly Relaxation (FAR) to reduce the solution space and make the system more amenable for modelling. By thenceforth placing the given system model within the context of Complexity Theory concepts, the authors then endeavoured to achieve a deeper understanding of the computational results achieved, by highlighting facets of self organisation, non-linearity, order/chaos dynamic and emergent behaviour.

The given initial stimuli for the ISE, being based upon a strategic and financially-motivated scenario, showed that in this case, the decision-making process exhibited some mild non-linearity (in terms of hysteresis-based responses) and self-organisation (towards a stable causal state). There was no visible incipient order/chaos dynamic as shown in the results, although for both the FCM and MA-FCM models only a single initial stimuli was used (for illustration purposes). Emergent behaviour was noted however, in terms of the implications of the nodal responses shown in both graphs plotted as well as a matrix of realised connectivities. This was perhaps the strongest indication of the complexity within the given case observed, wherein conditions of Direct Costs (DC), Efficiency (EF), Productivity (PR), Implementation / Functional Teams (IF), and Time Horizon (TH) were all appeared to play a lesser role in the dynamics of the system modelled, even though the case study firm's management suggested otherwise. In particular, a number of emergent relationship clusters were identified along lines of managerial control and intervention (MT, EM/ED), IS project assessment (RI, CR, CP, FP, BE/TB, IC), and consideration of stakeholder issues (AC, WT). In doing so, the authors suggest that these grouped factors ultimately determined the initial failure, and then success, of the IS evaluation and ERP implementation within the case organisation.The purpose of carrying out this experiment on the case data was not necessarily to produce a definitive, foregone, deterministic result, but to raise the question in an exploratory sense of how and if this approach could be applied to the field of business. As such, this research formulated a model of how complexity theory could be applied to a business situation – and in that sense, was a *representation*, as opposed to a formalism, of how a complex system, such as an organisation involved in a decision-making task, could be modelled.

As far as the authors know, there is very little if any method or work which has been published which provides this level of detail or granularity. The viewpoint and lens used for carrying out this evaluation of ISE decision-making behaviour has ostensibly been *post-hoc* (and can be said to be evaluated with respect to complexity theory characteristics in that sense also). Although facets such as order / chaos dynamic and emergent behaviour can only be seen *inter alia* of the response of social systems such as those investigated, it would be useful and interesting to develop methods and tools to carry out *in-situ* complexity modelling (in terms of including measures of complexity within business process models, say). More importantly, further investigations into what set of initial conditions lead to divergence from order, to a chaotic response would be required in order to provide closure to the usefulness of this technique. A method to achieve this may be to model a *series* of FCMs that are essentially "routes" through the MA matrix, and are individual policy statements that make up an MA solution. To model individual management behaviours then would also require a deeper analysis and categorisation of managerial psychological traits and sociological (or even pathological) behaviours.

Since no model can ever capture all the intricate detail of the real world (Pidd, 2004; Sharif, 2005) and from the experiences and lessons learned in this particular example, the authors therefore believe that the application of Complexity Theory to management situations is, in itself, complex (although it is hoped that this article goes some way to investigating the area). Undoubtedly there is a fair degree of expert / researcher bias in formulating the FCM and MA-FCM models of ISE decision-making. This is driven by subjective explicit and tacit knowledge on behalf of both the researchers as well as the observed case participants. This can be overcome by applying this technique to similar situations or by increasing the number of observations (experts), as well as initial starting conditions to cover a multitude of organisational criteria. Experimental validation (internal as well as external validity) would also be required to be confirmed, and could be achieved by involving stakeholders of the system in the modelling and analysis process. Whilst the MA-FCM (FAR) approach reduces the complexity and dimensionality of the system under consideration, it also potentially poses a threat to eliminating the richness of data and information which ultimately describes the behaviour of the system itself, and provides a quotient of complexity. By applying such a filter on the representation of such managerial decision-making scenarios, may lead to the loss of dynamic interrelationships, which could be the progenitor of chaotic or non-linear behaviour to be studied.

It would be useful to compare these results with those of ‘traditional’ complexity theory methods such as Neural Networks, Genetic Algorithms and Cellular Automata. Most, if not all, dynamic systems which are thought to exhibit complex, non-linear or even chaotic behaviour are generally modelled with respect to a time component. In this case no dimension of time has been included, as the given decision scenarios provide a snapshot of those choices taken by management during the ISE phase. Again, it would be useful to include some method to encapsulate the passage of time with respect to dynamic human behaviour. Thus, it may eventually be appropriate to develop and generate hybrid models which are based upon multiple AI or other complimentary models to overcome any potential ‘dimensionality/richness loss’ that could be attributed to a coarse modelling approach as in this fuzzy-based case reported here. Given these avenues of further research, the authors therefore believe that Complexity Theory can only be properly applied to management decision-making scenarios if models such as those highlighted and presented in this paper, are investigated and developed further.

REFERENCES

Ackermann, F., and Eden, C. (2004). Using Causal Mapping – Individual and Group, Traditional and New. In (Ed. M. Pidd). *Systems Modelling: Theory and Practice*. John Wiley, Chichester, UK, pp. 126 – 145.

Aguilar, J. (2005) A survey about Fuzzy Cognitive Maps Papers, *International Journal of Computational Cognition*, 3, 2, 27 – 33.

Axelrod, R. (1976) Structure of Decision: the cognitive maps of political elites, Princeton University Press.

Bass, B.M., and Avolio, B. (1995). *The Multifactor Leadership Questionnair*e, Mind Garden, Palo Alto, CA.

Bennett, R.H. (1998). The importance of tacit knowledge in strategic deliberations and decisions. *Management Decision*, **36** (9) : 589 – 597.

Bergmann, J., Paier, M., and Resetarits, A. (2003). Towards a roadmap of Complexity Research using a Bibliometric visualisation tool. EXYSTENCE Working paper, ARC Seibersdorf Research, Germany, April 2003.
Butler, M. (1997) Future Fantastic, *Information Week*, 19, 53.
Castiaux, A. (2004). Inter-organisational learning – Lotka-Volterra modelling of different types of relationships. In (Eds. M. Kennedy, G.W. Winch, R.S. Langer, J. I Rowe, and J. M. Yanni). *Proceedings of the 22nd International Conference of the Systems Dynamics Society* (CD-ROM proceedings), July 25th – 29th 2004, Oxford, UK. Wiley, UK.
Checkland, P, and Holwell, S. (2004). “Classic” OR and “Soft” OR – an asymmetric complimentarity. In (Ed. M. Pidd). *Systems Modelling: Theory and Practice*. John Wiley, Chichester, UK, pp. 45 – 60.
Connell, J., Cross, B. and Parry, K. (2002). Leadership in the 21st century: where is it leading us?. *International Journal of Organisational Behaviour*, **5** (2) : 139 – 149.
Coyle, R. G., Crawshay, R. and Sutton, L. (1994). Futures Assessments by Field Anomaly Relaxation. *Futures,* **26** (1) : 25 - 43.
Coveney, P., and Highfield, R. (1995). *Frontiers of Complexity: The Search for Order in a Chaotic World*. Fawcett Columbine, New York, NY, USA.
Farbey B, Land F, Targett D, (1993), IT investment: A study of methods and practices, Published in association with Management Today and Butterworth-Heinemann Ltd, U.K.
Farey, P. (1993). Mapping the Leader/Manager. *Management Education and Development*, **24** (2) : 109 – 121.
Gallagher, R., and Appenzeller, T. (1999). Beyond Reductionism, *Science*, **284** (5411), pp. 79.
Gleick, J. (1992). *Chaos*. Harper-Collins, London, UK.
Goldberg, D.E. (1989). Genetic Algorithms in Search, Optimisation and Machine Learning. Reading, MA : Addison Wesley.
Green, D. G. and Newth, D. (2001). Towards a theory of everything? - Grand challenges to complexity and informatics, *Complexity International*, **8** (Paper ID: green05). Available. [on-line]. http://www.complexity.org.au/ci/vol08/green05/
Guneralp, B. (2004). Exploring Structure-Behaviour Relations: Eigenvalues and Eigenvectors versus Loop Polarities. In (Eds. M. Kennedy, G.W. Winch, R.S. Langer, J. I Rowe, and J. M. Yanni). *Proceedings of the 22nd International Conference of the Systems Dynamics Society* (CD-ROM proceedings), July 25th – 29th 2004, Oxford, UK. Wiley, UK.
Hochstrasser B, (1992) Justifying IT investments, Conference Proceedings: Advanced Information Systems; The new technologies in today's business environment, 17-28.
Irani Z, Ezingeard J-N, Grieve R.J and Race P. (1999). Investment justification of information technology in manufacturing, *International Journal of Computer Applications in Technology*, 12, 2, 90 - 101.
Irani, Z., Sharif, A. M., Love, P.E.D., and Kahraman, C. (2001) Applying Concepts of Fuzzy Cognitive Mapping to model IT/IS Investment Evaluation, *International Journal of Production Economics*, 75, 1, 199 - 211.
Kauffman, S. (1995). *At Home in the Universe*. Oxford University Press, New York, NY, USA.
Kosko, B. (1991) *Neural Networks and Fuzzy Systems*, Saddle River, NJ: Prentice-Hall, 1991
Kosko, B. (1990) *Fuzzy Thinking : The new science of Fuzzy Logic*, London, UK : Flamingo Press / Harper-Collins, 1990.
Laws, K., and McLeod, R. (2004). Case Study and Grounded Theory: Sharing some alternative qualitative research methodologies with Systems professionals. In (Eds. M. Kennedy, G.W. Winch, R.S. Langer, J. I Rowe, and J. M. Yanni).

Proceedings of the 22nd International Conference of the Systems Dynamics Society (CD-ROM proceedings), July 25th – 29th 2004, Oxford, UK. Wiley, UK.
Lyons, M (2004). Insights from Complexity: Organisational change and Systems modelling. In (Ed. M. Pidd). *Systems Modelling: Theory and Practice*. John Wiley, Chichester, UK, pp. 21 – 44.
Majumder, D.D., and Majumdar, K.K. (2004). Complexity Analysis, uncertainty management and fuzzy dynamical systems: a cybernetic approach. *Kybernetes*, **33** (7) : 1143 – 1184.
Maani, K.E., and Li, A.K.T. Li (2004). Dynamics of Managerial Intervention in Complex Systems. In (Eds. M. Kennedy, G.W. Winch, R.S. Langer, J. I Rowe, and J. M. Yanni). *Proceedings of the 22nd International Conference of the Systems Dynamics Society* (CD-ROM proceedings), July 25th – 29th 2004, Oxford, UK. Wiley, UK.
McElroy, M.W. (2000). Integrating Complexity Theory, Knowledge Management and Organisational Learning. *Journal of Knowledge Management*, **4** (3) : 195 – 203.
Mittelstaedt, R. E. (2004). Correcting a culture that breeds mistakes. *Strategy and Business*, Fall 2004, p. 39.
Modjahedzadeh, M., and Andersen, D. (2001). Digest: A New Tool for Creating Insightful System Stories. *Proceedings of the 22nd International Conference of the Systems Dynamics Society*, Atlanta, Georgia, USA.
Montazemi A, and Conrath D, (1986), The use of cognitive mapping for information requirement analysis, *Manufacturing Information Systems Quarterly*, March, pp. 45 – 56.
Phelan, S.E. (2001). What is Complexity Science, really?. *Emergence* **3** (1) : 120 – 136.
Pidd, M. (2004). *Systems Modelling: Theory and Practice*. John Wiley, Chichester, UK, pp. 206.
Primrose, P.L. (1991) *Investment in manufacturing technology,* London, Chapman and Hall.
Reichel, A. (2004). (Re-)Structuration of System Dynamics. In (Eds. M. Kennedy, G.W. Winch, R.S. Langer, J. I Rowe, and J. M. Yanni). *Proceedings of the 22nd International Conference of the Systems Dynamics Society* (CD-ROM proceedings), July 25th – 29th 2004, Oxford, UK. Wiley, UK.
Remenyi D, Money A, Sherwood-Smith M, Irani Z. (2000) *The Effective Measurement and Management of IT Costs and Benefits (2nd Edition),* Butterworth Heinemann/Computer Weekly, UK.
Rhyne, R. (1995). Field Anomaly Relaxation – The Arts of Usage, *Futures,* **27** (6) : 657 - 674.
Ritchey, T. (1997). Scenario Development and Risk Management Using Morphological Field Analysis: Research in Progress. In (Eds. R.D. Galliers, C. Murphy, S.A. Carlsson, C. Loebbecke, H.R. Hansen, R. O'Callaghan). *Proceedings of the 5th European Conference on Information Systems (ECIS'05),* Cork, Republic of Ireland, 1997, Cork Publishing Company, Vol. 3, pp. 1053 - 1059.
Sharif, A.M. (2005). Can Systems Dynamics be effective in modelling dynamic business systems?. *Business Process Management Journal*, **11** (5) : 612 – 615.
Sharif, A.M., and Irani, Z. (1999). Research note : Theoretical Optimisation of IT/IS Investments. *Logistics Information Management,* 12, 2, 189 - 196.
Sharif, A.M., and Irani, Z. (2005). Knowledge Dependencies in Fuzzy Information Systems Evaluation. In (Ed. N. C. Romano, Jr.). *Proc. 11th Americas Conference on Information Systems (AMCIS) 2005*, August 11th – 14th 2005, Omaha, Nebraska, USA, Association for Information Systems, pp.1574 – 1583.
Sharif, A.M., and Irani, Z. (2006). Exploring Fuzzy Cognitive Mapping for IS Evaluation. Forthcoming in *European Journal of Operational Research.*

Simpson, P.K. (1990). Artificial Neural Systems : Foundations, Paradigms and Applications. San Francisco, CA : Mcgraw-Hill.

Small M, H. and Chen, J. (1995), Investment justification of advanced manufacturing technology: An empirical analysis, *Journal of Engineering and Technology Management*, 12, 1 / 2, 27 - 55.

Standish, R. K. (2001), On complexity and emergence, *Complexity International*, **9** (Paper ID: standi09). Available. [on-line]. http://www.complexity.org.au/ci/vol09/standi09/

Sowell, T. (2005). Fuzzy Logic for "Just Plain Folks". Available. [on line]. http://www.fuzzy-logic.com/Ch1.htm. September 2005.

Vroom, V. and Yetton, P. (1973). *Leadership and Decision-Making,* University of Pittsburgh. Press, Pittsburgh.

Walsham, G. (1993). *Interpreting Information Systems in Organisations*. John Wiley and Sons : New York, NY, USA.

Willcocks, L. (1994). Introduction of Capital importance, in Leslie Willcocks (Ed). Information management: the evaluation of Information Systems Investments. London : Chapman and Hall. 1 - 24.

Yin, R.K. (1994). *Case study research: Design and Methods – 2nd Ed*. Sage Publications, Thousand Oaks, USA.

Zadeh L.A. (1965). Fuzzy sets, *Information and Control*, **8** : 338 - 353.

Zwicky, F. (1969). Discovery, Invention, Research - Through the Morphological Approach, Toronto, Canada : The Macmillian Company.