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Human behaviour modelling in complex socio-technical systems – an agent based approach

Habilitation à diriger des recherches de l'Université de Grenoble-Alpes
Discipline : Informatique et mathématiques appliquées

par

Julie Dugdale

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Composition du jury :

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Alexis Drogoul	Directeur de Recherche, Institut de recherche pour le développement
Salima Hassas	Professeur, Université Claude-Bernard Lyon 1

Examinateurs :

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Pascal Salembier	Professeur, Université de Technologie de Troyes

To David and Ben

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Foreword

This manuscript describes my research contributions over the last 14 years and my future research directions. It spans my early works with the Cognitive Engineering Research Team at the IRIT laboratory in Toulouse, through to those conducted in my present position as leader of the MAGMA, Multi-Agents Systems Team, and as an Associate Professor at Université Pierre Mendès France. The route by which I arrived at MAGMA is somewhat diverse, having worked in teams from different disciplines: cognitive ergonomics, human-computer interaction and finally multi-agent systems. These experiences have strongly influenced my approach in analysing human behaviour and in developing agent based models and simulators. The choice to work in such different teams was made consciously and I have actively sought to draw in methods and techniques from other disciplines into my work. The reason for doing so was largely pragmatic; these disciplines brought both a fresh way of looking at common problems and they possessed expertise and skills that were absent or poorly practiced by my original discipline of artificial intelligence. In particular I was largely influenced by research in cognitive engineering and its focus on trying to understand the nuances of human interaction. In trying to promote a multi-disciplinary approach, from which I believe we can all benefit, I have tried to publish in a diversity of domains.

This document follows a roughly chronological description of my main contributions since arriving in France from the UK in 1998. My research work before this time is not covered in this manuscript. The reason for this is that while there are common themes, notably modelling and simulation, there was a transition in the focus of my work when I arrived in France. Although my previous research undoubtedly helped to form my approach[1], I became more interested in cognitive aspects and how to model human behaviours that were more representative of what happens in the real world.

My work on human behaviour modelling is applied to two application domains: crisis and emergency management, and energy management in the home environment. From a scientific point of view these domains offer particular challenges in modelling human behaviours and interactions. In an emergency or crisis situation, the interest is in modelling the extreme cognitive demands placed on humans when working under time-pressure in a highly stressful, emotional and rapidly changing environment. Conversely, in home situations, human behaviours, and in particular our interactions with others, are more subtle; relying heavily on our familiarity with our co-inhabitants. This means that it may be more difficult, from an external point of view, to perceive or understand what motivates our behaviours and interactions. As with a multi-disciplinary approach, working in the diverse domains of crisis management and energy management, is an enriching experience. Not only do we see the contrasts in how human behaviour differs between highly charged and relatively calm environments, but we also see the similarities, such as adaptive and self-organizing behaviours, that are present in both

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[1] In particular, I am referring to my work and supervision of my first PhD student, David Rozier. The topic was the qualitative modelling and simulation of physical systems for diagnosing multiple faults. The work proposed a strategy called MVDS (Multiple Variable Diagnosis Strategy) using a model based approach and employing simulation (Rozier, 1998) (Rozier 2001). The work followed a traditional reductionist approach by attempting to explain how a system functions by describing its component parts. The approach works well when we are dealing with complicated physical systems where the overall behaviour of the system can be determined from understanding how the individual components work. However, it is not appropriate when we try to explain the functioning of a complex system, such as human social systems.

cases. This manuscript describes my investigation into uncovering, modelling, and simulating human behaviours, in these different contextual situations.

Chapter 1 Introduction

The objective of this chapter is to explain my research problem and explain the scientific context of my work. I begin by introducing the main problems in human behaviour modelling. Then I describe the various approaches in tackling these problems, including the agent-based approach that I adopt. Following this, I summarise my contributions and describe how the manuscript has been organized into chapters. In each chapter I provide more detail on my contributions, the associated projects and details of student supervision.

1.1 Human behaviour modelling

For many years we have been striving to understand human behaviour and our interactions with our socio-technological environment. By advancing our knowledge in this area, we have helped the design of new or improved work processes and technologies. Historically, much of the work in analysing social interactions has been conducted within the social sciences. However, the advent of the computer brought an extra tool in trying to understand and model human behaviours. In addition, it also brought the possibility of predicting future situations through computer simulation.

The problem of modelling and simulating human behaviours gives rise to two main issues. Firstly, despite advances in artificial intelligence and in the cognitive sciences, our understanding of human behaviours and the factors that influence decision-making are limited (Sun, 2006). Unfortunately, behavioural processes and mechanisms cannot be understood purely from behavioural experiments (Sun, 2008). Thus computational models provide an essential complement to traditional social science approaches by allowing us to investigate and develop further our theories of social processes (Nowak and Vallacher, 2003).

The second issue in modelling and predicting human behaviours lies in the nature of the socio-technical systems. Human societies are a perfect example of a complex system exhibiting characteristics of self-organisation, adaptability and showing emergent phenomena such as cooperation and robustness. The essential element in understanding the functioning of complex systems is not in understanding how the individual components function, but is in understanding the non-linear interactions that take place between these components. Thus, the heart of complex socio-technical systems is the study of interactions[2] at the microscopic level and how they influence overall macroscopic system behaviours.

In addressing these issues, my work is concerned with the construction of computational models of human behaviour for the purpose of informing design through simulation. Specifically I am interested in modelling interactions and how these affect our decision making in complex work environments. The goal is to understand the interpretive and self-adaptive mechanisms that humans use to deal with problems, and how collective intelligence emerges and is used in problem-solving. Practically my work is used for the purpose of designing new ways of organising work situations or for helping to design new technologies. On a theoretical level my work explores the micro-macro link in complex socio-technical adaptive systems and the idea that seemingly unconscious, unplanned forms of cooperation and interaction, form higher level order.

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[2] That is, human-human interaction, human-technology interaction and human-environment interaction.

Whilst my work contributes in some ways to the domains of cognitive and social sciences, my focus is on addressing the challenges in the computational modelling of human behaviour.

Specifically, I try to address the following research questions:

- On a methodological level how can we develop adequate computational models of interaction that are sufficient to represent human behaviour?
- How do our interactions with each other and with our environment lead the emergence of social intelligence and mutual awareness, which in turn affects our ability to deal with work situations?
- How can our understanding of complex systems be applied to socio-technical systems and how can we engineer system robustness?
- How does context awareness contribute to decision-making in complex social systems and how may this be modelled?

My work is situated on different levels:

- At the theoretical level: by reflecting upon the nature of complex systems and its applicability to socio-technical systems; in particular I address the interrelated notions of robustness and resilience in such systems (Pavard et al. 2006, Dugdale and Pavard 2009, Pavard et al. 2008).
- At the methodological level: by using an interdisciplinary approach in adapting methodologies from the social sciences to the development of computational models (Dugdale and Pavard, 2000; Dugdale et al. 1999, Dugdale et al. 2010, Bellamine Ben-Saoud et al. 2005).
- At the practical design level: by providing designers with computational tools and frameworks that will help them to evaluate and design complex socio-technical systems (Salembier et al. 2009, Kashif et al. 2011, Binh et al. 2010, Dugdale et al. 2004).

1.2 Scientific context and my approach

The problem of modelling and simulating thought processes and behaviours has been addressed from a computational point of view in the domain of artificial intelligence (AI) (Russell and Norvig, 1995). Much of the work in this field concentrated on developing systems that could generate human-like answers, without examining the internal reasoning mechanisms actually used by humans in problem-solving or without studying human behaviours. However, one branch of AI called cognitive simulation, championed by the works of Simon and Newell at Carnegie Mellon University, attempted to formalize human-problem solving skills and simulate human thought processes. In parallel, in cognitive science, significant advances have been made in cognitive simulation with the development of cognitive architectures such as CLARION and ACT-R (Sun, 2007) (Anderson, 1993) (Kjaer-Hansen, 1995). These architectures provide a framework for modelling cognitive phenomena through specifying structures and modules. As such these cognitive psychology oriented architectures focus on the internal structure of human cognition and internal cognitive process independently of external factors. This is problematic since external factors in the environment greatly influence cognitive reasoning and thus human behaviour (Hutchins, 1995). In addition, cognitive architectures do not put sufficient emphasis on sociological aspects, collective actions, and social phenomena that are crucial in modelling human group behaviours. Rather than purely focusing on cognitive architectures, other cognitive simulation tools were developed to help with designing new work environments and tools (Cacciabue and Hollnagel, 1995) (Woods and Roth, 1995). These works concentrated largely on analysing specific problems such as the relationship between cognition and workload, or the modelling and explanation of human errors. Whilst these works contributed significantly to modelling human behaviour in a more realistic way, they were limited in their ability to account for emergent social and collective behaviours.

Another branch, called agent based social simulation, stemmed from distributed AI via multi-agent systems; here the focus was on understanding and modelling social behaviours. Rather than purely focusing on cognition, this approach recognises the social complexity of the artificial society and focuses on how social phenomena, such as cooperation, emerge through human behaviours.

My approach in modelling and simulating human behaviour follows the agent based paradigm. An agent is defined as an autonomous physical or virtual entity that is capable of acting upon and perceiving its environment, it can steer its activity towards achieving goals and it can communicate with other agents within the environment (Ferber, 1995). The use of agents in modelling human systems has several advantages over other approaches (Bonabeau, 2002). Firstly agent based systems are able to capture emergent phenomena that are so representative of complex adaptive systems. Secondly, they provide a natural description of a system, which as Bonabeau notes makes the agent based approach much closer to reality. Finally, they are flexible, allowing us to study social systems at different levels of abstraction by varying the complexity of our agents or by aggregating agents into subgroups.

On a general level, multi-agent systems can be grouped into three categories (Bossier et al. 2004):

1. **Simulation systems,** where the objective is modelling real world phenomena so as to understand or explain their behaviour. These include social, environmental or behavioural simulations.
2. **Resolution systems**, which are concerned with solving problems, as defined in AI, but extended to a distributed context. Thus these systems fall into the area of Distributed Artificial Intelligence (DAI). The objective is to implement a set of techniques for agents, such that they can solve a part of, or the entire problem, effectively and coherently.
3. **Integration systems**, in which agents act on the behalf of humans or users. Such user-centred systems give rise to issues of security and trust. Here, applications include E-commerce and automated buying.

Following Bossier's classification above, my work is situated in the first category of simulation. However, more precisely, it falls within the field of Agent Based Social Simulation (ABSS). ABSS lies at the intersection of three fields: agent-based computing, the social sciences, and computer simulation (Figure 1).

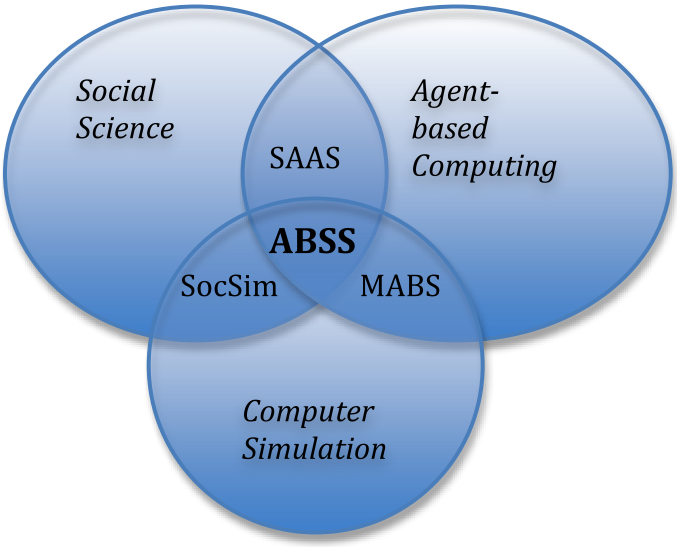

Figure 1: Three areas that constitute ABSS and their interrelationship (Davidsson, 2002)

From figure 1, *Agent-based Computing* can be seen to envelop Boissier's three categories of multi-agent systems as described above.

The second field, *Computer Simulation*, concerns the study of different techniques, e.g. discrete event and systems dynamics, for simulating any phenomena. In the above diagram, computer simulation may include work carried out in areas such as physics and mechanical engineering. The simulation systems referred to in Boisser's work lies at the intersection of 'Computer Simulation' and 'Agent-based Computing' where it is called MABS for Multi Agent Based Simulation. MABS is the use of agent technology for simulating *any* phenomena, not necessarily social phenomena. Agents might represent animals in an ecosystem or vehicles in traffic; so here we find works concerning agent-based traffic simulators and biological models, including Craig Reynolds important work on Flocking models (Reynolds 1987).

The third field, *Social Science*, refers to the set of disciplines, e.g. cognitive ergonomics, social psychology, and human factors, that study interaction among social entities. The intersection between computer simulation and social science, called SocSim for social simulation, concerns the simulation of social phenomena using any simulation technique, not necessarily agent based. SAAS, for social aspects of agent systems, lies at the intersection of agent based computing and social science. SAAS concerns the study, but not necessarily the simulation, of social aspects such as norms, institutions, organisations, co-operation and competition.

ABSS lies at the heart of the diagram and concerns the use of agent technology for simulating social phenomena on a computer. In ABSS, the agents are represented as software entities, which when put together in an artificial environment, form a society of agents, each being able to perceive, move, undertake actions, communicate and transform the local environment, much like human-beings in real society. Thus, in ABSS, the agents typically represent humans or groups of humans. ABSS focuses on the low-level specification of individual entities. This is why, using Epstein and Axtell's terminology, ABSS is described as being a 'bottom-up' approach (Epstein and Axtell, 1996). Or, to use Bonabeau's words, it is the creation of a microscopic model (Bonaneau, 2002). Thus ABSS does not attempt to specify global system behaviour or define a macroscopic model of the situation, but rather focuses on modelling individuals.

One of the earliest agent based models of social phenomena can be traced back to the famous model of segregation in 1971 (Schelling, 1971). Thomas Schelling showed that a small preference for one's neighbours to be of the same colour could lead to total segregation. Although it was not implemented on a computer we clearly recognise this as being an agent based model because it highlights autonomous decision-making and interaction with the environment. ABSS, as we know it today, came to prominence in the mid 1990s (Gilbert and Conte, 1995), (Gilbert and Doran, 1994). One of the major breakthroughs came from the seminal work of Epstein and Axtell with their Sugarscape model. In Sugarscape, agents inhabit a 2-dimensional grid environment where simple local rules determine how agents move around the environment, collecting resources such as 'sugar'. By progressively adding very simple low-level local rules the authors showed how it was possible to create complex artificial societies that exhibit a wealth of social-like behaviours from very simple entities (Epstein and Axtell, 1996).

Since that time, hundreds of agent-based social simulators have been developed. They have been used for predicting future situations, as training tools, for developing and formalizing theories, or for testing new technological designs or new ways of organizing work (Gilbert and Troitzch, 1999). My work is concerned with the last usage, in helping to design new technologies or new ways of organizing our work. Moreover, as a consequence of providing such an aid to design, ABSS can help to increase our understanding of cognitive systems (Woods and Roth, 1995) and cooperative social-technical systems (Amblard and Dugdale, 2011).

1.3 Challenges in the field of agent based social simulation

Despite all of the work in the area of ABSS, many critical challenges remain. One challenge concerns *adopting a good methodology* for designing and developing ABSS. An on-going controversy in ABSS, concerns the fundamental question of how to develop useful models of real-life social situations. Broadly there are two schools of thought. One follows the KISS (Keep It Simple, Stupid) philosophy. Here the aim is to develop simplistic models where much of the real world detail has been abstracted away. So although the topic being investigated is complex, the underlying assumptions should be simple (Axelrod, 1997). Although there are obvious benefits, e.g. in terms of ease of constructing the models, the approach has been widely criticised. The arguments can be reduced to the idea that models that are too simple only address simplistic problems that are not representative of the real world. The other extreme is a KIDS (Keep It Descriptive Stupid) approach (Edmonds and Moss, 2004) where the model is constructed by taking into account the widest possible range of evidence, including anecdotal accounts and expert opinion. The model is simplified only if and when the model and evidence justify this. Here we obtain a much truer representation of reality. However the disadvantages are that it may be very difficult to obtain the data to actually build the model, implementation is more complicated, and validation of the model and simulator are extremely problematic. The issue when simulating fine-grained aspects of human behaviour is to find the right balance between what is included in the model and what social phenomena can be generated. The approach adopted in my work falls in between these two extremes and follows that proposed by Rosaria Conte: "Keep it Simple as Suitable" (Conte, 2000). Here models are abstract enough to achieve an adequate level of generality, but no less complex than what is required by the purpose of the simulation. The original KISS, KIDS, and reformulated KISS approaches provide advice on designing models. However, the advice is very general and somewhat vague, and they lack a complete modelling method. In response, several methods and modelling techniques have been proposed, for example GAIA (Wooldridge et al. 2000), VOWELS (Demazeau, 1995), CoMoMAS (Glaser, 1996), MMTS (Kinny et al. 1996), Unified Approach (Sabas et al. 2002). Whilst these all provide the standard framework for modelling the agent dimension, some taking into account the deliberative behaviour of agents, they are largely intended for developing general multi-agent systems and are not specifically focused on modelling the social elements that are required in ABSS. Furthermore, they fail to provide a structure for analysing human agents in the design phase and for validating the model with respect to the observed human behaviour. It is in this area of developing a methodology that focuses on analysing human behaviours in-situ that I make a contribution.

A second challenge in ABSS concerns *modelling the nature of human interactions and the emergence of mutual knowledge and cooperation*. Interaction between agents is a core element of ABSS. Normally we think of interaction in terms of human communication, as in speech. This is usually modelled as message passing between agents and implemented using some agent communication language (ACL) such as KIF/KQML that is based on speech act theory (Austin, 1962), (Searle 1969). So when an agent receives a message, depending on the content, it invokes a reaction, for example revising its beliefs or performing some action[3]). More recently, the agent based community has looked at extending ACLs to model non-verbal communications, thus trying to replicate more human like interactions. This has been apparent in some works on Affective Relational Agents and Embodied Conversional Agents, which link facial expressions, emotions and verbal production (Rivière et al. 2012). As work in the ABSS domain has progressed, we have deepened our understanding of how collective behaviours emerge from agent interactions. Thus, researchers in the field have addressed such issues as how cooperation and coordination of a collective group emerges through simple local interactions (Doran et al, 1997) (Jennings et al. 1998). This point has been tackled from several perspectives, such as how social norms affect cooperation (Hollander and Wu, 2011) (Boella et al, 2007); the role of coalitions in successful cooperation and coordination (Salazar et al. 2011); and by applying a theoretical framework such as the Prisoner's Dilemma (PD) to study the role of interactions, and the emergence and maintenance of cooperation (Schweitzer et al. 2002) (Nowak and May, 1992). One of the main factors that differentiate these works is whether or not the agents share some mutual knowledge. So for example, in game theoretic approaches (e.g. PD), there is no assumption of mutual knowledge between the agents. Conversely, other approaches, e.g. using social norms, make the assumption that agents are commonly aware of these norms. However, if we are considering the goal of modelling human behaviours, based on real-situations where people are co-located and working towards a common goal, then the mutual knowledge assumption is more realistic. Mutual knowledge is obviously one of the most important underlying mechanisms in supporting coordination, cooperation and decision-making. The challenge here though, is to investigate how it emerges, what hinders its emergence, and how it is used in decision-making. These are questions that I aim to answer in my work.

A third challenge is to investigate ABSS from the point of view of *complex systems characteristics*. Modelling and understanding the main characteristics of complex social systems with agent based systems has been, and continues to be, a central challenge in social simulation (RNSC AEGSTT and MAPS3, 2011[4]) (Gilbert, 1995). Unlike the majority of the man-made engineered systems that behave in a linear or approximately linear fashion, human societies are different. They are complex systems having many non-linear interactions between their components and where the behaviour of the whole system cannot be determined by understanding the behaviour of these component parts. For researchers, the challenge has been to design agent interactions in such a way

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[3] Following speech act theory, all communications are actually treated as actions in an agent based system. Thus, the act of updating a belief is treated in the same way internally by agent as performing some action such as moving in an environment.

[4] RNSC AEGSTT and MAPS3, 2011. Réseau National des Systèmes Complexes. http://rnsc.fr/

that the overall behaviour of the system captures and uses the beneficial properties of complex systems, e.g. emergence and self-organisation, in order to solve a problem (Hassas, 2003) (Gleizes, 2004). Here the focus is largely on analysing the complex system properties of the computational system once it has already been developed. Another approach, and the one that I adopted, was first to identify and analyse these properties in a real social system before moving to the modelling phase. In many ways, this helps to provide a stronger basis for the subsequent modelling stage and facilitates validating the model and simulator. Nevertheless, we can see that these approaches are complementary. This application of complex systems theory to the analysis of real complex social situations forms my first contribution in this area. The second concerns one specific characteristic of complex systems, namely robustness. Robustness is an emergent property of complex systems and, from the point of view of design it is one of the most desirable features that a system can possess. Robustness and resilience are studied in many domains from biology (e.g. swarm intelligence) to safety management (Bonabeau et al. 1999) (Hollnagel et al. 2006). However, the common element in these works is that it is the interaction of agent components that produce an aggregate entity that is more flexible and adaptive than its components which thus leads to reliance and robustness.

The fourth challenge of ABSS that I address in my work concerns the notion of *context awareness for agents*. Context is any information that can be used to characterize the situation of an entity. The ability to reason from context is a crucial element to human interaction and plays a large role in influencing our behaviours. If the same kind of ability can be provided to software agents by making implicit information in the environment available to them, then more realistic behaviours would result. The important point to remember here is that the environment in an agent based model does not only relate to spatial issues and objects around the agent, but it includes other agents. Since most of the information that we use to make decisions in the real world is gained through our interaction with other people then 'social navigation' becomes an important element in context reasoning (Forsberg et al. 1998). Social navigation refers to the "*process of using cues from other people to help you find information and potentially to more fully understand what it is you have found*" (Wexelblat, 2002). The question for ABSS is how can we develop contextually aware artificial agents? The usual approach is to identify and model what we deem as being contextually relevant information. But, is it possible that artificial agents can be contextually intelligent without having to explicitly identify and represent what is contextually relevant information to the agent? It is in this area that I make my first contribution on how to give artificial agents contextual awareness without having to explicitly encoding it into the agent. My second contribution concerns the broader notion of assessing the contextual intelligence of different types of systems. My work focuses here on developing a framework to assess what degree of contextual information is necessary to make informed decisions.

The final point that I address is the tricky problem of linking an ABSS module to simulators that use more traditional underlying simulation models, e.g. mathematical. In some ways this is a culmination of many of previous works since it develops an ABSS that models fine-grained communication between agents, that exhibits complex behaviours, and that reasons with contextual information.

1.4 Contributions and organisation of the manuscript

From the above discussion on the key challenges within the area of ABSS my contributions can be summarized as follows:

- Integrating cognitive engineering and agent based social simulation. This contribution concerns the adaptation of a cognitive engineering methodology to the development of an agent based model and simulator (chapter 2)
- The investigation, through agent based simulation, of the construction of mutual awareness, through cognitive processes such as over-hearing (chapter 2)
- The application of complex systems theory to the analysis of real-life work situations (chapter 3)
- A clarification of the terms robustness, resilience and regulation and their relationship to the engineering of complex socio-technical systems (chapter 3)
- Modelling and reasoning with contextual awareness and non-verbal communication in ABSS. The development of a model of contextual activities to help the design of context-aware technologies in domestic situations (Chapter 4)
- Linking human behaviour models to control systems. The development of a co-simulator environment that couples agent based models of social behaviour with mathematical and stochastic simulation models (chapter 5).

The chapters describe in more detail my contributions to the field of ABSS. The manuscript roughly follows a chronological order, which was chosen in order to preserve the broader research context of what was happening in the field at that time. In addition, the flow of the chapters shows how new research challenges arose from what I was currently investigating.

In **chapter 2** I describe the work that was conducted when I first started in the Cognitive Engineering Research Team (formally called Groupe de Recherche en Ingénierie Cognitive - GRIC) at IRIT, Toulouse. I began working with GRIC in order to investigate the role of cognition and its representation in computational systems. My goal was to integrate the methods and theories used in cognitive science into computational models of human behaviour. It was at this time that there was a surge of interest in Agent Based Modelling. Recognising the potential of this approach in its ability to represent humans, their behaviour and knowledge, I attempted to marry the two disciplines.

This chapter thus describes my *first contribution* of application of a cognitive ergonomics methodology to agent based models. This methodology has been used for designing and developing agent based simulators in the vast majority of my work during the last 14 years, for example in (Bellamine-Ben Saoud et al. 2006), (Dugdale et al. 2006b) and more recently in (Kashif et al. 2011) and (Kashif et al. 2013). As an example of the application of the methodology I describe the development of an agent based simulator of an emergency call centre.

This simulator also covers my *second contribution* to human behaviour modelling. The simulator is described as a representative example of my work since shows how intricate cognitive mechanisms may be practically modelled in an agent based system. In this example I explore the nature of communications between human agents in the call centre and show how cognitive mechanisms such as broadcasting and overhearing contribute to the emergence of mutual awareness in a group of co-located individuals. I then describe how these mechanisms may be modelled and simulated and demonstrate how mutual awareness emerges and the factors that influence this process.

This work was conducted under two European funded projects COTCOS (Cooperative Technologies in Complex Work settings) and the start of the COSI (Complexity in Social Science) project. The work of my PhD student at the time (James Marshall, PhD completed 2002) also supported my contributions. After moving to France, I was remotely co-supervising James Marshall and arranged for him to work for a short period within the GRIC research team. The theme of modelling and simulating communications

is also addressed in more recent work with two PhD students, Parvaneh Sarshar and Sondre Glimsdal, under the SmartRescue project (2012-2015), financed by the Norwegian government. Here the goal is to take into account how new mobile technologies and dedicated crisis social networking applications improve mutual awareness and sense-making.
Related personal publications: (Dugdale et al. 1999), (Dugdale and Pavard, 2000), (Dugdale et al. 2000), (Bellamine-Ben Saoud, et al. 2005), (Dugdale et al. 2006a), (Dugdale et al. 2010), (Granmo et al. 2013)

Chapter 3 details my work in the area of complex systems theory applied to socio-technical systems. Whereas the previous chapter focused on modelling agents themselves, this chapter deals with the complex environment that agents, both human and artificial, operate in. Having first originated within the domains of mathematics and physics, over the last 20 years the theory has been applied to more diverse areas, including natural and living systems. Around the year 2000 researchers started to question if applying the approach could benefit the study of complex socio-technical situations.

The goal was to assess in what ways complex systems theory could overcome some of the weaknesses with current analytical methods and to see if, when coupled with agent based simulation, it could serve as a predictive tool.

My first *contribution* in this area shows how the fundamental concepts in complex systems, such as limited functional decomposability, emergence and self-organisation, can be used to analyse real-life work situations. I then analyse the notions of robustness and resilience, proposing clear definitions of these concepts and making the link between macro level emergent robustness and micro-level behaviours. My work then describes how we can work towards designing robust and resilient socio-technical systems.

It was in this context that I co-wrote an EC project focusing on the application of complex systems theory to social-technical work situations. This project provided the seed for a body of my work on complex systems theory: forming a special interest group on Emergence in 2004; organisation of an ISCRAM 2005 conference track on Complexity, Crisis and Robustness in Crisis Management; participation in the American funded project C2EC2 (Cognitive Complexity and Error in Critical Care) project from 2007-2012; and most recently my involvement with the RNSC (Réseau National des Systèmes Complexes) and the AEGSST (Approache enactive pour la Governance de Systèmes Socio-Techniques) networks.
Related personal publications: (Bellamine-Ben Saoud, et al. 2003), (Pavard and Dugdale, 2006), (Pavard et al. 2006), (Pavard et al. 2008), (Pavard et al. 2009), (Dugdale et al. 2010)

Chapter 4 addresses the importance of context for artificial agents. In real-life, humans are strongly influenced by the social, environmental and historical context in which they find themselves. In order to accurately model human behaviour the influence of context must be examined and incorporated into reasoning mechanisms in computational agents. The problem can be specified more precisely in the following question: How does context awareness contribute to decision-making in complex social systems and how may this be modelled?

My *contributions* in addressing this question have been from two angles:

The first relates to the problem of how to make computational agents contextually intelligent. As such it looks at the current limitations of the classical agent based social simulation approach and the fact that information that is contextually relevant to an agent must be explicitly represented in the model. My work examines what we are losing by having to define contextually relevant information to agents. It poses the question, is it actually necessary to identify and model contextual information; and if it is not, in what other way can we achieve contextually intelligent agents? My contribution looks at how human contextual intelligence can be exploited and integrated into agents by using virtual characters and a technique called participatory simulation.

The second direction of my work on context delves more into what context means in terms of human decision-making. My contribution in this area is in developing a modelling framework for contextual activities. With this basis, I then look at how this model can be used to help in the design of ambient technologies by employing simulation. The aim of this work is to assess exactly what degree of contextual information is necessary to make informed decisions and how it affects human behaviour.

The context for these works was initially the COSI European funded project and a French nationally funded NETCRISE project. Later the work was funded by EDF through the In-Situ project. My research was conducted in collaboration with two PhD students, Nico Pallamin and Mehdi El Jed. Although I was not a formal supervisor we worked together closely and published several articles as a result (El Jed et al. 2004) (Dugdale et al. 2004) (Darcy et al. 2003) (Darcy et al. 2002) (Dugdale et al. 2006b). In addition, my informal supervision of Yves Demazeau's student, Laurent Lacomme, at MAGMA for 1 year in the area of how context is used in human creativity also contributed in a general way to my work on context.
Related Personal Publications: (Darcy et al. 2002), (Darcy et al. 2003), (El Jed et al. 2004), (Pavard and Dugdale 2002), (Dugdale et al. 2004), (Dugdale et al. 2006b), (Salembier et al. 2009), (Dugdale et al. 2010), (Lacomme et al. 2010).

Chapter 5 Using agent based social simulation has proved to be a useful tool in designing new technologies and work practices, particularly in the areas of crisis and emergency management. However, it has been used predominately as a stand-alone tool. The challenge of linking social simulators to traditional simulators and control systems has rarely been addressed. The focus of this chapter is a body of work that addresses the issues of developing intelligent control systems by linking agent based simulators of human behaviour to simulators based on mathematical modelling of physical phenomena. Although my future works will look towards using this approach in crisis management, the application domain described in this chapter is energy management in home situations. This integration between different types of simulators departs from the traditional approach to buildings simulation, which normally addresses only the interaction between thermal, electrical and external environmental factors.

Incorporating realistic models of human behaviour into traditional control systems represents a huge challenge: in defining accurate models, in showing the impact of human behaviour on control systems and, on a practical level, in managing the integration of human behavioural models with physical models that are normally used to simulate and control systems. The *contribution* of this work is in showing how empirically based models of human behaviour can be successfully integrated with more traditional physically based simulation approaches. This is an important step since in the simulation community these two disparate approaches are rarely combined. What this gives us is a more powerful tool to model a wider variety of situations with each approach playing on its own strengths.

The work is conducted in the context of several projects and collaborations; the ANR funded SuperBat (Simulation Tools for Energy Management in Buildings from 2010 to 2014), the BQR Grenoble INP "Energie" project (2008-2011) and the Grenoble INP funded "SmartEnergie" project. In terms of student involvement, 3 of my Masters students and my current PhD student, Ayesha Kashif, have or are currently working on this subject.
Related personal publications: (Costa et al. 2009), (Binh Le et al. 2010) (Kashif et al. 2011), (Kashif et al. 2012), (Kashif et al. 2013).

Chapter 6 concludes the manuscript by first returning to my original research questions posed in the introduction and reflecting upon how my work has contributed to the domain of ABSS and the construction of computational models of human behaviour. I then discuss my vision of the future challenges in ABSS and based on this reflection I describe my research directions in both the short and long term. These directions are supported by newly funded projects, further collaborations, and the inscription of three new PhD students.

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Chapter 2 Human behaviour modelling

2.1 Introduction

The human behaviour that we observe in our social world reflects a web of interactions. Macro-level social phenomena, such as cooperation and coordination, emerge from and influence the micro-level interactions of individuals. Understanding and modelling these dynamics in an agent based system presents challenges at the methodological level (what is the most suitable approach to capture human interactions) and at the representational level (how can we represent the underlying mechanisms that support communications and how do they contribute to emergent phenomena). These are the two challenges that I address in this chapter.

The first contribution deals with how a cognitive engineering methodology may be adapted to the development of agent based models. This methodology has been used for designing and developing agent based simulators in the vast majority of my work during the last 15 years, for example in (Bellamine-Ben Saoud et al. 2006), (Dugdale et al. 2006b) and more recently in (Kashif et al. 2011) and (Kashif et al. 2013).

As an example of the application of the methodology I describe the development of an agent based simulator of an emergency call centre. This simulator also covers my second contribution to human behaviour modelling, which is investigating how the emergence of group mutual awareness arises from cognitive mechanisms such as broadcasting and overhearing.

This chapter is organised as follows. Section 2.2 begins by explaining the context of the work, namely the European funded COTCOS project. Section 2.3 describes the methodology that I use to design and develop agent based simulators. I first discuss the theoretical underpinnings of a cognitive engineering methodology and then show how it can be adapted to ABSS. The application of the methodology is described in section 2.4 by focusing on one of my works in particular – an agent based simulator for an emergency call centre. Here I explore the nature of communications between human agents in the call centre and show how communication mechanisms such as broadcasting and overhearing contribute to the emergence of mutual awareness in a group of co-located individuals. I then describe how these mechanisms may be modelled and simulated. Section 2.5 concludes this chapter by providing some general reflexions and perspectives about the work undertaken during this period.

2.2 Scientific and technological Context

The context for this body of work was the COTCOS (Cooperative Technologies for Complex Work Settings) European funded project that ran from 1996 to 2000. Broadly, the goal of the work was to develop well-grounded technologies and work-practices for supporting people in work situations. In this respect it was very close to the aims and ideals of works in the CSCW (Computer Supported Cooperative Work) domain. Indeed COTCOS was grounded in and heavily influenced by research in CSCW. Like CSCW, which adopts a multi-disciplinary approach, COTCOS brought together researchers from psychology, computer science, design interaction and cognitive science. The three main objectives of COTCOS were:

1. To overcome the limitations of existing single theoretical disciplinary approaches by advancing inter and transdisciplinary theoretical frameworks and methodologies.

2. To interrelate theories and methodologies for the design and assessment of systems for collaborative working in complex environment.
3. To answer industrial needs by looking at adequate information supports for working and learning environments.

The work of COTCOS drew upon several theoretical approaches including activity theory, distributed cognition, ethnomethodology and cognitive ergonomics. These provided frameworks for studying interaction and cooperation within the workplace. Alongside these theories, distributed artificial intelligence (DAI), and in particular multi-agent systems (MAS), was used as a computational approach to model cooperation. However instead of adopting an engineering science perspective that focused on the architecture design of MAS for distributed decision-making, a *natural system approach* to DAI was adopted. This emphasized understanding the collective activity of a group of people by bringing to the forefront the cognitive factors that underlie the communication process (Salembier and Ashtiani, 2000). Thus human organizational systems were studied in the light of the relationships, strategies and representations that people use for cooperating and coordinating their activities.

It was in this context that I arrived in the GRIC Team (Groupe de Recherche en Ingénierie Cognitive) at IRIT in 1998. By drawing upon the methods and theories used in cognitive science I aimed to make computational models of human behaviour that were more realistic representations of what happens in real social situations.

At this time computational approaches in studying and modelling human behaviour were mainly addressed through developing cognitive architectures or cognitive simulations (Anderson, 1993), (Cacciabue and Hollnagel, 1995), (Woods and Roth, 1995). However these approaches did not specifically address emergent social phenomena that resulted from micro-level interactions between humans and their environment. Conversely, works within the domain of CSCW looked specifically at these interactions and argued that the systemic concept of complexity and emergence dynamics were indispensable in studying the human cooperative behaviours (Schmidt, 2002b). However, in terms of providing computational tools, CSCW largely focused on designing technologies that could directly support the cooperative work of humans. It did not look at providing tools to help designers develop the technologies and work practices. These two approaches are at different levels: one working to design tools for the end-users themselves; the other, working to provide tools for designers, that would in turn help them to design tools for end-users. It is this second point that I aimed to address within the context of the COTCOS project by using ABSS. However, the traditional methodology used to develop ABSS lacked sufficient emphasis on analysing real human behaviours. On the other hand, the social science approaches used in COTCOS, and in particular those from cognitive ergonomics, provided a good framework for analysing human behaviours. The vision of constructing realistic computational models of human behaviour for the purpose of informing design through simulation was well supported by the objectives of the COTCOS project: coupling a cognitive ergonomics methodology with an agent-based approach (objective 1) and using the result to assess and redesign collaborative work in emergency and crisis situations (objective 2).

The following section describes how a cognitive engineering methodology has been adapted to ABSS. It begins with a discussion of the theoretical grounding of Francophone Cognitive ergonomics since the methodology draws heavily on these aspects. The cognitive engineering methodology is then described, followed by a description of how it was adapted to ABSS.

2.3 A Cognitive engineering methodology applied to ABSS

2.3.1 Theoretical foundations of Francophone cognitive ergonomics

The domain of cognitive engineering originates from the work of Norman who used the term to describe "*the science of user-centred design*" with the aim of "*understanding the fundamental principles behind human action and performance that are relevant for the engineering principles of design*" (Norman, 1986). Whilst cognitive engineering is a recognized scientific domain, Francophone Cognitive Ergonomics (FCE) has emerged as a specific approach in cognitive analysis that focuses specifically on the situated nature of human behaviour. The underlying premise of FCE is that the characteristics of the situation in which people are working are quintessential for understanding and modelling these people's situations (Leduc, 2011) (Visser, 1996). This focus on the environment and on the interactions that occur within it make FCE a particularly good approach for modelling human behaviour in complex socio-technical environments.

In addition to trying to understand cognition, its limits and the strategies that people employ in work situations, FCE draws upon other schools to influence its methodological approach (Pavard, 1998). One of these schools is Distributed Cognition. Here FCE, takes the idea that artefacts play a primordial role in cognitive activity because they structure cognitive and communicative processes and are used as tools for cooperation (Hutchins, 1990) (Benchekroun, et al. 1995). However, perhaps the biggest idiosyncrasy of FCE is that it makes a clear distinction between task and activity. Tasks are the normative accounts of work that people are requested or supposed to perform, whereas activities are the actual practices that people do in accomplishing their work. It is here that FCE gives its own interpretation to the notion of situated cognition (Theureau, 2004). The meaning is that the characteristics of the setting in which people are working are indispensible for a true understanding and modelling of human behaviour and work situations (Visser, 1996). Since activity analysis can only be uncovered by field studies (de Montmollin, 1991), FCE places a huge emphasis in its methodology of conducting field studies. For this it draws heavily on ethnomethodological practice, conducting a fine grained analysis of, not only what is said and done in the work environment, but what meaning is hidden behind the discourse or micro action (Garfinkel, 1967) (Bolzoni and Heath, 1997). Thus, interactions are closely examined, that is, interactions between actors, interactions between actors and artefacts, and interactions between actors and their work setting. Another theoretical framework that influences FCE is Relevance Theory (Sperber and Wilson, 1986). Here the notions of a mutual cognitive environment and broadcasted information are used to analyse the spoken dialogue between workers.

The above concepts are crucial points to consider when modelling human behaviour and provide the basis for the FCE cognitive engineering methodology described below.

2.3.2 Cognitive engineering methodology

The following methodology is widely adopted by the French cognitive engineering community and has been used to aid the design of many complex cooperative systems in domains such as air-traffic control (Benchekroun, et al. 1995), (Zorola-Villareal, et al. 1995), and off-shore deep sea diving (Pavard and Marchand, 1999). The goal of the methodology is to define functional specifications starting from a field analysis and a formal definition of the relationship between cooperatives processes and artefact characteristics. The methodology is composed of 5 steps:

Step 1. Task Analysis

Following the French ergonomic tradition, a clear distinction is made between tasks and activities. Task analysis documents the prescribed work (i.e. how the work is officially supposed to be conducted) whereas activity analysis (the second step of the methodology) documents how the work was actually performed. This distinction is extremely important since it is useful to know under what conditions people diverge from the prescribed way of working. Specifically task analysis aims at describing and understanding each specific task, what the management expects of the workers, how the management expects workers to perform the task, which tools and external supports are supposed to be used, how the tasks should be distributed amongst the workers, and what communications should be expressed and indeed how they should be expressed. In order to perform task analysis data is typically collected through interviews with management, who are responsible for the work organisation, and with workers. Documents, such as procedure manuals are also examined.

Step 2. Activity Analysis

Activity analysis determines how work is actually performed in the real work setting. Activity analysis is achieved through field analysis and allows observers to identify not only those actions related to the prescribed work, but also explicit (additional and known) or implicit (unconsciously performed) 'side' activities. Of particular interest is how people regulate or adapt their work when confronted with an overload (degraded) work situation. Traditional ergonomics does not usually place constraints on what to observe, but this methodology focuses on degraded situations, in addition to looking at 'micro-incidents' (Bressolle, et al. 1996) since ultimately these are the ones that are targeted for improvement. Activity analysis is typically performed through observation, from examining video and audio recordings of workers 'in action'.

Step 3. Formal Modelling of Regulation Mechanisms

This step deals with modelling the regulation mechanisms that people use to handle their work situation. The main unit of analysis is a scenario, which is a formal description of brief sequences of activities, lasting from a few seconds to few minutes. Scenarios are specially selected to show good examples of regulation mechanisms in either normal or degraded situations. An adapted version of speech act theory is used to encode and formalise the pragmatic rules of communications (Benchekroun, 1992). It is at this step that the actors beliefs and intentions are often represented. Graphical representations are frequently used to detail the interactions and cooperation between actors in the scenario and to show how environmental artefacts are used.

Step 4. Derive functional Specification

Based on an understanding of the regulation mechanisms used in nominal and degraded situations, new tools or work procedures are defined that aim to postpone the process of degraded cooperation. A *hand-based simulation* of what the scenario would become in a new situation, with new tools or ways of working, is then performed. This is done by modifying the communication rules in order to take into account the new working environment. Thus with the same input (e.g. external events, the intentions behind the communications) it is possible to visualize what would happen to the initial scenarios. A functional specification of the new cooperative tool is then developed in collaboration with stakeholders.

Step 5. Prototype and testing

The functional specifications are tested via prototype or mock-up. Stakeholders are again involved so that they may test the tool according to their own personal practices. In essence this may also serve to uncover ways of working that were not apparent during the activity analysis phase.

Several observations can be made regarding this methodology and its applicability to human behaviour modelling in ABSS. The methodology provides a solid framework to conduct a thorough analysis of the human interactions in the real world. A particular weakness of many ABSS is that the assumptions behind human behaviour that are used in the agent model are often lost, which are due in part to the weak methodological approach in ABSS (O'Sullivan and Mordechai, 2000) (Richiardi, et al. 2006). The benefit of the above methodology is that it explicitly highlights critical aspects of human behaviours, such as communication and cooperation, the role of artefacts, and actors interactions, etc. These elements epitomise the situatedness of work and are crucial to the development of agent based models of social situations. Whilst some of these aspects, such as actor interaction, are considered in current MAS methodologies, they tend to be addressed in the model design phase, with little attention being given to performing a rigorous analysis of the real-world situation. The cognitive engineering methodology also brings the advantage that it focuses on providing a solid corpus of empirical data through video recordings and observations, etc. This data is invaluable for agent-based model and simulator validation. Indeed one of the most often-mentioned problems with ABSS is the difficulty in validating the model and simulator (Dugdale, et al. 2010), (Midgley et al. 2007).

Whilst the strength of the methodology lies in its rigorous analysis of real social behaviours, its weakness lies in simulating the envisaged or desired situation. Here simulation is often done by hand or by computationally simulating only the communication; many of the other behavioural aspects are activities are left out of the computer simulation. The added benefit that ABSS can bring is in easing the simulation process and in increasing the breadth of simulated human behaviours.

2.3.3 Cognitive Engineering methodology for ABSS

Before explaining how the FCE approach may be integrated into an ABSS methodology, we start with a short description of how ABSS are usually developed (Edmonds 2001). Shown below in figure 2 is a typical methodology for developing an ABSS.

Abstraction Abstraction of the target system and development of the conceptual model incorporating the relevant aspects of the target system relevant to the study.
Design Formalization of the abstraction developed in the previous step in accordance to some theoretical framework(s) chosen and consequent development of the computer model.
Inference Execution of the model and exploration of the results.
Analysis Analysis/Interpretation of the results obtained during previous inference step; enhancement/clarification of model understanding.
Conclusion Round up with discussion of possible inferences about the investigated target system from the analysis of the simulation.

Figure 2: A commonly used ABSS methodology as proposed by Edmonds (Edmonds, 2001)

As can be seen above the development process starts with an abstraction phase where relevant aspects of the real-world system are identified. However, as noted by Edmonds and other authors, in practice this stage often receives little attention, possibly due to the lack of accessible methods for ABSS developers in analysing real world human behaviours. Thus the focus on analysing situated behaviour as a first step in model development is often given only cursory attention. It is here that the cognitive engineering methodology could be used to reinforce the abstraction phase of the ABSS methodology by exploiting its strength in analysing situated human behaviours.

Another interesting observation about the standard ABSS methodology is its lack of focus on validation, both of the model and of the simulator. ABSS have frequently been criticised for conducting only a cursory validation or, worse still, for not conducting any validation at all (Bharathy and Silverman, 2010) (Edmonds and Chattoe, 2005) (Midgley et al. 2007). Conducting a thorough validation is difficulty. As Gilbert states "*to validate a model completely, it is necessary to confirm that both the macro-level relationships are as expected and the micro level behaviors are adequate representations of the actors' activity*" (Gilbert, 2004). This requires ensuring that any emergent phenomena observed in the simulation are in line with what has been observed in the real situation, and also that the individual agent behaviours in the model truly reflect real human behaviours. The implication for a revised ABSS methodology is to place a greater stress on validation, making this phase explicit, and to ensure that an in-depth analysis of the real situation is conducted and sufficient data is collected.

Finally, and perhaps what is most striking, is the sequential nature of the process. The idea of returning to a previous step is not explicitly stated. This underestimates a common situation during the design phase when it is necessary to revisit the abstraction phase in order to reformulate a concept in the real situation.

Given these observations, an adapted methodology was designed that puts validation at the heart of the process, which reinforces iteration, and that extends the abstraction phase by focusing on analysing human behaviour in the real world situation (figure 3).

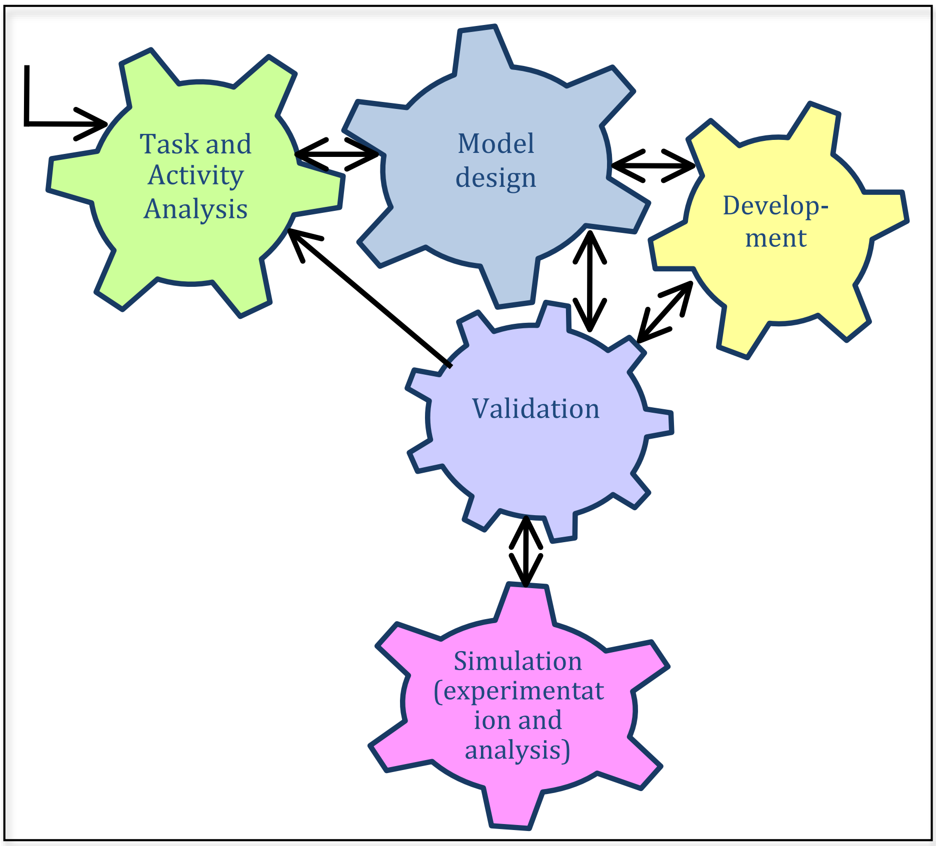

Figure 3: Adapted ABSS Methodology

The first step, Analysis, expands the Abstraction phase of Edmonds methodology by incorporating the task and activity analysis of the cognitive engineering methodology. The second step, Model Development covers Edmonds Design phase. In the cognitive engineering methodology, developing the formal model included representing the actors' beliefs and intentions. This aim can be realised in the revised methodology by employing the BDI (Belief, Desire, Intention) architecture (Bratman, 1987). Given the problem of ensuring that the model and simulator are an accurate representation of the real world, validation has been put at the heart of the methodology. Here it plays a central role in both validating the model and the developed simulator through using data obtained via field studies in the analysis phase. As in the Analysis phase, the Validation phase actively involves end-users and stakeholders. The final step, Simulation, covers experimentation and relates to the Analysis and Conclusion phases in Edmonds methodology. The bi-directional arrows and link from the validation phase to the analysis, ensure that iteration plays a major role.

The adapted methodology has been used in my works spanning several projects over the last 15 years, including the development of an ABSS for an emergency call centre (described below in section 2.4). This following section also describes my second contribution to human behaviour modelling in ABSS. This concerns investigating how mutual awareness emerges through human interactions involving cognitive mechanisms such as broadcasting and overhearing.

2.4 Communication and mutual awareness

This section describes modelling communication and the evolution of mutual awareness amongst members of a physically co-located team. The simulator was developed following the methodology described above and implemented by my PhD student, James Marshall, who was invited to work at IRIT as part of his PhD studies.

2.4.1 The role of mutual awareness

Efficient cooperation and coordination of work activities depend on a set of key dynamically interacting processes that lie at the heart of social behaviours. In work situations, members of the group are consciously aware of the activities and presence of their colleagues. Members of a work collective are constantly switching their attention to different aspects depending on what they have to do at a given time, in a given situation, and what they perceive as being relevant to their work. Mutual awareness is possible by observing or listening to what other people are doing. Artefacts or tools in the environment also play a role in supporting mutual awareness since they allow participants to understand and make sense of other people's actions and possibly to recognise their intentions. People combine the information provided by artefacts, what they hear or see, and their own knowledge of the situation in order to infer other participants' intentional states, such as their beliefs, desires or intentions. Communication between participants is the keystone that facilitates the process of mutual awareness. Communication allows participants to broadcast information about their activities, their intentional states, or other events. It helps a person to draw the other participants' attention to relevant events or to highlight any possible problems. Communication may be synchronous or asynchronous, verbal or non-verbal, or intended for one (mono-addressed) or several (pluri-addressed by broadcasting) recipients.

The result of mutual awareness is mutual knowledge[5]. This is knowledge that communicating participants share, and that they know they share (Krauss and Fusssel, 1990). Mutual awareness and the emergence of mutual knowledge plays such an integral role in coordinating actions and in collaborative decision making that having group members co-located in the same physical space is frequently chosen as the working configuration in many control rooms (e.g. Air Traffic Control, Space Mission Control, and Emergency Call Centres). Thus information can be exchanged and easily shared with the minimal perturbation of individuals' cognitive processes. This information sharing facilitates the emergence of mutual knowledge and can result in exceptional system robustness (Rognin et al, 1998) (Crampton, 2001). Unfortunately though, because of the fragile nature of the underlying processes, this situation is not guaranteed and under certain circumstances mutual knowledge fails to emerge and the system's efficiency rapidly deteriorates.

2.4.2 Modelling and simulating awareness

The objective of my contribution here was to investigate the emergence of mutual knowledge though ABSS and to try to model the human behaviours that underpin this crucial process. Although the concept of mutual awareness has been extensively studied in domains such as in cognitive ergonomics, organisational science, and ethnomethodology, there are very few works that deal with modelling and simulating this process. Through agent based simulation we hoped to understand more about the process of mutual awareness, how it is constructed and what factors lead to its decline. The work concerned modelling and simulating the communications and activities of

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[5] Mutual Awareness is a subset of the broader notion of situation awareness (Poizat et al, 2009). Note also that the notion of mutual awareness in complex work settings has been further extended with the work of Salembier and Zouinar who define 'shared context' as being a set of information items or contextual events that is mutually manifest to individuals at a given time and in a given situation. In this respect, what I refer to as being mutual knowledge loosely aligns to the shared context definition of Salembier and Zouinar (Salembier and Zouinar, 2004)

members of an emergency call centre (SAMU 15-18) in the south of Paris. The practical goal of the work was to help in a physical redesign and layout of the call centre since it was relocating to another building.

The emergency call centre serves about 1 million people. Its role is to dispatch fire-engines or ambulances, notify the on-call doctor and give medical advice over the telephone. The centre is composed of different types of workers, e.g. firemen, medical doctors and nurses. From an initial call, the health worker must assess the nature of the incident and decide on the most appropriate course of action. This process involves cooperation and communication with other team members who may communicate either directly (face to face), via artefacts (e.g. telephone), or non-verbally. To reduce the time taken to deal with an emergency incident, all of the health workers must try to be aware of ongoing events, that it they must develop a mutual awareness of the situation. Numerous factors affect the task of call management such as decision making under time constraints and the management of resources. The number of calls to the emergency centre was increasing and with this the efficiency of the centre, in terms of the time taken to deal with incidents and the efficient use of resources, etc. dropped.

The agent based model had to take into account not only the explicit tasks performed by the health workers (e.g. dispatching vehicles and creating and updating written reports), but it had to model cognitive and environmental factors (such as a health worker's ability to overhear a conversation, to remember which health worker is dealing with a particular incident and to model the dynamic level of noise in the room, etc.). We were interested in analysing what happens during an overload situation when the centre is inundated with emergency calls. In particular, the analysis step of the methodology focused on assessing the relationships between the following factors: the level of mutual awareness, environmental factors (such as noise level and spatial positioning of the health workers) and the ability to overhear. In addition, we wanted to assess how these factors affected the time to deal with emergency incidents and what changes occurred in cooperation and communication strategies.

The activity analysis step of the methodology examined the cooperation and communication processes of the health workers and found that the efficiency of the centre was heavily linked to the concept of mutual awareness. Indeed the role of mutual awareness in cooperative situations has, for many years, been well documented in the literature (Schmidt, 2002a) (Pavard et al. 1990) (Pauchet, et al. 2007). For the centre to be efficient, each health worker needs to be aware of ongoing events. In this way, if subsequent callers telephone the centre to report an incident that is already being handled then the health worker does not have to open a new incident dossier and can just inform the caller that the incident is already being dealt with.

Despite good technological supports for sharing information in the emergency centre, in normal situations the health workers update their mutual awareness through overhearing. Overhearing conversations can lead a worker to pre-empt a request from another work thus saving time. However, the overhearing process becomes less efficient when the workload increases and this results in a fall in the level of mutual awareness.

The ability to overhear is influenced by several factors: the first and most obvious factor is distance. If people are spatially close, they are more likely to hear what is being said. However, even if two people are very close, they will not be able to hear each other if the general level of noise in the room is high. Thus, the level of noise in the room is the second factor affecting the ability to overhear. From the activity analysis, we observed that when the centre is extremely noisy, people sitting next to each other would actually use the telephone to converse, rather than attempt a face to face conversation.

The third factor is the intensity with which a person is speaking. Even if two people are far away from each other, a person still might be able to overhear their conversation if they shout.

The final factor is a person's level of involvement with a task. If a person is dealing with an urgent problem, requiring full concentration, he will tend to 'shut off' from the outside world and not hear things that he would otherwise hear.

Interruptions are another important factor in communications. If a member of the team needs some information from someone who is busy then they have two options; to wait until the person is available, or to interrupt them. Activity analysis revealed that the decision to interrupt is based on the urgency of the calls of both the person wanting to interrupt and the person who could be interrupted. However, the interrupting person must try to establish if her call is more urgent than the task that is being handled by the other person. This requires modelling the beliefs that an agent holds about other agents in the environment. If it is more urgent, she will interrupt, making the other person put on hold his current caller until the query is dealt with. After the conversation, the person who is interrupted will resume his original conversation.

Communications must also address the problem of indirection. For example, reports from vehicles at the scene of an accident are transmitted back to the centre via a loudspeaker. Relating this report to the person responsible for sending the vehicle is of utmost importance. However, due to the level of noise, the person responsible cannot always hear the in-coming report and so the people sitting closest to the loudspeaker must relate the information. This can only happen if they know who is dealing with the problem (mutual awareness). If they don't then they must contact each person, interrupting them if necessary. The fact that the reports are not directed to the person dealing with the incident is a problem of indirection, which can lead to inefficiency (in terms of the time taken to deal with a communication).

From the analysis it was clear that the distance between people, the intensity of speech, the general noise level, the level of mutual awareness, the ability to overhear, the involvement a person has with a task, and the choice of interrupting, affect communication and cooperation. The next section explains how these behaviours and environmental factors have been modelled using an agent based approach.

2.4.2.1 Agent model

This section concentrates on how human behaviours have been represented in the agents. 'Inanimate' agents, such as vehicles and reports, are also part of the system but are not described here.

The ability to overhear is essential for establishing mutual awareness. Overhearing is a function of distance, general level of noise, intensity of speech and a person's involvement with their current task. The distance between the agents is a function of their physical position in the room, thus each agent is assigned x, y coordinates, allowing distances between agents to be calculated. The second parameter affecting the ability to hear is the general level of noise. However, noise is essentially an attribute of the environment, not of an agent. Thus, the level of noise will be discussed later. The third parameter is the intensity of speech. Activity analysis allowed us to identify that the health workers were ostensibly coding the urgency of their communication by increasing their illocutory force. Thus, an urgent call would be associated with a louder speech act. In the model, the intensity of speech of a communication is related to the seriousness of the incident. Since seriousness is considered an attribute of an emergency incident, we again defer our discussion of its representation until later. The final parameter affecting the ability to hear is a person's involvement with a task; the more involved a person is with his task, the less likely he is to overhear a conversation. Thus, an agent's involvement is modelled by assigning a level of busyness to an agent. Since this level is dynamic, it needs to be updated when a person becomes involved with, or finishes, a task.

Every time a communication occurs in the simulation between any of the health worker agents, every health worker's ability to overhear the conversation is calculated. Thus, for each time step, we calculate whom each health worker can hear. Overhearing plays an important role in mutual awareness. If a health worker overhears a conversation, it is assumed that it then knows about the incident, and thus details of the incident are added to the agent's belief set. Thus, each health worker agent keeps a record of all the incidents that it knows about. We calculate mutual awareness as the 'common set' of knowledge that a group of worker agent has about some incidents. Mutual awareness is dynamic, since information about the incidents is constantly being added to each health worker's belief list. Mutual awareness is therefore calculated at every time step of the simulation. In addition, an agent can search its own belief set for knowledge about a particular incident.

In the call centre, as in many other domains, communication often involves knowing when, or when not, to interrupt another agent. This decision is based upon the communication and the busyness of the agent who is to be interrupted. An agent's busyness is an attribute, determined by the seriousness of the incident currently being undertaken. The decision to interrupt is represented as described in (Benchekroun, 1992) by a two-dimensional grid, with seriousness of communication on one axis and the busyness of the agent who is to be interrupted on the other axis. Thus, agent A can interrupt agent B if the subject of the communication is serious and agent B is not busy. Conversely, if the subject of the communication is not serious and agent B is busy, then agent A will wait and not interrupt agent B. Waiting for an agent to become available or contacting another agent incurs a time delay. Thus each agent has an attribute that takes care of time delays in the simulation.

Activities that reflect the everyday responsibilities of the different health workers are also modelled. Depending on whether the health worker is a fireman, nurse, physician, etc. methods such as: take incoming phone call, create dossier, update dossier, relate report, dispatch vehicle, etc., are given to the agent.

2.4.2.2 Environment model

The emergency centre is an open system where agents (health workers) interact with their environment. The environment is modelled as an object. The main characteristic of the environment that affects communication and coordination is noise. The level of noise is principally a function of the number of people speaking in the room and the intensity with which they are speaking. The number of people in the room may be easily calculated and the intensity of speech is related to the seriousness of the emergency incident. In addition each emergency incident is modelled as a separate object with an associated seriousness as one of its attributes. We use the following formula, adapted from (Harris, 1979) to calculate the noise level:

$$60 + \sum_{i=1}^{n} 10 \log_{10}(NW_i \times U_i)$$

Where n is the number of incidents, NW_i is the number of workers dealing with incident i, U_i is the urgency of incident i.

The noise level being dynamic is calculated prior to any communication between agents since it affects the mode of communication (direct or by telephone) and the ability to overhear.

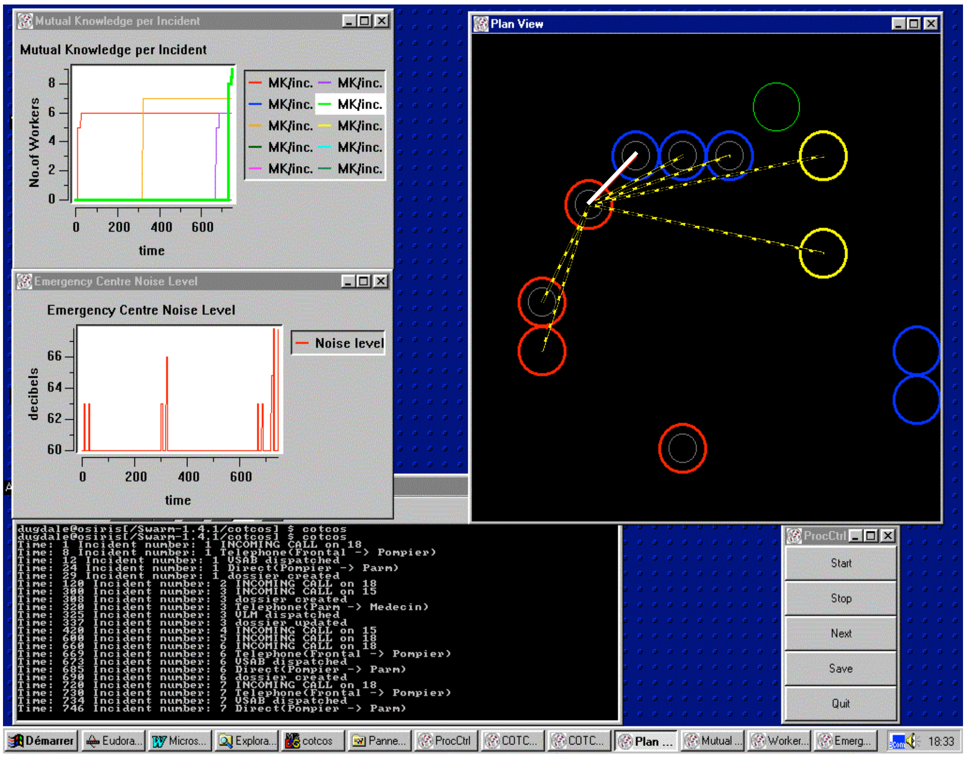
Artefacts play an important role in cooperation and communication (Benchekroun, 1992) (Martin et al. 1997) (Bressolle et al. 1995); one of the most important is the loudspeaker. In addition to the importance of the message content, the position of the loudspeaker within the room and its volume are critical. The loudspeaker and its attributes are modelled as part of the environment object, so that its volume and position can be changed.

Since incidents are modelled as separate objects it is easy to keep track of each incident separately and associate health workers agents with incidents. For each incident, a list of the health workers agents who have knowledge of that incident is kept. Many other details are stored in this object that allows tracking of the status of the call and the communications and their durations to which it relates.

2.4.2.3 Simulation

Two files feed into the computer simulator: a workers set-up file and an incidents set-up file. The workers set-up file contains details of health workers in the centre, such as their role and location. These aspects may be changed for experimentation, e.g. changing locations and role of agents. Likewise an incidents set-up file contains details of all the incidents that are to be handled in the simulation during one experiment. This too may be changed to reflect different workload situations for experimentation and validation[6].

Figure 4 shows a snapshot of the simulation in an overload situation when the incidents set-up file was loaded with incidents. The incidents and timings used in this experiment were taken from real incidents. The physical positions and roles of the health workers are the same as in the real situation.



```
dugdale@osiris[/Swarm-1.4.1/cotcos] $ cotcos
dugdale@osiris[/Swarm-1.4.1/cotcos] $ cotcos
Time: 1 Incident number: 1 INCOMING CALL on 18
Time: 8 Incident number: 1 Telephone(Frontal -> Pompier)
Time: 12 Incident number: 1 USAB dispatched
Time: 24 Incident number: 1 Direct(Pompier -> Parm)
Time: 29 Incident number: 1 dossier created
Time: 120 Incident number: 2 INCOMING CALL on 18
Time: 300 Incident number: 3 INCOMING CALL on 15
Time: 308 Incident number: 3 dossier created
Time: 320 Incident number: 3 Telephone(Parm -> Medecin)
Time: 325 Incident number: 3 VLM dispatched
Time: 337 Incident number: 3 dossier updated
Time: 420 Incident number: 4 INCOMING CALL on 15
Time: 600 Incident number: 5 INCOMING CALL on 18
Time: 660 Incident number: 6 INCOMING CALL on 18
Time: 669 Incident number: 6 Telephone(Frontal -> Pompier)
Time: 673 Incident number: 6 USAB dispatched
Time: 685 Incident number: 6 Direct(Pompier -> Parm)
Time: 690 Incident number: 6 dossier created
Time: 720 Incident number: 7 INCOMING CALL on 18
Time: 730 Incident number: 7 Telephone(Frontal -> Pompier)
Time: 734 Incident number: 7 USAB dispatched
Time: 746 Incident number: 7 Direct(Pompier -> Parm)
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Figure 4: Simulator showing overload situation

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[6] Validation was conducted by comparing the simulator output to the data from the activity analysis and by participation from the workers at the health centre. A detailed discussion of the model, validation and results can be found in (Dugdale et al. 2000) and also the problem of validation is discussed in (Dugdale et al. 2010).

The Plan View shows the positions of the health worker agents, represented as different coloured circles, according to their roles. Note, for clarity the tables at which the health workers are seated are not shown. A thick unbroken line between circles represents a direct face to face communication, whereas the dashed yellow lines show which health workers can overhear the conversation (given the factors affecting the ability to overhear). Blue lines (not shown in this case) between agents represents a telephone communication. The direction of the conversation from one agent to another is shown with other details, such as incident number, communications and actions, and time in the text window.

As the simulation progresses communications between the health workers are flashed across the screen. The snapshot shows only one communication, but at times, many communications occur simultaneously.

The simulation produces three graphs. The first, lower left in the figure, shows the noise level of the centre in decibels over time. The second graph shows the level of mutual knowledge per incident. Incidents are shown in different colours and the curve represents mutual awareness of the incident over time (the thick green line is because the user selected this incident at screen capture). A third graph, not shown in the figure, shows the average level of mutual knowledge over time.

Before reflecting generally on what this work contributed to human behaviour modelling in general, some specific results of this simulator are given. As expected the results showed that the ability to overhear falls when people are further apart. For overload situations when the centre is very busy, we saw how agents switched from direct (face to face) communication to communication by telephone; this being due to the increased level of noise in the room. In overload situations, compared to normal situations, the time taken to deal with the same incident increased due to calls being put on hold and increased communication times from interruptions and the unavailability of agents. The level of mutual awareness also fell in overloaded situations compared to normal ones. Further experiments finally allowed us to help redesign the real centre, suggesting optimal locations for specific groups of workers, etc. Although it is hard to attribute the 20% rise in centre efficiency solely to our interventions, feedback from the centre managers did in confirm the usefulness of the simulator in redesign.

2.5 General reflections

The work presented in this chapter has looked at two core aspects of human behaviour modelling: the methodology used to develop ABSS and the way macro behaviours result from local interactions. The description of the agent based simulator of the emergency call centre was presented as an indicative example that showed how detailed cognitive processes, such as overhearing, may be modelled and simulated in an agent based system.

By examining real human behaviours in-situ through the lens of cognitive ergonomics we see how the notion of interaction is more complex than simple explicit verbal exchanges. Instead the environment not only acts as an intermediary for communication but also plays a large role in modifying and shaping our behaviours, facilitating coordination and cooperation.

The focus in interaction is central to the two domains of cognitive engineering and multi-agent system, in dealing with human and artificial agents respectively. The challenge for ABSS has been to translate our observations of real world behaviours into more accurate agent representations – in essence building a bridge in between what we observe and how we model. The marriage of a cognitive engineering methodology with an ABSS one has helped us to identify what are the factors that truly affect human interactions and behaviours. Whilst the study of interactions is a key concept in both cognitive ergonomics and multi-agent systems, there is another field – complex systems – that puts interaction at its very heart and offers us a way of thinking about modelling, social processes and complex organisations.

Complex systems theory sees a system as being composed of interacting parts but where the result is much more than just the cumulative behaviour of the individual parts. The question at this time for me was could complex systems theory provide us with a way to understand and explain the behaviour of a society of agents? Would it provide an additional tool in analysing the behaviour of social systems? Would it be useful as a design concept when looking at socio-technical systems? Whereas this chapter looked at providing a framework for developing ABSS and modelling fine-grained human interactions, the next chapter looks at how complex systems theory pushed forward our understanding of complex social settings.

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Chapter 3 Complex socio-technical systems

3.1 Introduction

This chapter looks at my contributions in the area of complex systems theory applied to socio-technical situations. The chapter begins in section 3.2 with the scientific context of the work. The surge of interest in complex systems theory outside of the mathematics and physics domains began in the early years of this century when I was nearing completion of the work on modelling human interactions (chapter 2). Thus it made sense to return to analysing real life situations and analyse them with fresh eyes seeing what benefits this approach may bring. The idea was to understand what are the theoretical and methodological limits of traditional approaches, and what is the contribution of complex systems theory; section 3.3 examines my work in this area. Progressing from basic complex systems concepts, section 3.4 examines two specific characteristics of complex systems, namely robustness and resilience in socio-technical situations. These terms are often used interchangeably and my work aimed to clarify these terms by examining real socio-technical complex systems. Section 3.5 then shows how these characteristics could be translated to engineering concepts. Section 3.6 concludes this chapter with some general reflections on how complex systems theory has contributed to our study of human behaviour modelling.

3.2 Scientific and technological context

Modelling complex systems has received a considerable amount of interest in the last decade. Previous work on complex systems and complex systems theory concentrated on the more traditional sciences, such as physics, where the focus was on non-linearity. However, it was only at around the turn of this century that it started to be applied to more diverse domains such as economics (Tesfatsion, 2003a) (Tesfatsion, 2003b) (Tesfatsion and Judd, 2006), biology (Rocha, 1999) (Bonabeau, 1998) and urban science (Heppenstall et al. 2007) (Castle and Crooks, 2006).

Historically, one of the first centres of excellence of the complexity approach was the famous Santa Fe Institute that championed a transdisciplinary approach in complexity science. Towards the end of the 1990s this institution expanded its scope to the social sciences and humanities bringing a complex systems perspective to areas such as political science, psychology, history and archaeology.

The links between multi-agent systems and complex adaptive systems (CAS) are evident. Like complex adaptive systems, MAS are composed of multiple interacting components and place a strong emphasis on interaction. However, CAS focus on top-level properties, such as emergence and self-organisation, and in CAS the agents as well as the system are considered to be adaptive. Thus human societies with adaptive human behaviours are a perfect example of a CAS. Given the ability of MAS, and in particular, ABSS to model adaptive behaviours and generate emergent phenomena it is unsurprising that this approach was quickly adopted by many research groups, e.g. ACE (Agent based Computational Economics) at Iowa State; Mike Batty and Andrew Crooks at CASA (the Centre for Advanced Spatial Studies at UCL, UK), and Eric Bonabeau at ICOSYSTEM, to name a few.

It was in this context that in 1999 Bernard Pavard from the GRIC team and I co-wrote a proposal for the European funded COSI (Complexity in Social Science) project. Globally the objective of the work was to promote a new way of thinking about and modelling social processes and complex organisations. In this way it represented one of the first attempts to use complex systems theory in the study of socio-technical situations (Zaboutis and Wright, 2006). The COSI project aligned closely with the Santa Fe approach in exploring complexity science and promoting it in the social sciences. More particularly, COSI focused on how complexity science could be used to benefit the *design* of complex socio-technical systems. The goal was to move social sciences forward from an era in which psycho-social models of real situations were used largely for explanation, towards an era where the models could be used actively for prediction (Cilliers, 1998).

Broadly the approach was to use field studies to provide detailed descriptions of actors, their activities, their work environment and their interactions, and then to model and possibly simulate these situations. In this way the methodological approach built upon that which had been developed in COTCOS (chapter 2). Like the previous COTCOS project a wide range of disciplines were involved from the social sciences, each of which brought their own approach to analysis and modelling. The contribution from the computer science teams was to transform these works into models for simulation using an agent based approach. By being able to predict future situations, the simulators could then be used for helping to design new work situations. The domain of Agent Based Social Simulation was still very much in its infancy at this time. Many researchers were making the link between theoretical complex systems ideas, such as emergence, and their practical apparition in agent based simulators. However, applying complexity theory to situations of human interaction was still in its infancy, and even more so, using complexity theory and agent based simulation for design was extremely rare. These were precisely the areas that I focused on in my work.

Although this project was followed by other projects (such as the US funded C2EC2, Cognitive Complexity in Critical Care from 2007 to 2012), it provided the seed for a body of my work on complex systems theory. It led to the formation of a special interest group on Emergence in 2004, my organisation of a special track at the ISCRAM 2005 conference dedicated to Complexity, Crisis and Robustness in Crisis Management. More recently I have continued in this field through the RNSC (Réseau National des Systèmes Complexes) and the AEGSST (Approache enactive pour la Governance de Systèmes Socio-Techniques) network. More recently, the notion of robust socio-technical complex systems has been explored through the role of social media in crisis situations and a collaboration with the University of Tilburg in The Netherlands (Van de Walle and Dugdale, 2012), (Dugdale et al 2012), (Gonzalez et al. 2012).

In the following section I examine the main characteristics of complex systems as applied to real-life work situations.

3.3 Complex systems theory applied to the study of socio-technical situations

Whilst there are standard definitions of a complex system[7], we will provide a description in relation to our experience with the study of socio-technical systems.

> *A complex system is a system for which it is difficult, if not impossible to reduce the number of parameters or characterising variables without losing its essential global functional properties. (Pavard and Dugdale, 2006)*

A truly complex system would be completely irreducible. This means that it would be impossible to derive a simplified model from this system (i.e. a representation simpler than reality) without losing *all* of its relevant properties. However, in reality when

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[7] A system starts to have complex behaviours (non-predictability and emergence etc.) the moment it consists of parts interacting in a non-linear fashion.

viewed externally different levels of complexity obviously exist. The reduction of complexity is an essential stage in traditional scientific and experimental methodology (also known as analytic). After reducing the number of factors, deemed most relevant, this approach allows systems to be studied in a controlled way, i.e. with the necessary replication of results. This approach in itself need not be questioned. However, when considering complex socio-technical systems it is appropriate to analyse precisely the limits of the approach. The questions addressed in this work are: what are the theoretical and methodological limits of this traditional approach, and, what is the contribution of complex systems theory? To illustrate this discussion examples are used from the study concerned with the redesign of an emergency call centre (chapter 2).

Four specific properties of complex systems will be discussed in relationship to their usefulness to socio-cognitive modelling:

Property 1: non-determinism. A complex system is fundamentally non-deterministic. It is impossible to anticipate precisely the behaviour of such systems even if we completely know the function of its constituents.

Property 2: limited functional decomposability. A complex system has a dynamic structure. It is therefore difficult, if not impossible, to study its properties by decomposing it into functionally stable parts. Its permanent interaction with its environment and its properties of self-organisation allow it to functionally restructure itself.

Property 3: distributed nature of information and representation. A complex system possesses properties comparable to distributed systems (in the connectionist sense), i.e. some of its functions cannot be precisely localised.

Property 4: emergence and self-organisation. A complex system comprises emergent properties that are not directly accessible (identifiable or anticipatory) from an understanding of its components.

3.3.1 Non-determinism

Non-determinism of socio-cognitive processes is often considered as being due, either to a lack of knowledge of the observer about the analysed system, or to a disturbance of the system as a result of unforeseen causes (e.g. exterior events or noise etc.).

An analysis of the properties of complex socio-technical systems suggests that non-determinism can have an important functional role. We consider one of the most important mechanisms concerning cooperative systems: broadcasting (Rognin and Pavard, 1996). We show that this mechanism is non-traceable (i.e. that it is difficult, if not impossible, to describe explicitly the information flows that are relevant in understanding how a collective functions) and that it provides a structure for the management of the memory of the collective. Figure 5 briefly explains how the broadcasting mechanism operates.

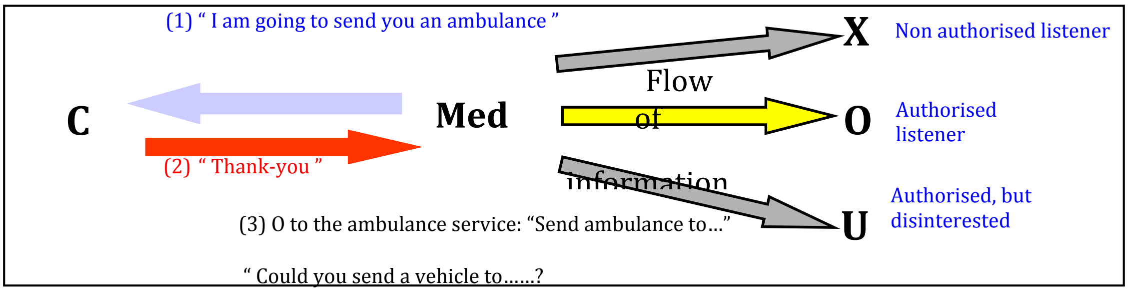

Figure 5: An example of the broadcasting mechanism. A caller, C, telephones a medical doctor (Med) at the emergency centre to request an ambulance. Several people, depending on their geographical

position and the volume of the communication, can overhear this communication. These people can be either authorized, unauthorized, interested or disinterested interlocutors. In this example, agent O overheard the conversation between the caller and the medic which continued with address details, etc. (1 and 2). Because of his spatial proximity to the medic and the volume of the communication, agent O dispatched an ambulance without the medic making an explicit request (see '3').

Broadcasting is an important mechanism for understanding the efficiency of a collective in situations of co-presence (real or virtual). Indeed, it is perhaps the only mechanism that allows information sharing at a low cognitive cost. The classical theories of communication (mainly dyadic between sender and receiver) have seldom analysed its functional role (Decortis and Pavard 94), although its cognitive components are described with precision (Goffman, 87).

3.3.2 Limited functional decomposability

According to the traditional reductionist approach, a system that is functionally decomposable is one whose global functioning can be completely deduced from knowledge of the function of its sub-components. A truly complex system cannot be represented by combining a collection of well-defined functional components. A principal obstacle to the functional decomposability of complex systems is the dynamic and fluctuating character of their constituent functions. The interaction with the environment, as well as the learning and self-organisation mechanisms makes it unrealistic to regard such systems as structurally stable.

An interesting property of socio-technical systems is their capacity to reorganise rapidly their functional structure. Depending on the context, human actors may significantly modify the "rules of the game" and, for example, change their cooperative mechanisms. This change can occur without direction from a central authority. The example below, which describes a cooperative episode between several actors working in the same room, illustrates this type of mechanism. The episode is based on the broadcasting mechanism: a loudspeaker (held by a medic in the white shirt in the photograph) passes on the radio communications, transmitted by ambulances at the scene of accidents, to the rest of the centre's personnel.

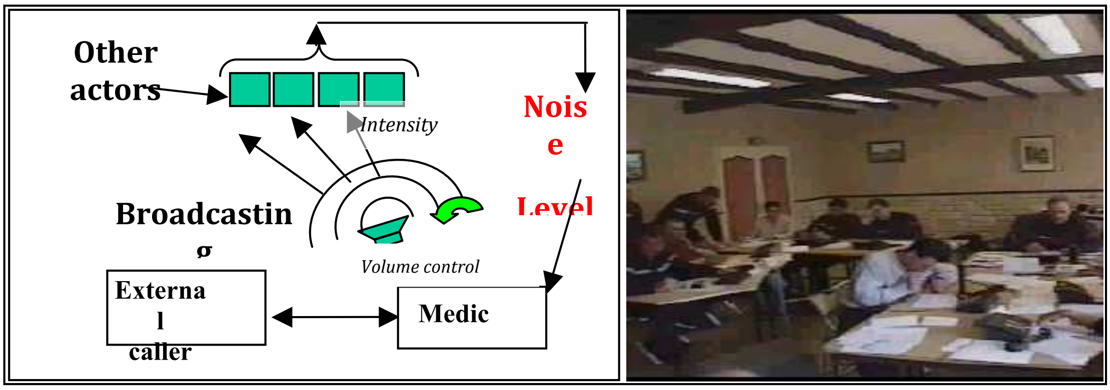

Figure 6: An example showing the flexibility of structural properties of a communication system. The mode of transmission of information between the actors depends on environmental factors, such as ambient noise, and the informal cognitive control of individual actors; in this situation it is the estimated interest of the message to the collective group. A medic changes the volume of the loudspeaker, depending on the semantic content of each message and the level of noise in the room. This allows him to adjust the scope of broadcasted message, i.e. the number of people hearing the message. Thus he optimises the way information is distributed to the collective.

The structural properties of a communication system, in this example it is the *mode* of information distribution, depend on environmental factors and a semantic analysis of the content of the message. We can see that the structure of the communication system, on which the efficiency of the collective depends, is subject to real time informal adjustment mechanisms. If this situation had been analysed according to the functionalist paradigm, the emphasis would have been on dyadic communications (e.g. the face to face and telephone communications between agents). Peripheral mechanisms and factors, such as broadcasting and ambient noise, would have been treated as more or less disturbing secondary events. However, these mechanisms are essential in order to understand the efficiency of the collective. The agent based simulator, described in chapter 2, showed how communications were regulated to the collective by adjusting the volume of the loudspeaker.

3.3.3 The distributed character of information and representations

The notion of distributed information conveys different concepts. In its most commonly accepted meaning, a system is said to be distributed when its resources are physically or virtually distributed on various sites. The concept of distribution supports the concept of redundancy, when some distributed resources are redundant.

The concept of distributed representation also exists in the field of cognitive psychology (Zhang and Norman, 1994) (Hutchins, 1990) (Hutchins, 1995) where artefacts or tools in the environment play an important functional role in organisation of reasoning and the transmission of knowledge. Within the emergency control centre, the supporting artefacts include screen representations of the current status of emergency calls as well as personal notes made by the actors. Artefacts supporting cognition may also be found in other domains, for example, the use of flight strips in air traffic control. Here, air traffic controllers, who work in pairs, use the flight strips that contain information such as the aircraft's call sign and destination, to help them communicate and coordinate their actions (Bressolle et al. 1995). Hence, some cognitive properties, such as memory and problem structuring, are partially supported by artefacts that are distributed in the environment. In some sense this notion is close to the concept of physically distributed systems.

By viewing the socio technical system as a distributed system in the connectionist sense we can start to understand the robustness of the collective in its ability to process data and information. Here, a distributed system is one where it is not possible to localise physically the information since it is more or less uniformly distributed between all of the objects or actors in the system (Figure 7).

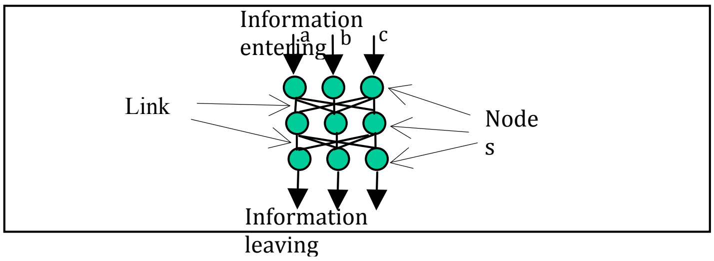

Figure 7: A connectionist system; a simple neural network. The information arriving in the system is distributed between a set of neurons as a function of the strength of each link. The strengths of the links are gradually adjusted using a learning mechanism that compares the actual behaviour of the network with the desired behaviour.

The learning mechanism ensures the distribution of the functional properties of the network (for example the property of recognition) between its neurons. When a network learns how to recognise shapes, or to associate actions with some conditions in the environment, the learning mechanism will distribute the information throughout the connections in the network. Thus it is not possible to attribute a particular functional role to any one of the connections in the network.

The notion of robustness will be covered later in this chapter. However, such a network of distributed information offers some interesting characteristics of robustness. The term “distributed representation” is inappropriate here since we cannot identify any form of representation in such a network. The representation is “dissolved” in either the nodes or the links of the system. Hence, a distributed system, in the connectionist sense, does not distinguish between concept, representation, and context, since these three entities are “encoded” simultaneously on the same support.

The following example is taken from the emergency centre. The aim of the collective is to maximise cooperative behaviour between the actors in order to respond in the best possible way to events in the environment, such as unexpected calls and work peaks, etc. The efficiency of this type of collective is based on a situation of co-presence, allowing information to be distributed by broadcasting and overhearing. Figure 8 shows this type of information distribution between actors and shows the importance of the interaction between environmental factors, such as the noise level and space constraints, and more central processes, such as the control of modes of communication.

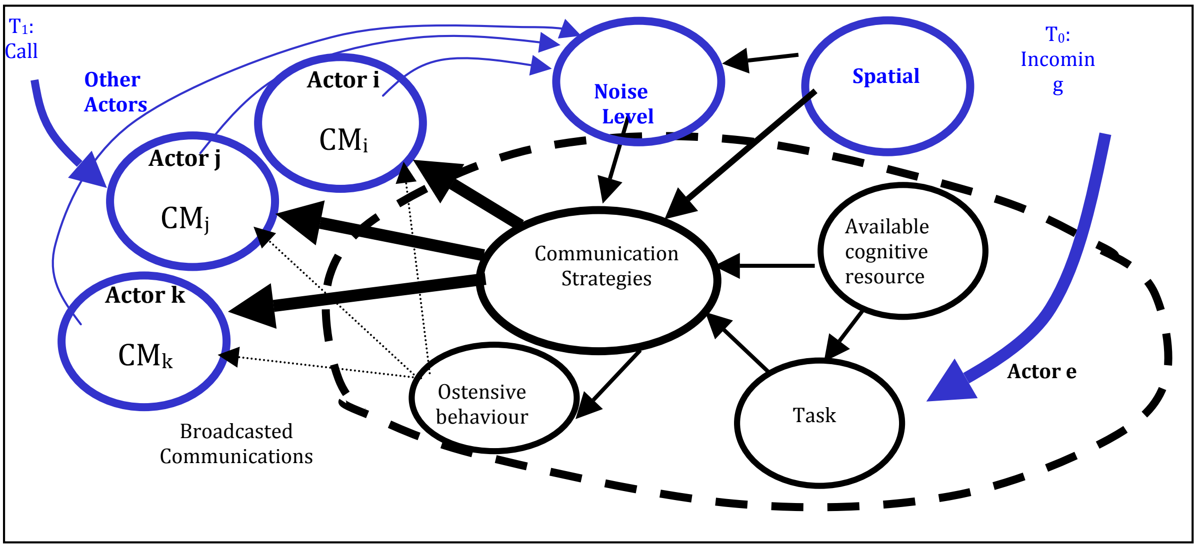

Figure 8: The distributed nature of cooperative systems in the connectionist sense. The diagram shows a collective composed of several actors shown by the circles labelled actor i, j and k. At time T_0, an incoming call is dealt with by actor e that adopts a communication strategy that tries to control the distributed character of the message. Verbal information (shown by thick black arrows) is distributed in a non-deterministic way through broadcasting to actors i, j and k. This is done according to environmental characteristics such as the noise level, the spatial constraints (the distance between the actors), the cognitive resources (workload) and other factors such as postural or gestural ostensive behaviours (shown by small dotted arrows) and allows actors to control their listening behaviour (Benchekroun, 1994). If at time T_1, a call arrives that is related to a previous call, but is received by an actor other than e, the collective will be able to handle the call because of the common memory (CM_i, CM_j and CM_k) established through the broadcasting mechanism.

We can see that a collective in a situation of co-presence, possesses characteristics that are comparable to those of a connectionist system. The information is distributed between the actors, with some redundancy, due to the broadcasting mechanism. Such a system can be regarded as complex because part of its functions cannot be reduced to a representation where it is possible to locate precisely a relevant piece of information. Neither the actors nor the observer can, at a given moment, give a deterministic plan of this process.

3.3.4 Emergence and self organisation

Intuitively, a property is emergent when it cannot be anticipated from knowing how the components of the system function. Emergence is not due to incomplete information regarding the components of the system, but to the non-linear and distributed character of the interactions. It consequently appears as if the system can, by its multiple local interactions, behave along some global emergent features, which may allow it to evolve towards more effective modes of organisation (self organisation). If a system is capable of self-organisation, its functions evolve over time so that they can respond better to the demands of its environment. In this sense, a complex self-organised system cannot be described as functionally stable.

Certain cognitive and communication processes in a collective correspond to this definition of emergence. Interestingly many examples of emergence are often explained as being in some way beneficial to the system. However, it is important to realise that some emergent phenomena can be detrimental to the functioning of the system. An example of this was observed in the emergency call centre with the emergence of a degraded behaviour of the actors. The difficulty occurred during a period of intense telephone activity: a critical time where it is necessary to manage calls effectively. Paradoxically, it was also the time where the collective became dysfunctional, i.e. incapable of responding to an exterior request. The ergonomic analysis highlighted the importance of the interlocution and broadcasting mechanisms in the regulation of emergency calls: the actors were taking into account the ostensive behaviour of their colleagues in order to determine whether or not they could interrupt a busy colleague. Furthermore, the collective memory, which is constructed via broadcasting, was affected. The dysfunction was due to both the unavailability of agents and the fact that as the workload rose, agents became increasingly unable to acquire information from their colleagues via overhearing.

It is thus a purely local interaction between agents linked with the distribution of information mechanisms that produced a global emergent behaviour. Interestingly whilst the actors recognised this emergent degraded efficiency they could not explain how it was caused and indeed could not find suitable behaviours to sufficiently rectify the situation.

3.3.5 Discussion

The above section examined the usefulness of the complexity paradigm in analysing socio-technical cooperative systems. The analysis was conducted retrospectively of the agent based simulator development described in chapter 2. This was principally due to the circumstances of my work around that time. Nevertheless, the application of complex systems theory to a real-life socio technical system was a necessary in order to more fully understand human behaviour and consequently to model it in a more realistic way.

The characteristics of complex systems described above are not treated within the framework of classical analytical approaches. However, we can see that they are essential to understand certain functional aspects of cooperative work, and in particular the possible robustness and the dynamic nature of socio-technical systems (Mitchell 98). The classical analytical reductionist approach is particularly weak in explaining the emergence of functional properties, despite the fact that in socio-technical complex systems, the strength of the collective lies in such properties. Thus the goal was to try to find an intermediary position between the analytical and complexity approaches that would allow us to understand real situations in better way.

We saw from chapter two that the broadcasting mechanism is at the heart of the distribution of information between agents in a socio-technical system. By using complexity theory we found that the mechanism is non-traceable and non-deterministic. Furthermore, by identifying the distributed nature of this mechanism we can hypothesise that the robustness of the overall system, i.e. the capacity of the system to handle unforeseen data, is functionally related to the concept of a locally distributed control of information. These mechanisms are principally concerned with the local interactions between actors and are not represented at a central organisational level where certain functional properties (e.g. reliability, robustness, or the occasional abnormal operation of the collective) emerge.

The following section delves deeper into the notion of robustness and examines its relationship to resilience and regulation. Whilst these terms are often used interchangeably in practice it is important to make a conceptual distinction between them.

3.4 Robustness, resilience and regulation

Robustness has become a central issue in many scientific domains from computing to biology, through ecology and finance (Bonabeau et al., 1996) (Doyle & al., 2005) (Kaufman, 1993) (Lewontin & Goss, 2005) (Walker & al., 1995). However, there is no globally agreed definition of robustness and the situation is further blurred by its relationship to resilience and regulation. Indeed, the terms robustness and resilience are often used interchangeably and are very broadly interpreted to mean the ability of a system to remain stable and function correctly in unforeseen environmental conditions. Thus a robust or resilient system is one that must be able to adapt its behaviour to unforeseen situations, such as perturbations in the environment, or to internal dysfunctions in the organisation of the system, etc.

However, there are conceptual differences between robustness and resilience, and it is only by understanding the concepts that underpin these two terms that we can begin to design functional socio-technical systems. The notions of robustness and resilience are closely linked to regulation and so we will start by addressing this aspect.

Complex systems use different kinds of regulation in order to maintain their performance or simply to survive. Three broad categories of regulation can be identified:

a) Functional,

b) Structural,

c) Structural and emergent.

The aim of classical or functional regulation is to restore the initial functionality of the system by maintaining certain behavioural variables. Classical engineering, cybernetics, and reliability engineering are mainly concerned with the concept of functional regulation. That is, when a perturbation arises in the environment, the regulation mechanism will return the system or its output to its default or expected value. Usually, the initial functionality of the system is maintained. However, there is no change to the internal structure of the system. These regulations generally resort to 'feedback' type mechanisms that aim to ensure the stability of the system's behaviour.

Secondly there is structural regulation. The aim is still to maintain the performance of the system, but the internal structure of the system may be changed. This change may be intentional, for example, it may be done by an actor within the system in order to adjust the behaviour of the socio-technical system. To illustrate this type of regulation we will use a simple example from Air Traffic Control. When air traffic becomes congested, the air traffic coordinator assesses the situation and may intentionally change not only the systems parameters but also its internal structure, i.e. how the system is organised. This is done in order to promote the potential ability of the system to handle the situation (Figure 9).

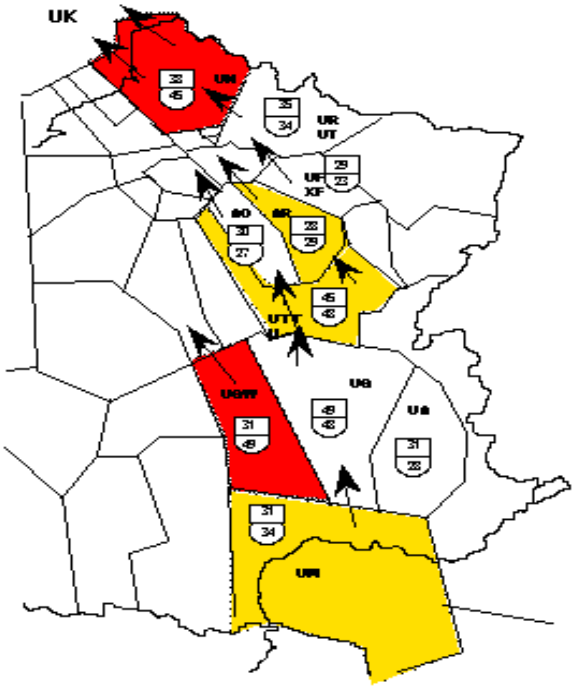

Figure 9: An example of structural regulation in Air Traffic Control (ATC). When some sectors (shown in red or dark grey) are very busy because of the large number of aircraft, they may be subdivided by the ATC manager and assigned to new ATC controllers (from Salembier, 1994).

With structural regulation the functional aim of the system is still maintained. In the example, the functional aim is to maintain the flow of air traffic and avoid congestion. Structural regulation works well in this case if the manager has a good overview of the situation in order to make a rational decision.

The third type of regulation is emergent. Here the structural change may emerge in a ‘non-intentional’ or self-organisational sense. In this case, the stakeholders do not control the mechanisms that govern the system. Instead they result from distributed decisions that are usually taken at a local level, by field operators, without any global vision of the situation.

In some situations, for example in large scale crisis situations, it may not be possible for a manager to have an overview of the situation and what is happening in the environment (i.e. there is a lack of information, or the information may be incorrect, etc.) (Dugdale et al, 2006a). As a consequence, the manager may not be able to make a rationally informed decision. At this level, emergent and self organizing processes may arise to restructure the system (Dugdale et al, 2010). In some cases, there may be no conservation of function (Salembier and Zouinar, 2002). That is, the emergent phenomena could change the local functionality of the sub-components.

An example of emergent regulation is the crisis resulting from Hurricane Katrina in 2005. Here, emergent and self-organization were important processes responsible for recovery. Soon after Hurricane Katrina the communications infrastructure was destroyed, isolating the victims and drastically reducing the coordination capacities of the normal rescue groups (Comfort and Haase, 2006). Soon after, other actors[8] spontaneously started to restore communications using technologies such as Wi-Fi networks and WiMAX. Their goal was to rebuild locally the communication links between the crisis sites and the external world. These efforts happened in spite of attempts by official organisations to limit the volunteers' involvement[9]. These spontaneous interventions are typical of self-organisation mechanisms that cannot be anticipated (figure 10).

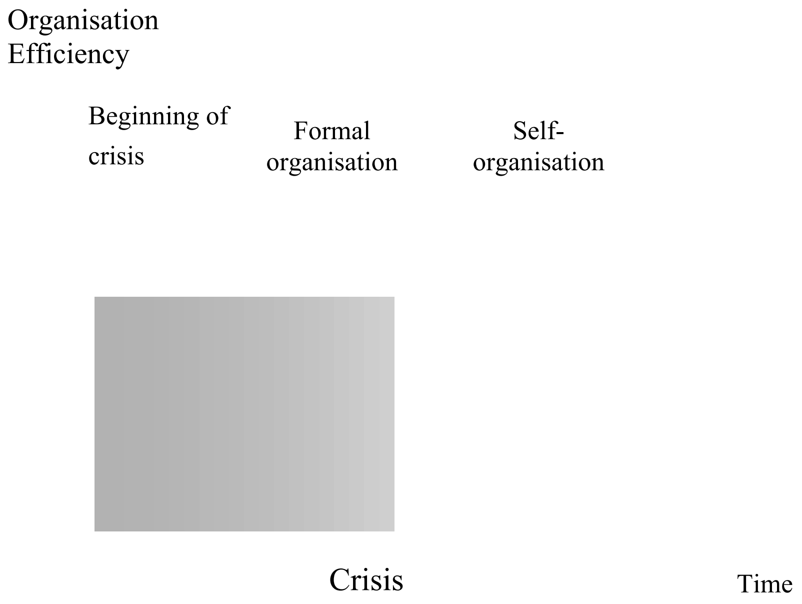

Figure 10: The dynamics of self-organization and institutional mechanisms in crisis situations: the case of Hurricane Katrina. The self-organization phenomenon (dotted curve) depicts the action of teams of volunteers who spontaneously tried to re-establish communications. The black continuous curve shows the evolution of the formal organization. Note that the amplitude of the curves and their development over time does not have an absolute value and is shown only to illustrate the positioning of the self-organization phenomena in crisis situations.

From this example, we can see that emergence is a mandatory mechanism for recovery when a socio technical system nears a crisis situation. If we consider designing emergency systems, it is useful to discriminate between the different types of regulations: a) functional, b) structural, c) structural and emergent.

Returning to the original definition of a robust or resilient system, as being one that can remain stable and adapt its behaviour to unforeseen situations, we can see that it does not sufficiently discriminate between different types of regulation. *Functional regulation* aims to return the function of the system to its initial stage whereas *structural or emergent regulation* implies a modification to the intentional or non-intentional internal

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[8] For example, teams of people from large companies, private groups, etc.

[9] From 'Associated Press' (http://radioresponse.org/wordpress/?page_id=46) Mercury news, October 4, 2005 Mathew Fordhahl. "The spontaneous wireless projects by groups that simply wanted to help -- government mandate or not -- is spurring interest in how to deploy the latest in communications technology and expertise in a more organized fashion after future disasters. Teams from large companies, private groups and the military converged on the Gulf Coast in ad hoc fashion to set up wireless networks, all the while battling bureaucracies that didn't seem to understand the agility and flexibility of the technologies being marshalled".

structure of system.

From this view, functional (type a) and structural regulation (type b) is related to resilient systems, whereas structural and emergent regulation (type c) is related to robust systems. Following this, we see that the notions of resilience and robustness refer to different concepts.

According to McDonald, resilience represents '*the capacity of an organizational system to anticipate and manage risk effectively, through appropriate adaptation of its actions, systems and processes so as to ensure that its core functions are carried out in a stable and effective relationship with the environment*' (McDonald, 2006). Likewise, Woods defines a resilient system as one which is able to monitor the boundary of its organization capability and which can adapt or adjust its current model (Woods, 2006).

However, the views of McDonald and Woods do not adequately address the behavior of robust complex systems where new functions could emerge by self organisation in an unpredictable way (such as the emergence of a new structure or a new organisation). However, Buchli and Santini follow a similar view to ours that captures the link between the complex systems properties of self-organisation and robustness (Buchli and Santini, 2005). These authors argue for harnessing this property in a 'complexity engineering' approach.

The following section examines the link between engineering and regulation and argues that the three levels of regulation can be associated with different types of engineering: *resilient engineering* that is concerned with the aim to bring back the system in its initial conditions; and *robustness engineering* which is able to harness the more complex (and hidden) properties of self-organized processes.

3.4.1 From resilience to robustness engineering

Following the distinctions above, three different types of engineering are required.

1) *Classical engineering* that is based on a functional approach in order to control simple regulation mechanisms.
2) *Resilience engineering* that focuses on situations where it is possible to make reliable plans and where coordinators can anticipate the situation. The implicit hypothesis of this approach is that the organiser or the regulating system has a reliable model of the environment and that the functions for correcting any dysfunction do not deviate from what is expected. A resilient system generally aims to restore the initial functions of the system without fundamentally questioning its internal structure in charge of the regulation (Woods, 2005) (Woods, 2006). Whilst it is true that in some situations the structure of the system may be intentionally modified, this modification is undertaken when the actors consciously decide the organisational changes. The traditional approaches to reliability and security usually rely on resilient engineering. Engineers strive to return the system to its initial state maintaining its original functions.
3) *Robustness engineering* that refers to the behaviour of complex systems and distributed systems. Robustness engineering deals with non-deterministic processes such as those found in crisis situations. In terms of engineering the goal is to harness the more complex and hidden properties of self-organisation. The problem is that there is no guarantee that the function of the system will be maintained. Indeed, new functions can emerge. For example, a new organisation or new objectives for a company, etc.

The different types of engineering can been seen below in figure 11

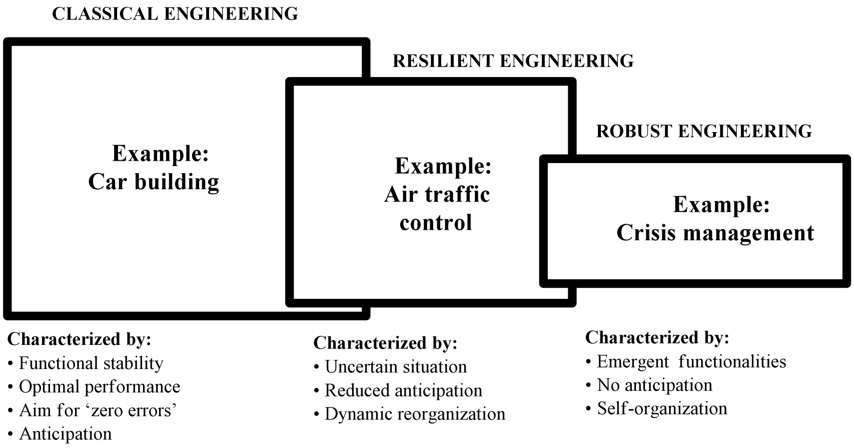

Figure 11: Three types of engineering

Classical engineering, the type used for example in building a car, is characterised by the functional stability of the components with a focus on optimal engineering performance and the goal of zero errors. There is also some degree of anticipation of future situations. An example of resilience engineering with intentional reorganisation is the air traffic control problem described earlier. Here the situation is uncertain and there is a reduced anticipation of future problems but the dynamic reorganisation of the structure often leads to a successful outcome.

Robust engineering is appropriate in situations where future events cannot be anticipated, such as in crisis situations. Self organisation is a common feature of good crisis management. For example the formal coordination between key player crisis organisations in crisis management is often pre-defined according to hierarchical response plans. Indeed, a huge emphasis, perhaps misplaced, is given to these kinds of plans (Mendonça and Wallace, 2007). However, other non-crisis organisations or volunteer groups provide crucial support and thus new inter-organisational networks emerge through a process of self-organisation. It is these networks that as a whole provide the necessary support. This was the case in Hurricaine Katrina where non-crisis related agencies provided the critical first response before federal organisations arrived[10]. More recently this self-organising phenomena has become more apparent with the upsurge of volunteer groups self-organised through social media such as Facebook and Twitter (Van de Walle and Dugdale, 2012), (Dugdale et al 2012), (Gonzalez et al. 2012).

3.5 General reflections

This chapter has looked at the contributions made in understanding and designing complex socio-technical systems; first through analysing what complexity actually means in real-life situations and then by reflecting on the engineering implications of robust and resilient systems. Returning to the questions posed at the end of chapter two, we wanted to know if complex systems theory could provide us with a way to

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[10] Over 500 organisations were involved in responding to the crisis caused by Hurricane Katrina, just under 50 percent of these were non-profit, private or special interest organisations. Only 4 days after the event did a sizable infusion of support arrive from federal agencies (Comfort and Haase, 2006).

understand and explain the behaviour of a society of agents? Would it provide an additional tool in analysing the behaviour of social systems? Would it be useful as a design concept when looking at socio-technical systems?

Complex systems theory when applied to social situations adopts a functionalist approach in the sense that the overall macro-level functional behaviour of society is derived from the micro level interactions of its constituents. In particular it focuses on emergent macro-level phenomena. Thus the benefit of complex systems theory over traditional analytical methods is in its focus on emergent and self-organised human behaviours.

Complex systems theory has allowed us to enrich the descriptions of human behaviour by providing us with an additional tool with which to describe and analyse social systems, their functioning, and performance. When this is coupled with the predictive ability of ABSS it gives us a powerful tool in seeing how such systems evolve and this in turn helps us in designing future work situations or new technologies. Complex system theory bridges the gap between the individual behaviours and collective functions. However it has also provided us with a bridge between real world human behaviours and computational world of ABSS. It has allowed us to study emergent and self-organised human behaviours in the real world and then represent and simulate them in computational world.

Complex systems theory emphasizes the capacity of human agents to construct social systems *without* necessarily fully knowing or understanding how these systems will perform and can be controlled (the "Frankenstein phenomena"). However, the self organising and adaptive nature of such systems can provide a mechanism to manage unintended and unanticipated consequences both of self generated crises (e.g. economic problems) or natural crises (e.g. Hurricanes and Tsunamis). Thus the more an organisational system is unstructured (such as in a crisis situation), the more we need design solutions to be engineered that are able to promote self organizing processes.

The concepts of robustness, resilience and regulation in the framework of the design of socio-technical complex systems have been clarified. The hypothesis was that these concepts could only be clearly differentiated by considering their systemic properties. Resilience and robustness can be differentiated by the importance and dynamics of self-organised processes. These processes are not the result of causal mechanisms controllable by an organisational structure. Instead, they result from distributed and non-deterministic processes.

Robustness and resilience are complementary concepts because they cover two types of dynamics:

- A dynamic where it is possible to anticipate or return the system to its initial state.
- A dynamic where the information flow is no longer compatible with any organised systems.

Despite a better understanding of self-organised systems, the practical application of engineering robust systems has proved to be extremely difficult and remains a challenge. What is clear though is that ABSS, by allowing us to experiment with micro-level behaviours and observing self organising phenomena, will be an important tool in helping to design robust socio-technical systems.

The impact of complex systems theory can be summarized as:

- A better understanding of complex systems and their dynamics. In turn this supports the need to engineer and manage complex socio-technical

systems.
- A better understanding of the complex environment in which engineered systems exist, e.g. regulatory and robustly engineered systems.
- A better understanding of the design process for complex systems.

The interest in complex systems has gathered momentum over the years as is evident from the increasing popularity and longevity of many complex systems conferences[11], continued and recent funding opportunities[12] and large federative research structures involving hundreds of researchers[13]. Amongst the myriad of topics of interest covered in the domain there is a recurrent theme of complexity and information; what information is available to complex systems? How can it be characterised, accessed and modelled? What are the dynamics of information in complex systems? The following chapter deals with this subject in the scope of human behaviour modelling. Specifically it addresses the information that humans use in their decision making – that is, the notion of context and contextual awareness in complex systems.

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[11] For example, International Conference on Complex Systems; European Conference on Complex Systems

[12] EC ICT FET Proactive Calls in Dynamics of multi-level complex systems, and fundamentals of collective adaptive systems

[13] RNSC (Réseau National des Systèmes Complexes)

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Chapter 4 – Context awareness in human behaviour modelling

4.1 Introduction

In real-life, humans are strongly influenced by the social, environmental and historical context in which they find themselves. In order to accurately model human behaviour the influence of context must be examined and incorporated into reasoning mechanisms in computational agents. The problem can be specified more precisely in the following question: How does context awareness contribute to decision-making in complex social systems and how may this be modelled?

My contributions in addressing this question have been from two angles:

The first relates to the problem of how to make computational agents contextually intelligent. I begin by looking at the current limitations of the classical ABSS approach and the fact that information that is contextually relevant to an agent must be explicitly represented in the model. As an example, imagine that you want to eat in a restaurant this evening, you arrive by car in front of two restaurants, the car park of one of them is full, but in the other there are no cars. This contextual information may tell you something of the popularity of those restaurants, which contributes to your decision of which restaurant to choose. This kind of contextual information, and how it may affect decision making, would need to be explicitly coded into the computational agent. Section 4.3 addresses this issue and examines what we are losing by having to explicitly define contextually relevant information. It poses the question, is it actually necessary to identify and model contextual information; and if it is not, in what other way can we achieve contextually intelligent agents?

The second contribution of my work on context delves more into what context means in terms of human decision-making. My contribution in this area is in developing a descriptive model of contextual activities. With this basis, I then look at how this model can be used to help in the design of ambient technologies by employing simulation. The aim of this work is to assess exactly what degree of contextual information is necessary to make informed decisions and how it affects human behaviour. Section 4.4 details my contributions in this area.

4.2 Scientific and technological context

Although the above two lines of research relate to the study of context they have been conducted in two separate projects:

- The first line of research was a continuation of the COSI European funded project and a nationally funded NETCRISE project. The aims of these projects, concerning context, were to investigate social interactions and the role of context with a view to improving agent based interactions in an artificial world. As with many of my works, the application area was emergency and crisis management and practically the project sought to improve coordination and communication in this area by integrating existing technologies and by developing new technologies. My research was conducted in collaboration with two PhD students, Nico Pallamin and Mehdi El Jed. Although I was not a formal supervisor we worked together closely and published several articles as a result (El Jed et al. 2004) (Dugdale et al. 2004) (Darcy et al, 2003) (Dugdale et al. 2006b) (Dugdale et al. 2010). More recently, the problem of how to make agents more contextually aware has been continued through the ANR MOCA (My Little Artificial Companions World), 2012-2016 and with working with Wafa

Benkaouar, a PhD student of MAGMA member Sylvie Pesty. Although still in its early stages, this work looks at modelling interactions between humans and virtual agents (including robots) taking into account specific contextual settings. The definition of interaction scenarios is the subject of a recently accepted paper (Benkaouar et al, 2013).

My work began by looking at how far the classical agent based approach to social simulation went in being an accurate representation of social interactions. From this starting point, the agent approach was extended in working with virtual characters. Here, a virtual character is considered to be a visual representation of an agent possessing all of the usual agent characteristics such as autonomy, etc. To situate my contribution within the general agent community it can be seen to border on the field of Embodied Conversational Agents or ECA (known as Agents Conversationnels Animés or ACA in the French Agent Community). ECA are virtual representations of humans that can engage in a conversation, either with another ECA or with a human, using verbal and non-verbal communication and with realistic and believable gestures and facial expressions, etc. (Pesty and Sansonnet, 2005) (Buisine et al. 2010). ECA research is not typically concerned with aspects such as the quality of synthetic graphics etc, rather it focuses on replicating human-like interactions in virtual characters and address issues such as how emotions and personality affect interactions and behaviours. This focus on interaction and behaviour links my approach to this area.

- The second line of research was conducted within the In-Situ project funded by EDF. The theme of this project was to analyse and model shared context for the design of cooperative technologies in domestic situations. One of the main goals of the project was to define an analysis and modelling framework that explicitly integrated contextual aspects. The approach was to start by identifying the different levels of contextual information that humans use (Quéré, 1997) and then see how these levels could be translated if they were implemented in an intelligent artificial system. The resulting framework can then be used to assess and guide the design of new ambient technologies. This work obviously touches upon the areas of context-aware computing and in particular ubiquitous computing. The purpose of ubiquitous computing is to amplify human activities with services that can adapt to the circumstances in which they are used (Coutaz et al, 2005). Like other research works in ubiquitous computing, I focus on the notion of context. However, rather than adopting a technology led approach, I adopt a human led one. Instead of starting with technology and looking at what contextual information may be obtained through sensors, I look at context from the point of view of the human and try to assess what equivalent level of context abilities any ambient technologies would need.

4.3 Contextual intelligence in agent based social simulation - towards a mixed agent world

Despite impressive advances in ABSS, it suffers from several weaknesses. The most problematic is the lack of reality in the social interactions between agents. In humans, behaviour is guided by social interaction, which in turn is grounded in interpreting context. A human will see and then interpret the situation knowing the history of the interaction, using their own cultural background, drawing upon their own experience, and with a specific perception of other people and artefacts in that environment, etc. This raises huge challenges for agent based modelling. Since there is no generally accepted model of social interaction in the social sciences, the approach largely adopted in the ABSS community is to model agent interactions as simple messages, for example by using an Agent Communication Language (ACL). However, this is quite restrictive and does not reflect the richness that we see in human-human communication. All notion of non-verbal communication, which people use in real-life, is lost. Similarly, the contextual factors that strongly influence our decisions must be explicitly declared to the agent and how the agent then reasons with this knowledge must be formally represented, using rules for example.

What we are essentially losing by substituting the human for this rule-governed agent is the contextual intelligence that the human can provide in that situation. The central issue lies in the derivation of, and reliance on, the rules in ABSS. For such an approach to yield useful results we must have at least a reasonable understanding of the complex interactional mechanisms that operate in real-life social systems. This is necessary in order to formulate our agents' simple rules. Combining the rules with the agent and environment representation, we are then armed with a self-contained abstract model of the real situation. The assumption then behind this model, is that all of the 'intelligence' of the system is embedded in its representation. It could be argued that only simple (unintelligent) rules are being used and that the intelligence is an emergent feature of the system. Whilst this may be true, the point remains that the intelligence is embedded in its representation and therefore is also constrained by that representation (Pavard and Dugdale, 2002). In the case of real human contextual intelligence a person employs all of his or her 'cognitive rules' and background experience, etc. to guide decision-making and interact with other people

Another problem with traditional agent based social simulators is their difficulty in being able to sufficiently immerse the user in the simulation or to give a feeling of presence. Immersion is the subjective feeling that a user has when they are completely involved in an artificial world to the point that he or she is virtually cut off from the surrounding real-world. Presence refers to the feeling, mediated through a technological device, of being in a place. An extension of this is social presence (Biocca and Harms, 2002), which is the sense of being with another person in a mediated environment. Both immersion and social presence greatly help a person to use their own contextual intelligence in a virtual world.

Finally social interactions in ABSS lack the notion of reflexivity and indexicality that are crucial concepts in human interactions and in understanding human behaviours. Indexicality refers to the fact that, in the real world the meaning of actions is sometimes ambiguous and that disambiguation is obtained by referring to an external context. In non-verbal communication a simple example of indexicality is when a person identifies an object by pointing to it (figure 12).

Figure 12 Coordination of activities in the real world through indexical gestures. In the leftmost image, the man points to a distant location while looking at the woman to see if she can see the object to which he refers. The woman responds negatively and expresses her doubt by a self-contact gesture. The central image shows the next stage of the interaction, the woman requests a disambiguation both verbally and by gestures. The rightmost image shows a different situation where the two people show their mutual understanding via synchronous pointing and the repetition of a verbal message.

Reflexivity refers to the reciprocal influences that take place during human interaction. This is evident in mirroring body posture, the orientation of eye-gaze to regulate turn-taking during conversation, or an emotional reaction to facial expressions or voice intonation, etc. Both reflexivity and indexicality are often based on a complex set of contextual information (including non-verbal communication).

In summary ABSS is particularly weak on how non-verbal communication is represented by agents. This channel of communication, together with reflexivity and indexicality provides important contextual knowledge that people use to make decisions and interact with others.

Following these weaknesses the goal was to extend traditional ABSS in order to reproduce the complexity of real social interaction. In our approach the user is free to exploit all his or her contextual intelligence in order to drive social interaction. Thus we follow the 'human in the loop' paradigm, rather than a 'closed society' approach that is indicative of traditional ABSS. The human in the loop paradigm consciously integrates the human into the simulation system. Thus rather than trying to model human contextual intelligence directly in the agents, they take the form of virtual characters that are partially controlled by the humans.

The result is a distributed virtual reality platform that allows a group of users to interact simultaneously in a shared virtual environment (Figure 13). The users are represented in the virtual world by their avatars and whilst they have some degree of autonomy, they are largely driven by the users. Therefore in the simulation, the user employs their *own* contextual intelligence and the users communicate with each other *through* the virtual environment. In addition, the users' own problem solving capabilities including the influential emotional and cultural aspects, are employed.

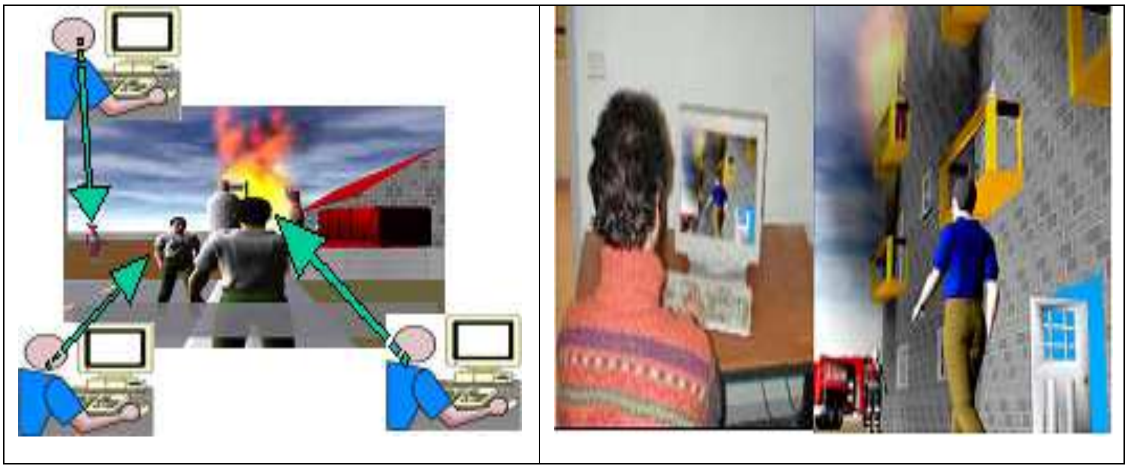

Figure 13: On the left is a schema of several users guiding their characters in the virtual environment. On the right, a user is driving his virtual character and on the far right there is a screenshot of the environment.

The fundamental consequence of enhancing a system with contextual intelligence is that the behaviour of the agents is closer to what would be expected in reality (figure 14). This is because the actions of the human user, and implicitly the rationale behind these actions, are transmitted to the artificial agent. Thus the agent acts in a far more complex manner compared to an agent that is just reacting to a set of predefined rules. For example, as the user surveys the virtual environment he is selecting what constitutes relevant contextual information in order to determine his response. This selection process, and the resulting actions, is far more complex than in the closed society agent model.

Figure 14: Depending on the context, the same character exhibits different behaviours and non-verbal communications. The stance of the virtual character on the right is not only to protect itself from the fire but it also non-verbally communicates the intensity of the fire to any other fireman in the proximity.

One of the main challenges in this approach is deciding which actions are under the automatic control of the virtual agent and which are controlled by the user (following Greenhalgh et al. 1997 this is known as the involuntary/voluntary dichotomy). The direct control of the virtual agent is a reliable solution only for voluntary gestures, such as pointing to an object, but it is inappropriate for some parts of non-verbal communication such as involuntary gestures and facial expressions. In order to analyse these interpersonal social interactional factors in more depth we analysed real-life interactions during the training exercises of fire-fighters. Here we adopted an ethnomethodological approach. Ethnomethodology (Garfinkel, 1967) is used to study social interactions and aims to understand how people make sense of their social environment. According to ethnomethodology all meanings are context dependent and non-verbal behaviours, such as gestures, play a primordial role in interpreting the message. Two of the main concepts in ethnomethodology are indexicality and reflexivity. As expected, and in line with previous research, the results of the analysis showed the huge importance of non-verbal communication. However, we also found that when verbal communications are impossible (e.g. when fire-fighters are encumbered with breathing apparatus) fire-fighters rely totally on non-verbal communications, indexicality and reflexivity as the main mode of communication.

Scientifically, this is an interesting situation since it allowed us to study an extreme form of non-verbal communication that does not occur in everyday situations. The analysis also allowed us to identify common norms of non-verbal social interaction, for example, turning your head when another person enters your field of view, using hand beat gestures when talking, turn your head when someone is speaking to you, etc. These actions and gestures are performed unconsciously by humans and thus need to be generated automatically by the virtual characters. Figure 15 shows an example of how the unconscious action of turning one's head when someone enters their field of vision was represented in the system.

Figure 15: On the left, a snap shot from the real situation; on the right the representation in the virtual world.

The validation of the model was based on a series of ethnomethodological experiments that were performed to directly compare social interactions between users in the real world and those in the virtual environment. In essence we were evaluating the non-verbal communication skills of the virtual agents and how contextual intelligence was used within the system. In general we found that a users contextual intelligence can be successfully integrated into the agent world and that providing abilities for indexicality and reflexivity in the virtual characters greatly enhance non-verbal communications. On a practical level, some automatically generated gestures can increase the quality of interactions in the virtual world. However, an excess of automation can distort the user's feeling of immersion and can also prevent the user identifying himself with his avatar. (Dugdale et al. 2006b) (Pallamin, 2008).

To summarize, the underlying stand-point of this work was that contextual information does not need to be represented explicitly within an artificial agent. Instead, it is possible to use a human's own contextual reasoning by putting the human in the loop in the simulation system. This overcomes the limitations of traditional ABSS and makes an agent's ability to reason with context closer to what we observe in the natural world.

4.4 A model of contextual activities

My second contribution concerned a body of work aimed at developing a model of contextual activities to help with the design of ambient technologies in domestic situations. The work was a result of a 3 year collaborative project with EDF and the Tech-CICO research team at the Université de Technologie Troyes. Part of this work involved a joint co-supervision of a Master student who developed an agent based simulator investigating the role of expectations and routines in home situations (Costa et al. 2009)

The basic premise of ambient technologies is that they need to be aware of the context in which they are working. However this raises a number of questions:

- what contextual capabilities need to be incorporated into systems and services?
- exactly how much and what type of contextual information should be included in these technologies?
- what value do context sensitive services give in helping to manage individual and collective situated activities in different social contexts?

Practically, the aims of this work were to develop:

1. A method for *analysing* individual and collective situated activities in domestic settings.

2. A tool to help the *design* team to assess different implementations of context-aware systems in a household using different criteria such as energy, comfort or safety. In this way the tool would be a complement to more traditional evaluation methods such as usability testing or user-based evaluation.

In the recent years many studies have been conducted in order to better understand the articulation between ambient technologies and the social organization of domestic activities. These studies adopt a variety of approaches, ranging from narrative descriptions of domestic life gained through ethnographic studies attempting to assess the impact and role of technologies on domestic life, to more technology led views which tend to focus on computational, rather than social aspects of domestic life (Jackie Lee et al, 2006) (Schmidt, 2005).

The adopted methodology was first to examine ethnomethodological studies of home situations, focusing on how people interact with technologies and services. This was done in order to identify the issues that are relevant to context modelling. Secondly we used data, provided by EDF from living labs, and videos and narrative descriptions of real home situations, in order to complete the set of issues identified in the first step. Seven issues were identified as being relevant to reasoning about context and consequently included in the model (Dugdale et al, 2005) (Salembier et al. 2009):

- *Routines* as a resource for efficiently organising individual and collective activities at a low cognitive cost (Crabtree and Rodden, 2004) (Tolmie et al, 2002),
- The *role of artefacts* in the domestic situation. The interpretation of an artefact's state at a given moment determines the local context of use. (O'Brien et al, 1999),
- The role of the *organisation of domestic space* is a contextualised way of organising activities (Shadbolt, 2003),
- *Implicit communication* between actors in the physical environment. These communications may or may not be related to the actions of the actors (Crabtree, 2003),
- The *mutual awareness* that an actor has of others activities defines the context of activity for that actor (O'Brien et al, 1999),
- The *dynamics of actor engagement*. The actors may need to manage different concerns in parallel,
- *The evaluation of an actor's availability* is an important aspect in defining the context for the actor and for other actors (Dugdale et al, 2005).

The vision was that ambient intelligent domestic services such as lighting and heating could have different levels of contextual capability. However, in order to define these levels it is important to make a clear distinction between the notions of environment, context, and situation. For this we drew inspiration from a generic classification of Quéré (Quéré, 1997) who identified three complementary categories of "contexts": environment, context and situation.

1. Environment
An environment can be defined as a relatively stable structure composed of a location, and in which different objects are present. For example, we can speak of the kitchen as an environment defined by more or less precise physical boundaries and by the artefacts disseminated in this physical space.

2. Context
The context enables meaning to be given to an event such as someone else's behaviour or a signal in the environment. Context enables the justification of

meaningful actions. Broadly speaking, context can be seen as an "interpreted environment".

3. Situation
A situation can be seen as an environment "ordered" by the experience through time and space of this environment. This ordering is made possible by configurations that are walkthroughs in the environment, paced by actions involving available resources.

To explain the distinction consider the following example:

> *"X intends to purchase an object O. She goes out of her place, but realizes that it is raining; she then goes back home in order to get an umbrella. On the stairs she meets one of her neighbours; she chats with him for some minutes. She then goes upstairs to her flat but has forgotten the reason why she came back. She goes out and notices a traffic jam in the street; she also realizes that she is late and therefore decides to take the metro."*

Following figure 16 different **environments**: home, stairs, etc. are populated by objects (e.g. other people), and include different events (e.g. rain, meeting someone, etc.) Environments are interpreted in terms of background knowledge. This **contextual** set allows X to give meaning to events, to generate and justify actions. For example, if there is traffic in the street, it's likely that the whole area will be crowded, therefore don't take the car (X is already late due to meeting the neighbour); so X takes the metro. The **situation** is the ordered experience in time and space, containing different episodes (expected and unexpected) that take place in a succession of environments. Alternatively we can see it as a sequence of different contexts.

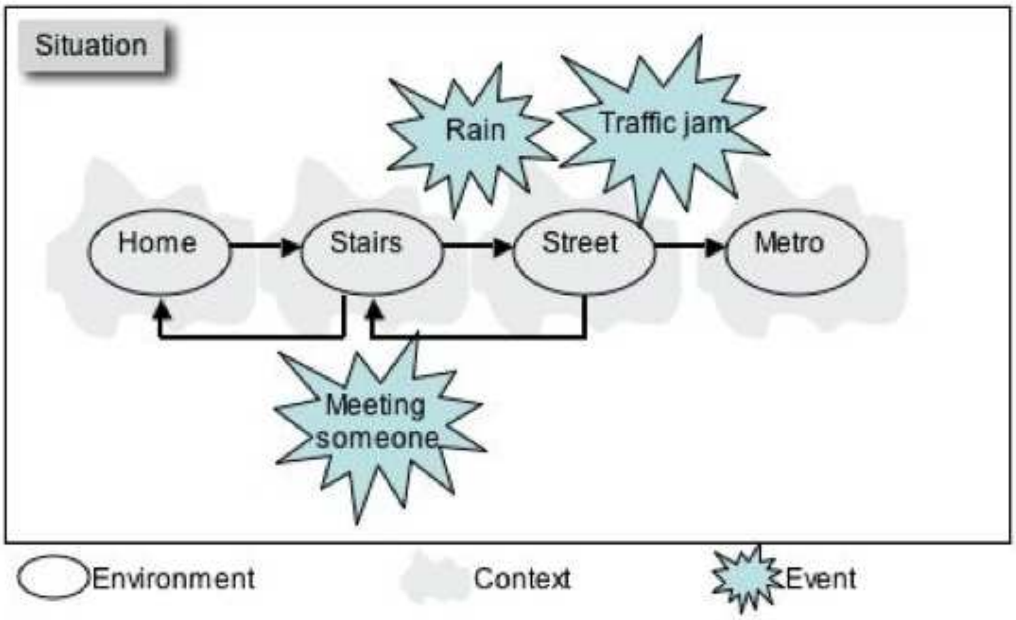

Figure 16: Environment, context and situation

From an analytical point of view, this three-layer framework makes an explicit conceptual distinction between the three, often confused, terms. Furthermore, it provides a basis for interpreting and situating the 7 issues identified above and provides a foundation for examining real world scenarios.

The above three-later framework has been translated into a technological equivalent, shown in table 1 below:

Environmental equipment level (Equivalent to 'Environment' in figure 16)

Here an ambient intelligent system describes events in the physical environment as raw sensor data using physical sensors in the environment. These sensors can detect physical events, such as a doorbell or phone, as well as behavioural events such as opening a fridge or entering a room. In essence the environmental equipment level concerns tracing the state of technological artefacts and the presence or location of people in domestic space.

Epistemic equipment level (Equivalent to 'Context' in figure 16)

Here an ambient intelligent system would have background knowledge, such as knowledge of household routines or common-sense knowledge. This is used to interpret occupants' behaviours.

Historical equipment level (Equivalent to 'Situation' in figure 16)

Here an ambient intelligent system has the ability to keep a trace of actors' commitments and activities and to use this information in reasoning.

Table 1: Technological translation of the Environment-Context-Situation Model

It is also necessary to define different points of view. In the real world, actors in the same physical environment may have different perceptions of the context, i.e. what is contextually relevant for one person may not be contextually relevant for another. To account for these different perceptions the notion of a point of view can be introduced (table 2 below).

Actor point of view

Different actors may interpret an action in different ways. Since the same context, as seen by an external observer, may vary for each actor it can be interesting to differentiate between these viewpoints. Most of the time the "context for the agent" remains an individual, situated experience of the world, which is only accessible by the agent himself/herself. But the actor's motive for performing an action may be publicly known if it has been made explicit, for example by a communicative act. However, very often there is no evidence for a motive or the internal states of an actor. The external observer therefore does not know the motive or has to infer it from perceptible manifest facts and background knowledge.

The idea is to compare the views of different actors at a given time and to analyse how different actors interpret the situation differently. This may be used to inform the design process and, more precisely, to check to what extent a system that has different contextual abilities (table 1 above) would be able to interpret a situation in a useful way in order to act appropriately.

Analyst point of view

This may be seen as a hypothetical, idealistic viewpoint. We can imagine an omniscient, ubiquitous observer who could have unrestricted access to all the events and facts in the environment, including the motives of the different agents.

This viewpoint is often considered as the “God’s eye view” in computational simulations where the external observer can see all viewpoints. The interest of using such a viewpoint is that it provides a reference to systematically compare the results of the application of different individual viewpoints to a theoretical optimum.
System point(s) of view This refers to the different kinds of ambient intelligent systems that we may design (detailed in table 1 above). Here we can have systems that only use environmental equipment (i.e. using only sensors), or they may additionally have epistemic abilities by incorporating background knowledge into their reasoning; finally they could also incorporate historical knowledge. By modelling these different types of system, a designer can evaluate what extra value different types of contextual systems give to occupants.

Table 2: Defining different viewpoints

The framework was evaluated in a series of experiments to show what additional information taking into account different levels of context could provide (Salembier et al. 2009). The micro level evaluation used excerpts from real scenarios taken from an empirical study in domestic situations. The scenarios focused on energy management issues, such as the lighting management. Using the framework we were able to see the situations from different points of view (actor, analyst, and systems). In terms of helping with the design of ambient technologies it was interesting to use the ‘systems’ viewpoint to see if a proposed system could manage, for example, the lighting in a satisfactory way for the occupants. In terms of reducing energy consumption, a basic ‘environmental level’ system equipped with sensors faired well. However, it could not take into account the habits and behaviours of occupants; for example turning on lights in an adjacent, unoccupied room, in order to provide extra light where a person was working. Using the different viewpoints and by testing different types of system, such as an epistemic level system, this aspect would be well-managed.

The macro level evaluation used different criteria, such as comfort, safety, cost, etc. to show how the different types of systems (environmental, epistemic, historic) would behave. Figure 17, taken from (Salembier et al 2009) shows the lighting duration, in minutes, for different rooms in a house, with different systems (in this case environmental and epistemic) compared to a reference scenario of the real-life situation.

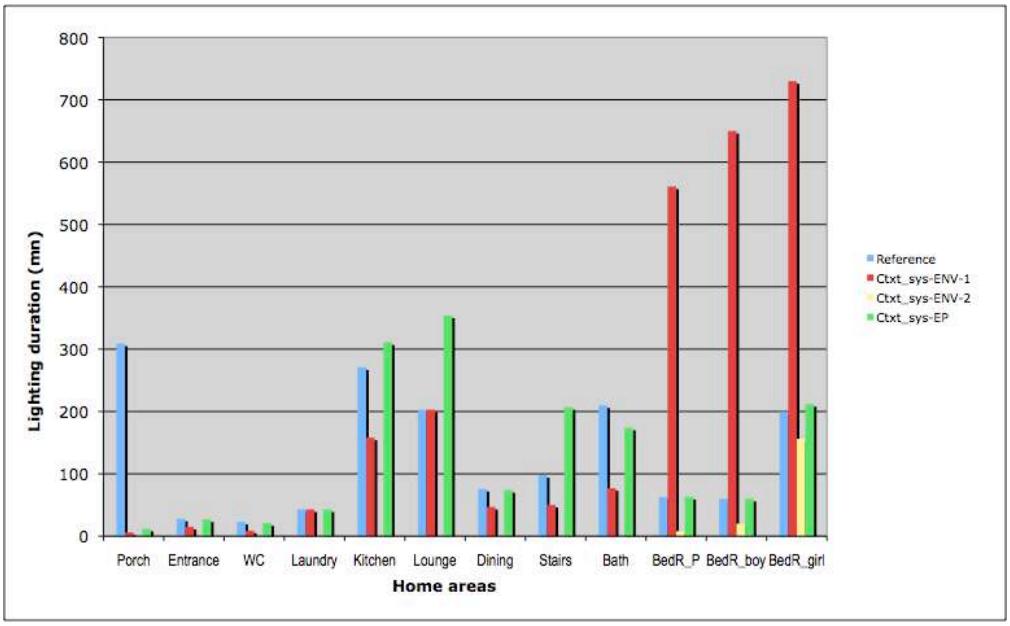

Figure 17: Lighting duration for different technological systems

Broadly the results of the work show that if we just consider energy consumption, then episodic level ambient intelligent systems (shown in green) sometimes perform worse, depending on the room, than an environmental level system with sensors (in yellow), i.e. they result in more energy consumption. However, if we look at other criteria and how the lights are actually used in a household (using the micro-evaluation), we can see that energy saving is not always the top-priority, particularly in family situations. For example, staircase lights are frequently left on in family homes for security reasons, and householders sometimes prefer a constant light level rather than lights going on and off (comfort). Thus by looking at different points of view, by taking into account different criteria, and by considering different types of system, the framework can help designers to analyse how different technologies will fare when implanted in a home situation.

4.5 General reflections

This chapter has argued for the necessity of taking into account context when considering human behaviours. Two contributions were presented; the first investigated how human contextual intelligence can be integrated into agent based simulation. This approach falls into the broad area of participatory simulation, which is concerned with incorporating the user or expert into the simulation process. Frequently, participatory simulation is used to overcome problems with data collection and analysis (Bousquet and Le Page, 2004), or to complete an agent model (e.g. the work at the Ishida and Latsubara Laboratory at Kyoto University). In my work however the participatory approach was adopted in order to exploit the contextual intelligence of the human.

The second contribution looked at developing a modelling framework for contextual activities. Here the goal was to look at how human's reason with context and how this information would be used to inform the design of ambient technologies.

From the perspective of ABSS, the question is how does this work on context impact modelling and simulation using an agent based approach? The first contribution helps to highlight the weaknesses of the traditional ABSS approach by exposing our assumptions about how we usually model context. Although having the human drive the virtual character overcomes the problem of having to explicitly model what is contextual relevant information, it brings additional challenges since we must delimit what actions are under the control of the virtual character and what are under the control of the human.

For the second contribution, we can use the framework for contextual activities as a pre-requisite to modelling context in agents since it provides a way to focus our attention on understanding how we reason about context and the effect it has on our behaviours. This in turn helps to increase the validity of any agent based models. The work has been subsequently used and extended in collaboration with two masters students (Utku Ketenci and Mihail Velichkov) and a current PhD student (Ayesha Kashif). Specifically these works, which are described in the following chapter, focus on modelling and simulating the coordination of human activities when reasoning about context. The increasing movement towards ambient intelligent devices have led us to question if we can simulate human behaviours and the underlying reasons for behaviours in sufficient detail as to develop intelligent control systems. The following chapter details my most recent works that explore this issue.

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Chapter 5 Incorporating human behaviour into intelligent control systems

5.1 Introduction

The previous chapter showed the importance of taking into account contextual information in modelling and simulating human behaviour. This information is used as a basis for decision making, resulting ultimately in human actions and behaviours. However in order to be used productively it is necessary to go one step further and to demonstrate how human behaviour models may be incorporated into control systems. This chapter addresses some on-going work on this topic specifically in the area of energy management.

A standard control system, such as that for heating, is typically regulated by predefined schedules (e.g. with the occupant defining the schedule for when the heating should come on or go off during the day) and/or by explicit interaction (e.g. with the occupant manually controlling the heating temperature as needed). The system itself does not contain any explicit model of the occupants. However, more sophisticated control systems, under the remit of smart homes, are now being designed. These systems aim to take into account human activities in a more integral way. Nevertheless the models of human behaviour incorporated into such systems remain weak and typically only account for the presence or absence of people in a space (Hagras et al, 2004). The complex behaviours of humans are not modelled, nor are the underlying reasons why people behave in certain ways. Incorporating realistic models of human behaviour into control systems represents a huge challenge: in defining accurate models, in showing the impact of human behaviour on control systems and, on a practical level, in managing the integration of human behavioural models with the physical models that are normally used to simulate and control systems. The work described in this chapter is current work on how human behaviour models developed and actively incorporated into control systems.

5.2 Scientific and technological context

The above line of research was largely conducted in collaboration with the G-SCOP laboratory under three specific projects. The first is the ANR funded SuperBat (Simulation Tools for Energy Management in Buildings) project that is coordinated by EDF and which runs from 2010 to 2014. The goals of the project are to develop a new generation of tools that better address the shifting economic and social needs of stakeholders concerned with energy management, including building designers, energy providers, and individual energy producers and consumers. Previous approaches developed tools that predicted energy demand based only on physical models (e.g. mathematical models of thermal transmission of building materials and of appliance demands). The goal now is to move towards more finely grained predictive tools where minute to minute prediction replaces the coarsely-grained hourly predictions, where individual appliance usage can be predicted, and where physical models are integrated with realistic and usable models of occupant behaviour.

The second project that ran from 2008 to 2011 was funded by the BQR Grenoble INP "Energie" initiative and was concerned with developing flexible methods and tools for energy simulation in buildings. Again, here the scientific focus was on the intelligent management of energy through using simulation as both a design and control tool. Both of these projects involved my supervision of a PhD student (Ayesha Kashif) and a Masters student (Mihail Velichkov).

More recently, the ANR funded Maevia project, which started in January 2013 and will run for 3 years, looks at developing models applied to energy and ventilation. This project looks more specifically at air quality and the robustness of low consummation buildings (Bâtiment de basse consommation 'BBC') against the occupant. Put simply, it aims to assess what is the tolerance of BBC buildings to human behaviours. Working with a new co-supervised PhD student, Khadija Tijani, this work will build on the work of my current PhD student, Ayesha Kashif, in extending the agent based model of human behaviour to assess indoor air quality.

These works not only draw upon my previous work in context modelling, but also use ideas from a study on human expectations. This was conducted with a Master 2 Research student, Utku Ketenci. Specifically we were interested in how our expectations about other people's actions affect our own decision-making and behaviour. A practical exploration of reasoning with expectations was conducted by developing an ABSS tool. To complement this study, work on formalizing the notion of expectations and their relationship to human behaviour in control systems was conducted in collaboration with researchers from the Federal University of Rio Grande in Brazil (Costa et al. 2009).

5.3 Behaviour models in intelligent control

In this section we will show how human behaviours impact energy consumption and how such behaviours may be incorporated into an intelligent control system for the purpose of energy management. Here the particular focus is on predicting energy consumption through the development of simulation tools to help with the design of control systems in Smart homes. Current attempts at simulating energy consumption focus predominately on physical models of buildings and appliances (for example, heat transmission models of buildings and building materials, temperature dissipation models etc.). Fundamentally this is an incomplete and partial approach since it does not address the effect of human behaviour on energy consumption. As Lee Schniper and Stephen Meyers state in their influential book

> "*People, not machines, make the decisions that affect energy use. Insight into the human dimension of energy use is key to better understanding future energy trends and how to act effectively to manage them.*" (Schipper and Meyers, 1992).

Given that buildings account for 30-40% of global energy use (Huovila, 2007), our behaviours in home or work situations play an important role in the goal of reducing energy consumption and CO_2 emissions. Consequently one of the cutting edge topics for the energy modelling research community concerns incorporating human behaviours into energy simulation models.

A common way to model human behaviours is to use basic presence/absence models, i.e. use sensor information to indicate if a person is present or not in the home. However there are a number of problems associated with these kinds of models. Firstly, these models tend to be used for appliances where energy is consumed only when they are turned on, e.g. lighting. Although this approach may achieve significant energy reduction, it is often at the expense of the occupant's comfort. As has been found in many field studies and as we found in our previous works (c.f. Chapter 4) this approach does not take into account some common human behaviours (e.g. putting a light on in a room in order to throw light into an adjacent room, putting lights on in uninhabited rooms as a 'welcome' to the arrival of guests, leaving stair-lights on as a security measure when children are present, or temporarily leaving a light on in an uninhabited room as a cognitive reminder to go back and complete some task. In addition such presence/absence profiles are not sufficient for appliances that have continuous energy consumption such as fridges and freezers that constitute a significant part to home energy consumption and where human behaviours (e.g. keeping the door open for a long time or putting warm food in the fridge) dramatically affect consumption.

Some authors have proposed that one way of looking at human behaviour is to consider physical needs: *"There are certain physical needs that people must meet in order to survive. There are other needs that make people more comfortable. In the specific ways they strive to meet these needs, people are different"* (Honeycutt and Milliken, 2012).

A need is satisfied according to the context of the individual (chapter 4) and this includes their expectations of the situation. An expectation is a belief, centred on the future, of what is considered the most likely thing to happen. Expectations are based on many different factors, such as our perceptions of, and trust, in other people, their actions, what has happened in the past, and the current environmental context; in short our expectations are *situated* (Piunti et al. 2007).

Following the identification of expectations as a strong factor influencing human behaviours a body of my work was devoted to exploring how expectations could be modelled and simulated, and in assessing their effect on human behaviours in domestic situations. Using the results from previous work (Dugdale et al. 2005) (Salembier et al. 2009) I worked with researchers from the Federal University of Rio Grande in Brazil whose aim was to develop a formal model of expectations in multi-agent systems. This model was based on developing a behaviouristic notion of expectation, centred around the effects of actions that people or artificial agents perform at a given moment, within the context of some routine. Routines were used as a focal point since in most practical agent based systems, including human ones, there is a notion of continuous functioning over time, but more specifically a repetitive, periodic functioning that is known as a routine. Indeed in domestic situations, routines are crucial in coordinating domestic activities and are a valuable cognitive resource for ensuring that activities are performed in an efficient and complete way (Crabtree and Rodden, 2004) (Tolmie et al. 2002).

This work on formalizing expectations can be seen as complementary to that performed by Castelfranchi and his colleagues (Castelfranchi, 2005) (Piunti et al. 2007) in that it takes an objective, rather than subjective, view of expectations. In our work on formalizing expectations we consider two kinds of expectations: (i) *expectations of actions*, that is some set of actions that occur in the performance of a routine over a given time, and (ii) *expectations of facts*, which are expectations that some facts become true, with a certain degree, as a consequence of some set of actions occurring in a given routine at a given time (Costa et al. 2009).

Some aspects of this theoretical approach were modelled in the second body of work that was concerned with developing a simulator that showed the effect of expectations on human behaviours. Here, we used a BDI (Belief, Desire, Intention) architecture to model an expectation as a belief that an agent has in a future action or fact. In this work we showed how agents in the simulation coordinated their activities based on their expectations of each other and on facts that happened in the environment. Moreover, what was more important was to see how the agents adapted their activities within a routine when an expectation failed (i.e. agent x was expecting agent y to perform a task and had incorporated agent y's future actions into its routine. When agent y failed to perform the task, and thus agent x's expectations has failed, agent x had to reorganise the tasks in its current routine).

Taking the ideas of modelling expectations and routines in a BDI architecture the model was enhanced in the scope of the SuperBat project and with my PhD student, Ayesha Kashif, in order to develop simulation tools for energy management.

5.4 Model of inhabitants’ behaviours in domestic situations

To examine the importance of inhabitants’ behaviours regarding energy consumption we can analyse how consumption varies across different appliances in different houses. Several energy consumption databases are available, however our projects on energy management are based on using the IRISE database[14]. Here 2 different categories of houses were selected based on the number of occupants: 2 person houses in category 1, and 5 person houses in category 2. Also all houses in both categories have the same appliances.

From the results in figure 18, we can see that in the 1st category in the 2 person house ”H2000902”, the inhabitants have the highest consumption for the washing machine as compared to other appliances. The likely cause is behavioural: for example the habit of washing a small volume of clothes frequently, rather than washing a larger volume less often.

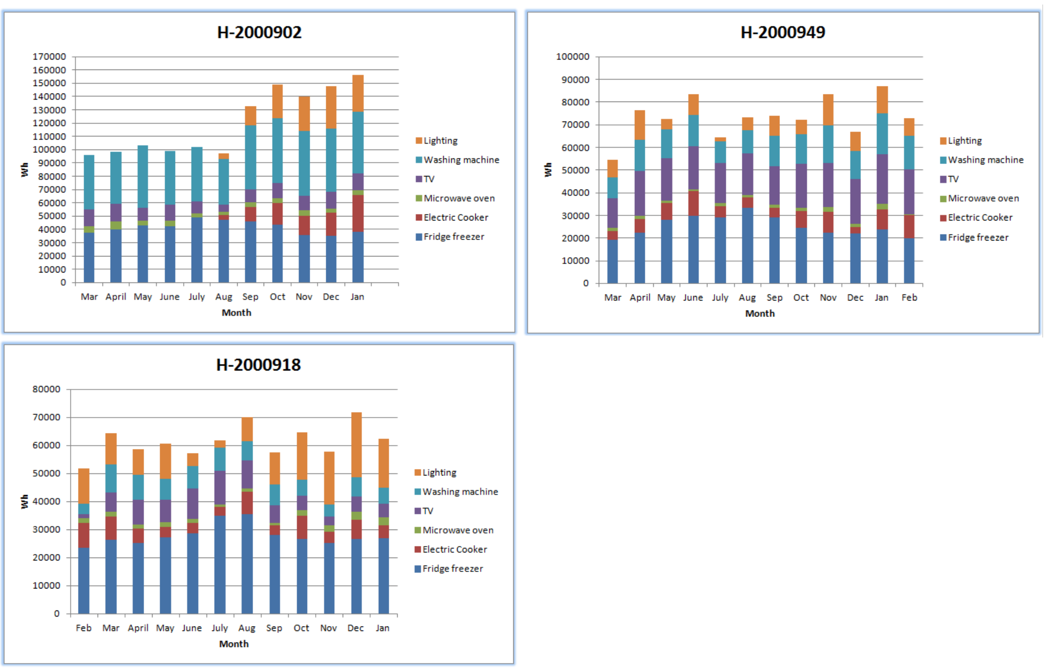

Figure 18: Energy Consuming Activities for 2 person houses

Similarly, in the 2nd category (figure 19), inhabitants in house “H2000945“ have the highest consumption for the TV as compared to other houses. Again the likely cause is simply behavioural differences in TV usage.

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[14] The IRISE database was constructed as part of the European Residential Monitoring to Decrease Energy Use and Carbon Emissions (REMODECE) project. IRISE contains energy consumption data, for each appliance from 98 French houses, recorded at every 10 minutes, over a one-year period.

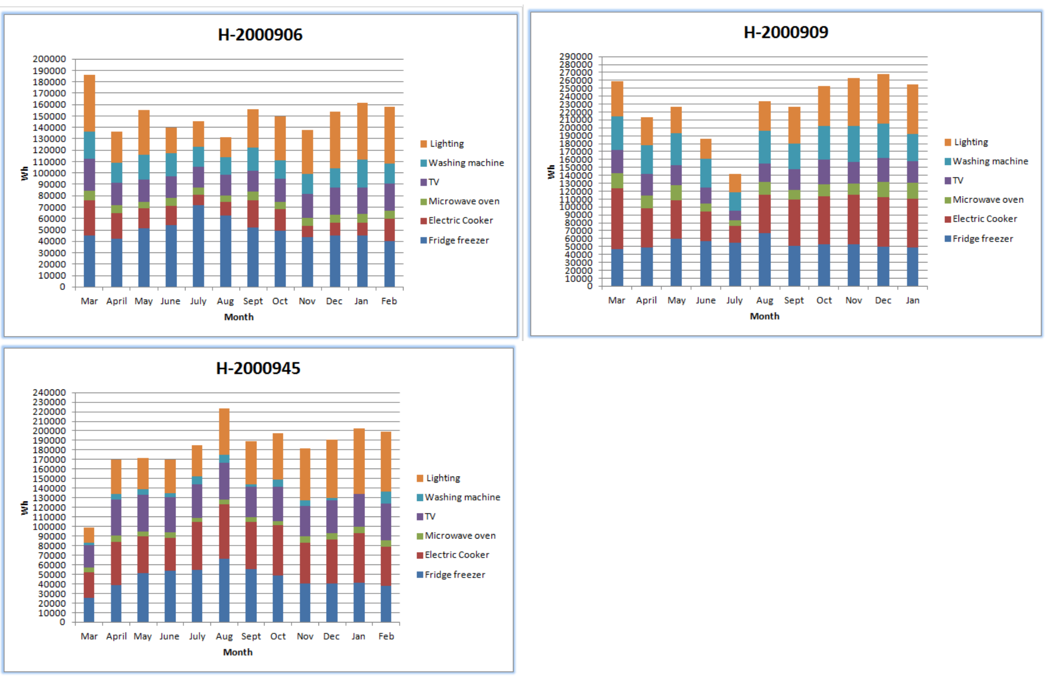

Figure 19: Energy Consuming Activities: 5 person houses

However, the problem with the IRISE database, and indeed most databases concerning energy usage, is that the data is related to energy consumption of the appliances or the household itself; it is not related to individual human activities or the reasons behind an activity. Thus the link between the inhabitants' basic energy consuming behaviours and the resulting consumption is missing. This poses a large problem in developing a model of human behaviour and subsequent simulator since we cannot link behaviours to consequent consumption.

To overcome this weakness a more detailed ethnographic study was undertaken in order to establish this link (Kashif et al, 2012). This follows the methodology proposed in chapter 2, and the focus on field studies. By monitoring the usage and energy consumption of an appliance together with recording the activities performed by individuals, and reasons behind these activities, we could make a first link between energy consumption and human behaviours.

The developed model is based on the notion of needs that arise from internal and external factors. For example, an inhabitant's own internal perception of hunger may invoke a need to eat. This need is realized by the activities of preparing and cooking food that in turn imply using energy appliances. Of course, external factors, such as the suggestion to eat from another inhabitant or the fact that the household routinely eats together at 8pm may also invoke the need to eat. In this way, we build on my previous works concerning modelling expectations and the importance of routines in home situations. Figure 20 shows a basic causal model of this relationship.

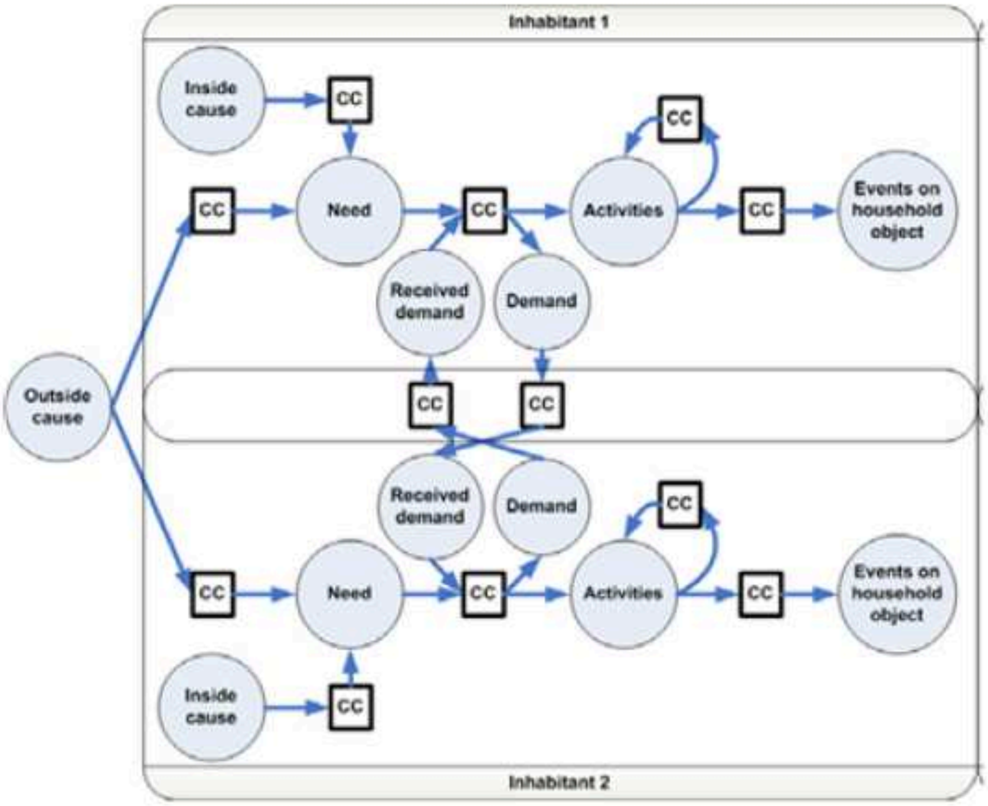

Figure 20: Causal relationship in BDI model.

In the figure CC stands for the causal condition: if a cause is satisfied, an effect is created. In the case of many inhabitants, a need of an inhabitant can cause not only personal activities but also activities of other inhabitants. Following the BDI architecture, an agent's (or inhabitant's) beliefs are set from their perception of the environment. Here the environment refers to the surroundings of the agent, including the actions of other agents, and also the agent's internal environment. For example the agent can self perceive hunger, but the desire to eat will not be invoked unless a certain threshold is reached, or is it the time to eat, or a suggestion to eat comes from another agent. If one of these things happens then the desire is converted to the intension to eat, which will involve some activities or behaviours and consequently some use of appliances. The approach also involves modelling other factors, such as time, other contextual factors, reasoning mechanisms and communicative abilities[15].

This framework has provided us with the ability to link human behaviours to energy consuming activities whilst at the same time modelling the underlying beliefs and reasoning mechanisms that invoke those activities in a realistic way. Thus, not only are we able to evaluate behaviours with respect to energy cost criteria, but we can also reason on comfort, security or eco-friendly behaviours criteria as well as seeing the effect of social norms and routines and basic physiological needs.

5.5 Simulator coupling

Whilst we have provided a model of human behaviour and linked it to energy consumption, we also need to take into account include the more traditional aspects of

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[15] A fuller description is given in (Kashif et al. 2012); (Kashif et al. 2011), (Binh et al. 2010).

energy simulation into the approach. Conventional techniques of physical simulation in the building sector are based on deterministic models of physical phenomena (conduction, convection, radiation, etc) and on conservation equations (mass, energy). Currently, models can take into account thermal phenomena and ventilation, etc. and their coupling with the building shell. This is usually done by modelling individual heating, ventilation, cooling, and lighting components in multi-zone buildings. In addition, meteorological conditions are also considered and incorporated into the equations. These models provide us with a reasonable accurate assessment of energy consumption, but without the 'disturbance' due to the occupants. However, since occupant behaviour is not considered we lack crucial information on how the appliances are used on a shorter, minute by minute, time scale and thus we are unable to have an accurate assessment of power demand.

The novelty of our work lies in linking together different kinds of simulators; those that model inhabitants behaviors and those dealing with physical aspects. Figure 21 shows the interoperability between the four modules in our co-simulation environment.

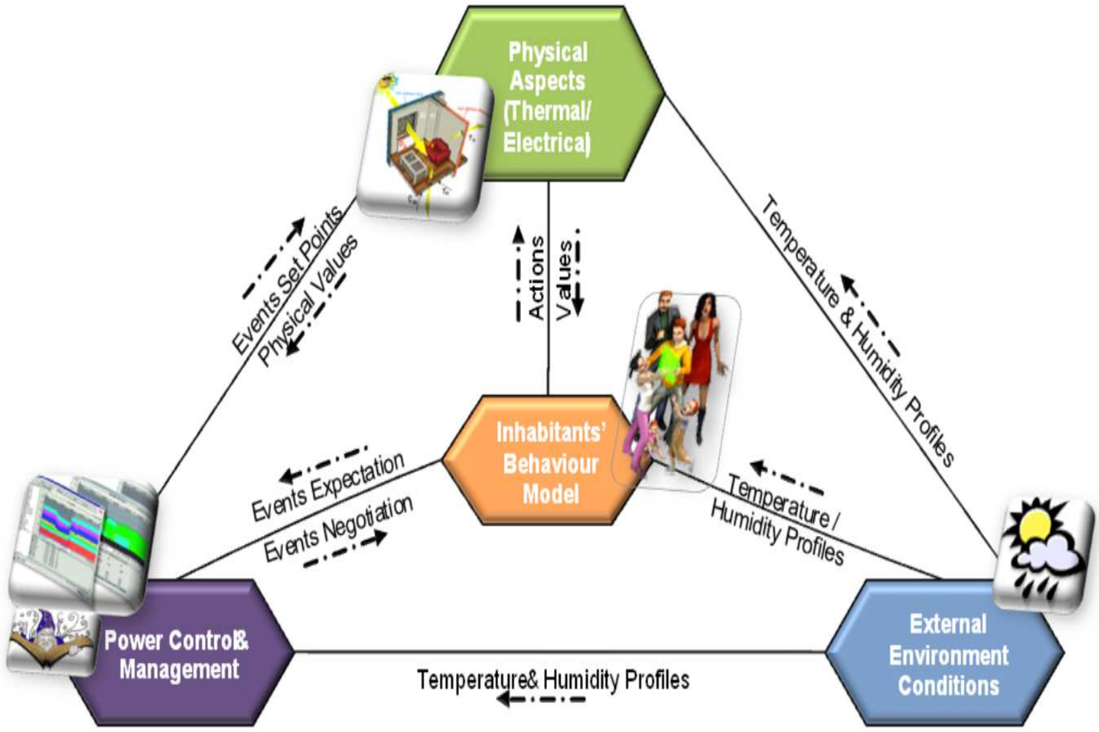

Figure 21 Interoperability between the different modules in a co-simulation environment

The inhabitants behaviour module is central to this environment and receives data from four other modules. All of the modules, apart from that dealing with Inhabitants' behaviour, are written in MatLab/Simulink and developed by the G-SCOP and G2E labs. The External Environment conditions module provides information concerning the external temperature and humidity to the other modules. In the Inhabitants' behaviour module this information may affect the occupants' beliefs, which may invoke some actions, for example by turning on the air-conditioning if it is too hot. These actions are sent to the Physical Aspects Simulator that contains thermal and electrical models of the various appliances and the building itself. Using the information of the inhabitants' behaviours the Physical aspects Simulator will calculate the power consumption of the various appliances. This information is then sent to the power control module that maintains, for example, set points for temperature in the building. Inhabitants' expectations concerning, for example the level of heating, etc. are transmitted to the Power control and Management Module. This module may in turn start some negotiation with the inhabitant. For example, the module could inform the inhabitant of the consequences of their expectations (in terms of energy usage, temperature and cost), and from this information the inhabitant could revise their expectations. Alternatively, the Power control unit could advise the inhabitant of other ways of achieving their expectations[16].

The four modules/simulators interact, mutually influencing inhabitants' behaviours, energy consumption and power control mechanisms. From this cycle we can see capture and efficiently manage energy consumption in the building.

5.6 General reflexions

The overall work of this chapter is formed from tying together various bodies of works on context, expectation modelling, simulator coupling, and human behaviour modelling. The work is still continuing, in particular in the area of validation where the challenge is firstly to calibrate the results of the simulator with what we observe in real life. Agent based social simulators, being representations of real-world complex systems, are notoriously hard to validate. The problem is in ensuring that their output is representative of the real-world situation. Comparing simulator output with what is observed in the real world follows what is usually termed an 'evidence driven' approach. Whilst the approach generally works well, because of the notion of sensitivity to initial conditions of complex systems, we cannot expect that the output of the simulator to match perfectly with that which is observed in the real world. Nevertheless we should expect that it adheres to trends observable in the real world (Dugdale et al. 2010).

Significantly the work in this chapter represents an important contribution since it departs from the traditional approach to buildings simulation, which normally addresses only the interaction between thermal, electrical and external environmental factors. At a higher level the work has demonstrated how empirically based models of human behaviour can be successfully integrated with more traditional physically based simulation approaches. This is an important step since in the simulation community at large these two disparate approaches are not usually combined. What this gives us is a more powerful tool to model a wider variety of situations with each approach playing on its own strengths.

This chapter concludes the main body of this manuscript, in the following chapter some general conclusions of the contributions are drawn. In addition, I reflect upon how agent based social simulation and human behaviour modelling may progress in the near and more distant future.

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[16] Currently we have proved with a very basic prototype that this information exchange and the interaction between the modules are possible. However the internal reasoning of the Power Control Unit and the design of the interface will be further developed in forthcoming project.

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Chapter 6 Conclusions and future research directions

6.1 Reflections

This manuscript has described my research works and contributions over the years where the central theme has been to develop realistic computational models of human behaviour with the specific goal of aiding design. The scope of my work is firmly planted in the domain of agent based social simulation where the main issues revolve around using artificial agents to represent humans. In addition to behaviour representation, the focus is on analyzing the interactions that agents have with each other and with the environment in which they are situated. The approach leans towards social theories that stress the role of emergence and contextual intelligence. This is in contraposition to classical cognitive modelling and a strong artificial intelligence approach.

The first challenge in ABSS posed in chapter 1 concerned the issue of what constitutes 'usable' models. While the two main approaches of KISS (Keep it Simple) and KIDS (Keep it Descriptive) have their weaknesses, the "Keep it Simple as Suitable", advocated by Conte and followed in my work, could lead to sufficiently complex models. However, the link between this philosophy and its practical implementation is vague. In my works I have tried to address this point by adapting a cognitive engineering methodology for developing ABSS. The focus is on using empirically based models of human behaviour that are uncovered by targeted field studies highlighting activity analysis rather than task analysis. This forms the basis of how, at a methodological level, we may develop adequate computational models of interaction that are sufficient to represent human behaviour.

I then tried to show how the emergence of mutual knowledge in a group of co-located agents can emerge from local interactions, and furthermore, that this emergent phenomenon can be the key to efficient and effective functioning of the collective. Interaction is one of the undisputed cornerstones of multi-agent systems. Within multi-agent systems we try to replicate direct interaction, indirect interaction, or stimergic[17] interaction. Direct interaction involves, for example, imitating verbal or written communications between humans. Indirect interaction may include imitating the non-verbal behaviours that humans use to communicate, such as gestures and postures, whilst stigmergic interaction concerns communication via the environment. What has rarely been examined is how very basic human cognitive mechanisms, such as overhearing, can constitute a valid form of interaction that can be modelled and simulated in artificial agents. This was one of the points that I focused on in addressing the second research question of how our interactions with each other and with our environment affect the emergence of social intelligence and mutual awareness that affects our ability to deal with work situations.

The third research question concerned how our understanding of complex systems could be applied to socio-technical systems and how can system robustness be engineered. This question puts the complexity of human behaviour at the heart of the problem and exposes the delicate and intricate coupling between a human and its environment. In design, the common approach to achieve robustness is by predicting the conditions in which a system should operate, and then designing a system that will

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[17] Stigmergy was first introduced by Pierre-Paul Grassé, a French biologist, in 1959 in observing the behaviour of social insects and how they leave traces in their physical environment as a form of communication in order to collectively coordinate their work. However, stimergic interaction is also a human phenomenon, as can be seen for example with user contributions to Wikipedia, and thus can be put to use and modelled in multi-agent systems.

operate well within those conditions. Yet how can we understand and predict *a priori* all of the interactions and perturbations that will take place within even a moderately complex system. In a complex system, small changes can result in unexpectedly large differences in overall system behaviour, possibly taking the system outside the intended operating bounds foreseen by the designer. This fragility is often seen as a flaw, yet the strength of self-organizing processes, seen so often in human systems, readily overcomes these problems. In the frame of answering these issues my response was to make a firm distinction between robustness and resilience and to suggest that we should in future focus on engineering systems that support self-organizing process, rather than staying within the bounds of traditional engineering approaches.

Such is the influence of context on human behaviour, that it can be argued that the two are inseparable. Context is dynamic and individual to the person; these aspects pose significant challenges to human behaviour modelling with artificial agents. My response to the question on modelling context was to tackle the problem from a slightly different angle and to distribute the problem by adopting a more participatory approach of exploiting human contextual intelligence. The issue of how context awareness contributes to decision-making, which formed part of the initial research question regarding context modelling, was tackled by proposing a framework for modelling contextual activities. This forms the basis by which we can handle the dynamic and individual nature of context modelling in artificial agents.

The final chapter described my most recent works on human behaviour modelling. Here a challenge was to span the chasm between high level automated control and low level human behaviour modelling reasoning with beliefs, desires and intentions. The utility of agent based social simulation for the social sciences appears clear. Yet, its usefulness in other areas is only just beginning to become apparent. Encapsulating human behaviour in the social part of 'socio-technical' systems is a more holistic approach and the integration of social simulation models into control systems that feature humans at their core should be more widely accepted. This point brings me to my perspectives for future work.

6.2 Future research directions

Based on my previous and on-going work, the plans for my future research are to stay within the domain of agent-based social simulation focusing on modelling interactions and behaviours.

6.2.1 Short term

In the short term my work focuses on investigating *information dispersal* within a community of agents. Recent years have seen an explosion of the use of social media in our society, with applications such as FaceBook and Twitter. Although such applications were originally designed for leisure, their use in professional work, such as crisis and emergency management, has now become standard practice (Dugdale et al. 2012) (Van de Walle and Dugdale, 2012)[18]. Amongst other issues, this has prompted research concerning the efficiency of information dispersal in a virtual collective formed through dynamic network associations. In addition, work has been conducted to analyse the emergence of mutual knowledge in on-line social networks. Whilst these issues have been studied empirically and reproduced by multi-agent systems (e.g. the work detailed in chapter 2 was an example of this), a more solid theoretical grounding on information propagation has been missing. Thus, my work in this area looks at if information propagation and the emergence of mutual knowledge can be explained using a concept

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[18] See also the work of Leysia Palen and her team on Crisis Informatics, at the University of Boulder, Colorado https://www.cs.colorado.edu/~palen/Home/Crisis_Informatics.html

from physics: the percolation mechanism (Broadbent and Hammersley, 1957). As was studied in physics, percolation concerns the movement and filtering of liquids through a porous material. If we interpret the material to be people in a network, then we may assess how information propagates, or filters through, the network and if there is a point where information becomes mutually known (the percolation point).

> *In practical terms, this line of investigation is being realised through collaborations with IRIT and ENSI and has recently produced its first results (Dugdale et al. 2013)*

My second area of future research is also concerned with social networks and in particular the role played by mobile devices. Smartphones are equipped with ever more advanced sensor technologies, including an accelerometer, digital compass, gyroscope, GPS, microphone, and camera. This has enabled entirely new types of smartphone applications that connect low-level sensor input with high-level events. Imagine an emergency situation, such as a fire aboard a large passenger ship; could we use local and Smartphone sensor data in computer simulations to provide real-time information to passengers and emergency managers on the best evacuation routes? Can we then transmit the result of those simulations (i.e. directions on the best evacuation route given the spread of the fire and location of people) directly to passengers and emergency managers via mobile devices? These are the questions that I aim to address in modelling and simulating crowd behaviours for evacuation. Although evacuation models and simulations have been around for some years now, such applications do not model sensor information and how real-time instructions given to victims affect human behaviours. At the most immediate level, this investigation is focused on modelling simple human behaviours, such as movement. However, we can envisage modelling and examining how more complex human behaviours, such the emergence of panic, can be incorporated into these simulations.

> *In practical terms, this line of investigation is being realised through two projects. The first is the SmartRescue Project, funded by the Agder Utviklings og Kompetansefond project, that looks at how simulations and SmartPhones may be used for real-time threat assessment and evacuation support in emergency situations (Granmo et al. 2013).*
> *PhD Co-Supervision: Parvaneh Sarshar, Sondre Glimsdal*
> *The second is the ANR funded RiskNat LIBRIS project, undertaken in collaboration with the PACTE social sciences Laboratory in Grenoble. This project looks at modelling human behaviour of citizens in Beirut, Lebanon, after an Earthquake.*
> *MSc Co-Supervision: Truong Hong Van (IFI, Vietnam)*

The third area for short term future research concerns addressing in more detail the notion of resilience (defined in chapter 3). Whereas my previous work tried to distinguish between the 2 concepts of robustness and resilience, my plans now are to focus on practically designing resilient environments through modelling and simulation. The context of this work is again emergency and crisis management, in particular looking at the resilience of cities against natural disasters. The resilience of a city to withstand and recover from a disaster depends on many aspects, e.g. resilience of buildings, resilience of physical infrastructures such as dams, and preparedness in putting adequate plans and procedures in place, etc. From a human behaviour point of view, I am interested in how individuals and communities contribute to having a resilience environment and how human behaviour may change in response to new plans and procedures.

> *In practical terms, this work is followed through a new project proposal intended for submission under the ANR funding scheme. The project, called DREAMS (Designing resilient environments through advanced modelling and simulation),*

aims to assess how coastal cities in South East Asia can be made more resilient to climate change. The experimental tool that will inform policy makers involves multi-scale and multi-model agent based simulation.

6.2.2 Long term

We are entering a new era of computing. Software agents are becoming increasingly prevalent in our environment; they are embedded in the fabric of our society in ambient technologies, they are found in the technological supports that we use, and are manifested as embodied conversational agents or robots. This is leading to an inevitable increase in interactions between software agents and humans, resulting in the emergence of mixed human-agent societies.

Currently very little is known about the interactions that will take place in these new societies, what kinds of cooperative behaviours will develop, or how human behaviours and intelligent agent behaviours will be modified through these interactions. We know that humans exhibit an unconscious response to digital media as if they were interacting with other humans (Reeves and Nass, 1996). Could the same be true when humans interact with agents? Will humans exhibit pro-social behaviours towards software agents that are on a par with those they exhibit towards humans? What kind of emergent behaviours will be observed in mixed societies, and will artificial agents be able to identify and react to these phenomena just as people do in human societies? Humans already rely on agents as a cognitive support in their environment; will artificial agents grow to reply on humans as a cognitive support as well?

The focus of my future work is therefore two-fold: firstly to explore characterising direct and indirect behaviour of human towards agents by modelling and simulating these mixed societies. Secondly, from an artificial agent point of view, to explore how agents behave in these mixed societies. If we can characterize and understand the interaction that humans have towards software agents embedded in new technologies then this will allow us to construct agent systems that work synergistically and cooperatively with humans.

On a practical level the ground has been laid for the first step of this investigation through the ANR CONTINT project called MoCA (Mon Petit monde de compagnons artificiels) that started in late 2012. The theme of mixed societies is central to the MoCA project where the goal is to create a world of artificial agents (virtual or robotic) that interact with humans in a social context. In MoCA the human and artificial companion relationship is explored with the emphasis on social behaviours. Specifically we address what characterising traits artificial agents must possesses in order for them to be socially acceptable by humans. The goal here is to investigate how artificial agents may form life-long relationships with humans. The first step has been to create scenarios where we imagine humans interacting in natural ways with various agents, such as robots and virtual characters. Drawing upon the work of my current PhD student in modelling human behaviours, we have modelled these scenarios in the Brahms simulation environment. First results of this work have shown how interactions in a hybrid society, composed of artificial agents and humans, may be expressed in a semi-formal way (Benkaouar et al, 2013).

On a more general level, the ideas of collective and social intelligence will need to be expanded. At a macro-level, human-agent society is seen as the result of the interaction between components at the micro-level. Agents, and more generally our future software systems, are increasingly exhibiting characteristics that are closer to natural systems than with our previous traditional software systems. In these systems, decisions will be shared collectively by this mixed society with the goal of co-constructing a solution or a new viewpoint on the problem. Thus the notion of *collective intelligence* is taken further than just referring to the emergence of human group intelligence. In future it may refer to the intelligence that emerges from the collaboration and interaction of both human and software agents. Likewise the notion of *social intelligence*, which refers to the human ability to effectively navigate complex social relationships (Kihlstrom and Cantor, 2000) (Thorndike, 1920), will need to be extended to artificial agents. Agent based modelling has several roles to play here. The first, as authors such as Rosaria Conte have extensively and convincingly argued, it is a powerful tool for the study of human intelligence (Conte, 2002). Thus agent based models are used to provide a firmer behavioural foundation for collective and social action. Leading on from this understanding, the second challenge is to design socially intelligent agents that are capable of meaningful interaction with humans, adapting their behaviours in order to promote collective intelligence in the mixed society. Finally, agent based modelling has a role of play in informing the future design of mixed systems through modelling and simulating both human and artificial agents.

These issues highlight what it means to have artificial agents that are capable of real social interaction, where hybrid societies jointly make sense of their world and co-construct solutions.

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