Developing an ABM-driven Decision Support System in the Emergency Services

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Keywords: Decision Support System, Co-evolution, Connectivity, Agent-Based Model, Domestic Fire Risk Behaviour.

Abstract: The research presented here outlines an application of Agent-Based Modelling (ABM) used to support strategic decision-making in the emergency services. Here the resulting ABM-driven Decision Support System (DSS) (called 'Premonition') is designed to help practitioners engage with a complex and dynamic environment of co-evolving fire risk behaviours through time. Social change is presented here as a process by which behaviours co-evolve within connected networks of agents. ABM is identified as a beneficial approach to simulate changing household behaviours and the influence of social networks, environmental factors, and also fire service interventions within the Sheffield City region, UK. This project seeks to develop a DSS which supports the stages of 'intelligence', 'design', and 'choice' as the decision-maker moves from identifying problem areas, establishing possible strategies for intervention, and predicting possible outcomes of alternative courses of action.

1 INTRODUCTION

As public services face budgetary cuts in many European countries, a 'more-for-less' mantra pushes public sector managers to look for greater efficiencies and value added decision-making. This is particularly so with emergency services who are faced with frontline realities on a daily basis. Strategic decision-making in this arena aims to support the protection of some of society's most vulnerable, whilst balancing decreasing budgets. Decision Support Systems (DSS) may be seen as an ever more valuable part of the effective management of resources in this public service context. DSS have gained increasing relevance in business and industry since the 1970s, and particularly with the advent of data warehouses, on-line analytical processing, data mining and the Web in the 1990s. However, this paper focuses on current developments in model-driven DSS as an important support tool for managers to embrace a more dynamic and evolving (co-evolving) problem environment. The paper focusses on Agent-Based Modelling (ABM) as an emerging approach in DSS to help develop decision-makers' understanding of the complex social environments through which they operate.

Understanding and predicting the behaviours of households within a community is an important factor in the planning and operationalisation of activities in public service. For example, an important part of the South Yorkshire Fire and Rescue, UK (SYFR) Integrated Risk Management Plan 2013-17 has involved the exploration of community fire risk. Through the geo-demographic mapping of socio-demographic lifestyle profile data (MOSAIC) the service aims to improve their information provision to the public and fire prevention work. Previous academic studies can support our understanding of community behaviours in relation to fire risk so as to help services work on prevention measures in both a strategic and targeted manner. For example, research has shown that fire risk due to the behaviours of some households differ for particular demographic and socio-economic groups (Smith et al., 2008; Taylor et al., 2012). By using socio-economic factors to classify households into low, medium, and high fire risk groups, preventative measures in the form of information and support may be targeted at those most in need. The expectation therefore is that aggregate risk may be reduced over time in these localities thus reducing the frequency of emergency interventions in those geographic areas.

Dobson, S., Burkitt, M., Breslin, D. and Romano, D.
Developing an ABM-driven Decision Support System in the Emergency Services.
In *Proceedings of the 18th International Conference on Enterprise Information Systems (ICEIS 2016) - Volume 2*, pages 151-157
ISBN: 978-989-758-187-8

Secondly, statistical approaches may be used to carry out detailed historical analyses of changing patterns of behaviour. This enables resource planning and allocation and for decision-makers to anticipate need. This kind of method represents a simple model-driven approach to DSS but it is not without limitations. By classifying households into groups based upon socio-demographic factors there is an assumption that behaviours are static. In this sense, membership is ascribed based on a notion of shared characteristics and therefore fire risk by association is intrinsic. The model does not account for changing behaviours or the influence of one's environment or social connections. Using a linear model for projecting historical data forward to predict future outcomes will again assume a stable (static) problem environment.

This paper outlines research into the development of a practical model-driven DSS for implementation in the emergency services with SYFR. It uses ABM to develop a dynamic understanding of changing behaviours within a community. Whilst the model draws upon socio-demographic and historical data as used in the approaches outlined above, the research also explores the interacting mechanisms which drive behaviour change. As such the authors present a simple framework for modelling social change seen as a process of co-evolution between community networks (Breslin et al., 2015; Dobson et al., 2013). This approach shifts the focus of attention from individual households to the connected and co-evolving sets of behaviours that they represent. To further advance this approach, we have developed an ABM-driven DSS to simulate changing household behaviours within the Sheffield City region. This DSS draws on historical data of fire incidents and direct community interventions undertaken and collated by SYFR over the last 5 years (e.g. home safety checks, fire safety campaigns etc.). The project aims to improve organisational decision-making through the three stages outlined by Simon (1960). These are: a) the 'intelligence' stage of searching for problems (i.e. the identification) by helping to identify areas of risk; b) the 'design' of inventions aimed at reducing risk; and c) 'choice' of a course of action based upon predicted outcomes of interventions (i.e. the exploration of alternatives). As such it is anticipated that the developed DSS will become a valuable tool in optimisation of resource allocation planning of operations as well as community prevention work.

2 DECISION SUPPORT SYSTEMS

Decision Support Systems (DSS) can be defined as "computer-based tools that help users in a problem solving environment to improve their productivity and decision-making ability" (Bayraktar and Hastak 2009, p1357). Since the 1970s DSS have evolved and gained greater prominence in organisational strategic and operational decision-making (Lauria and Duchessi, 2006; Chung et al 2004; Shim et al., 2002; Keenan 1998; Jagielska, 1993; Jensen, 1990). Shim et al (2002) outline that it was Gorry and Scott Morton (1971), whose integration of Anthony's (1965) categories of management activity and Simon's (1960) description of decision types, were perhaps most influential in defining the concept of DSS. For Anthony (1965), management activities involved strategic, management (or tactical), and operational controls; layers of organisational decision-making which are now universal tenets in management thinking. Simon (1960) presented problems for decision-makers as existing on a continuum from 'programmed', which are routine and repetitive problems that are well structured and easily solved, to 'non-programmed'. Non-programmed problems are unique, ill-structured and more difficult to solve, i.e. 'wicked problems' (Rittel and Webber 1973). To represent this continuum Gorry and Scott used the terms 'structured', 'semi-structured', 'unstructured' to develop a framework based upon Simon (1960) incorporating the search for problems (intelligence), the development of alternatives (design), and the analysis of alternatives (choice) (Shim et al 2002).

DSS can be thought of as incorporating a wide range of technics and applications to help decision-makers with the processes of 'intelligence', 'design' and 'choice' such as artificial intelligence, expert systems, database querying and analytical predicative modelling. However, the purpose of DSS is not to provide a direct solution, but simply to add value to any system output when reaching a decision (Bayraktar and Hastak 2009).

From the early 1990s DSS benefitted from emerging developments such as data warehouse, on-line analytical processing (OLAP), data mining, and the Web. Lauria and Duchessi (2006) outline that DSS tends to fall into two main categories comprising of either narrow or broad definitions. The narrower or data-driven definitions include these emerging applications, such as OLAP and data mining, which enabled users to combine numerous databases through explicitly defined ontological relationships so as to enable multiple combinations of data elements for analysis over time. Data was able to be presented in various graphical formats to support decision making. “Data mining applications identify specific, unknown patterns in databases and data warehouses that typical queries cannot reveal” (Ibid 2006, p1574).

Broader, model-driven DSS aimed to expand upon techniques to solve complex and sometimes unstructured problems using quantitative and/or qualitative models. A model-driven DSS comprises of three components (Shim et al., 2002) which integrate, 1) data management/database; 2) model management involving one or more models applied to the problem, and; 3) dialogue management which enables users to change some input variables and initiate database and model management elements of the DSS: “via the dialog module, users interact with a DSS and can perform sensitivity, or “what-if,” analyses to gain more insight into the problem and its potential solutions” (Lauria and Duchessi, 2006, p.1574).

Numerous model-driven methods of DSS have supported the management of risk in decision-making such as Decision Tree Analysis (Apolloni 1998), Cause-Consequence Analysis (De Meaux and Koornneef 2008; Lee et al 2008), Analytic Hierarchy Process (Andreica 2009), Monte Carlo method (Hart 2008; Horstmann 2006) and Bayesian Networks (Xiacong and Ling 2010). The modelling which supports DSS has been subject to much research and Cho (2007) identifies three generic strategies which have shaped development in organisational and decision-making arenas.

Initially reductive and simplistic computational models have aimed to isolate key causal relationships between data (Dodin and Elmaghraby 1985; MacCrimmon and Ryavec 1964). To address the limitations of these approaches, scholars have pursued a second, more computationally intensive, means of increasing predictive accuracy. Cho (2007) identifies broad approaches (which include some of those described above) within this second strategy, these are the one-time update approach; the Markov Chain Monte Carlo (Virto et al 2002), and Bayesian networks. The Bayesian approach (Covaliu and Soyer 1996) involves developing an acyclic network of sequential and causal activities or elements in a model with assigned probabilities. As elements become known through observation within the network, probabilities of outcomes are updated according to Bayesian statistical inference. A third strategy lies between these two ultimately static approaches, which aims to maintain both levels of simplicity whilst also accounting for complex cyclical and dynamic dependencies and interactions of feedback between activities.

DSS in the 21st century is described by scholars as being characterised by collaborative decision-making and collaboration platforms to support increased connectivity and data sharing. Here we see a migration of decisions made by individuals to ones made by diverse groups or even multiple firms (Shim et al 2002). However, as Keen (1987) identified in the late 1980s, there is also a need to explore increases in computing power to extend model-driven DSS to embrace much more fluid, emergent and nuanced picture of the decision environment. Mitroff and Linstone (1993) suggest that this kind of shift would include consideration of much broader organizational and cultural factors than have featured in past DSS. In the work presented here we present DSS in the public service environment as needing to reflect changing and dynamic processes of co-evolving parts within a social system. The emergency services is used here as an example of how a more responsive and dynamic decision-making context can benefit from an ABM-driven DSS approach.

3 AGENT BASED MODELLING

“Agent-based modelling is a computational method that enables a researcher to create, analyse, and experiment with models composed of agents that interact within an environment”. (Gilbert 2008, p2)

Agent-based models (ABM) consist of agents modelled to interact with each other and the environment through a set of predefined rules or heuristics. Agents are broadly defined and are distinct parts of a program representing social entities such as individuals, groups, organisations or wider social, political or economic institutions. Agents may be defined as interacting and responding to physical feedback through movement, as explored through the analysis of swarm behaviour, or as in the case of this research may be purely social entities interacting on a behavioural level. As such, broad ranges of complex adaptive systems have been modelled using ABM frameworks. A Flexible Large-scale Agent Modelling Environment on the Graphics Processing Unit (FLAME GPU) (Richmond et al 2010) has been used for this project. The technology merges the modelling power of ABM with that of 3D graphics. The resulting framework enables very large-scale simulations with a massive number of agents to be processed and visualised in real-time with both 2D and 3D representation of the environment. Examples of FLAME GPU ABM research range from modelling the illegal drug market (Romano et el 2009), to investigating innovative methods for training public service staff working within the community, to a simulated social crowd for the training of CCTV operators to spot malicious behaviours.

3.1 ABM-driven DSS

Given the complex and dynamic nature of decision-making environment through which SYFR operate (due to shifting household behaviours over time) it is suggested here that the co-evolutionary process through which change occurs may be further understood through models. As described above, previous approaches have used models to estimate fire risk which have remained statically defined and therefore unresponsive to change. By extending these methods through the development of an ABM-driven DSS we propose that the dynamics of change are better reflected to the decision-maker. In ABM the changing behaviours of specific households (or 'agents') are modelled computationally. These agents are viewed as interacting heuristically within a network of other households which define the geographic community. The heuristics and agents for the model are broadly outlined in the next section, and also underpinned by literature reported on more fully in a forthcoming publication dedicated solely to the model specification. These include the influence of connections upon household behaviour within a close social network in relation to changing domestic behaviours (i.e. smoking, consumption of alcohol, use of electrical appliances and cooking practices). A target community in South Yorkshire (United Kingdom) was simulated over time through an ABM approach to illustrate the emergence of patterns of behaviour within a complex system of interacting parts. A key advantage of ABM for DSS is that it provides a simulated dynamic environment enabling the decision-maker to carry out 'what-if' experiments which would otherwise be impossible in live scenarios. This helps the decision-maker to develop approaches and design choices which maximise opportunities for positive change.

4 THE MODEL

The purpose of the model is to investigate the impact that different intervention methods are likely to have on fire risk in different areas, based on knowledge about the people who live in the area. Each individual household in the area is explicitly modelled, and includes details about the individual behaviours and fire risk factors of the people living in the household, as well as a representation of their household level social network. The simulation represents a set of different intervention methods, which can be used to predict which interventions are likely to have the most impact under different conditions. Each intervention can have both a direct influence on a household, and an indirect influence via the household's social network.

Data on fire service callouts has been provided for the development of the DSS ranging from 1st April 2009 until 1st December 2014. This contains deliberate, accidental and unknown incidents, both dwelling and non-dwelling. Each record contains detailed information about the incident, along with an Ordnance Survey grid reference.

Data from the Home Safety Check (HSC) reports has also been provided for the period between 2009 and 2015. Each record in the data set contains a street address, date, a single question and corresponding answer. There are 70103 data rows, which correspond to roughly 1589 households, which have one or more repeat checks for different years.

Finally, MOSAIC demographic data containing household level classifications for every household in the area was also used to create the agent-based model of fire-risk behaviours and comprised of 4723 unique records in total for the area.

4.1 State Variables and Scales

Three different agent types have been identified; these agents represent an individual household, fire incidents and interventions.

The **Household** agent represents an individual household within the area. This can be the occupants of an individual house, or a flat within a larger building. The **Household** Agent contains all the parameters that define an individual household in the area. Each household has a unique identifier and a location which determines its physical location in relation to other households. A household also has a set of Risk Markers, which are used to determine the Risk Factor, which is the relative risk that an individual household will have a fire. The Risk Markers are derived using all available information about the households in the area. The Risk Factor fluctuates in response to external influences and the gradually decays over time back to the baseline.

As individual households are influenced by both interventions and the influence of social connections, the **Household** agent maintains an individual social network, which connects it to other households in the area. These relationships are modelled as properties of a **Household**, each with a directionality and weighting, representing the amount of influence that one household has over another.

The households are influenced both directly and indirectly via their relationships by interventions and fire incidents. **Intervention** agents can have different types, representing the range of different interventions that can be performed, such as leafleting campaigns, home safety visits and shock campaigns. An intervention will typically have an area of influence, a strength, representing its effectiveness, and duration, representing how long the influence of the intervention will last. A **FireIncident** agent represents an individual household fire, which could potentially spread to other households, and cause fatalities in one or more households. For historical time periods, fires are based on the actual fire incidents. For future time periods, fires are random, based on statistical analysis of the available data. When a fire occurs, it is assumed that the occupants won't change. However, there will be an initial area effect of reduced risk in the surrounding households. The magnitude and radius of the effect will be related to the incident severity. Changes to the neighbourhood are not modelled, and the households remain the same for the duration of the simulation.

A general systems diagram illustrating the DSS (called 'Premonition') can be seen in figure1. Here the inputs may be regarded as both data and also management decisions. Management decisions comprise of the levels suggested by Anthony (1965). These are operational (planned operational interventions and infrastructure), tactical (performance measures) and strategic (policy and budgetary considerations). The 'Premonition' ABM-driven DSS combines these data and organisational knowledge inputs through a model management and processing component and dialogue management (graphical user interface, GUI). The key output is in the form of GIS mapping presented sequentially with

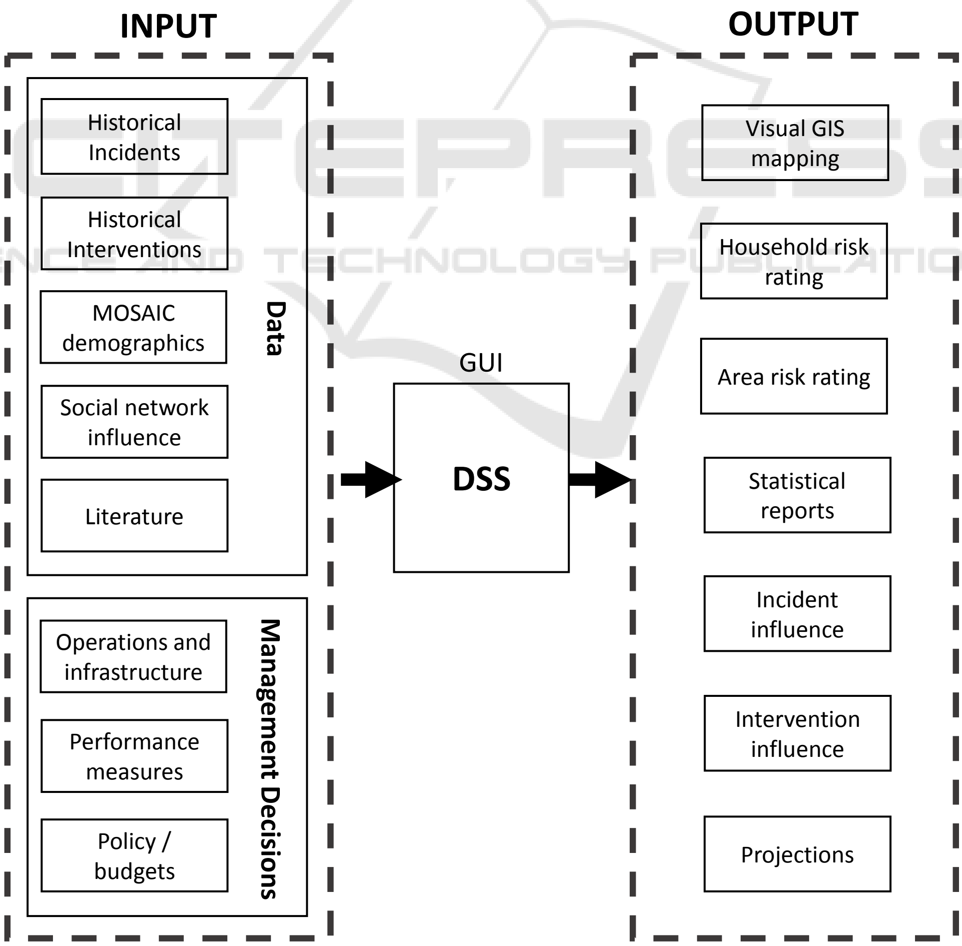

Figure 1: General system diagram for the 'Premonition' ABM-driven DSS.

1 day time steps illustrating incidents, interventions and shifting household fire risk over time.

5 DISCUSSION

This work adds to ongoing research which considers the dynamics of networking processes and the nature of connected behaviours which change and develop over time. As such the resulting model aims to 'embed' the decision-maker in this process to provide a richer and more nuanced picture of the ever changing environment that they are working in. The more cohesive and close-knit the network, the more interpretive heuristics are shared between households (Breslin, 2011; Dobson et al., 2013), and as a result the fewer the opportunities for different interpretations and with this possibilities for variation and innovation. In these close-knit communities, local authorities and service providers need to be closely engaged and embedded in order to affect change. Interventions should therefore be targeted at key thought leaders, and positioned in terms of local issues. On the other hand, in more sparsely connected networks opportunities for change are increased. However, interventions here would tend to be more costly given the difficulty in reaching such diverse groups. In both instances households which are more socially isolated present the greatest challenge.

Validation is key to developing the predictive power of ABM. In a sense the validation process involves comparing and then fine-tuning the model to reflect actual recorded behaviours of households. In this study data will be drawn from three key sources. In the first instance, a generic model of changing fire risk behaviours is constructed drawing from extensive academic and industry-focused research noted above. Second, past research on fire risk behaviours and trends, including both published reports and data obtained by SYFR, is used to adapt the generic model. Finally, region-specific data collated by SYFR is used to fine tune the model. This final process allows both historic data trends and the local experience and expertise of SYFR staff to be incorporated into the model. Once validated, the model can be expanded to include other regions both locally and nationally, to predict changing trends in fire risk behaviours. In addition the model can be further developed to consider other types of household behaviours, for example related to health and social care. In sum, once validated, the co-evolutionary model can be generalised to simulate changes in other household behaviours using the developed understanding on connected social networks.

6 CONCLUSIONS

Understanding and predicting the behaviours of households within a community is an important factor in the planning and operationalisation of activities for the SYFR emergency service. To help support decision-makers in this environment the paper has focussed on the development of an ABM-driven DSS to help develop decision-makers' understanding of the complex social environments through which they operate. Whilst the model has drawn upon socio-demographic and historical data as used in existing approaches, the research has also explored the interacting mechanisms which drive behaviour change. The framework for modelling social change is seen as an ever shifting interaction between agents within a system. Three key agent types have been identified in this study representing individual households, fire incidents, and interventions. The DSS is able to provide decision-makers with an historical view of fire events and interventions in the target area but also model changes in fire risk behaviours. Whilst socio-demographics play an important part in the baseline risk of households, interventions, fire events and the influence of primary and secondary social networks all combine to influence changing fire risk behaviours over time. Using this tool it is anticipated that decision-makers may calculate the modelled aggregate risk for an area and explore 'what-if' scenarios of various possible planned interventions such as targeted information provision and community support.

ACKNOWLEDGEMENTS

The authors would like to thank Steve Chu, Steve Fletcher, Graham Howe, Mick Mason, Nicola Smith, Ian Standeven and colleagues at South Yorkshire Fire & Rescue for help and support in the development of this research.

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