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Modelling human social behaviour in conflict environments using complex adaptive systems

Stein Malerud

Norwegian Defence Research Establishment (FFI)

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Approved by

Stein Malerud	Project Manager
Espen Skjelland	Director of Research
Jan Erik Torp	Director

English summary

Experiences from the military operations in Afghanistan and Iraq have demonstrated the importance of understanding human behaviour. In an effect-based approach to operations so called ‘behavioural targets’ are emphasised, which implies the ability to impact human behaviour in a favourable manner. For instance a desired ‘behavioural target’ is to win the ’hearts and minds’ of the population in order to ensure support and compliance with the peace process. Despite the focus on human behaviour, there is a lack of adequate models to support decision making with regard to human social behaviour. The aim of this study is to review and explore models of complex adaptive systems (CAS) and to assess their applicability to support analysis of human social behaviour in conflict environments.

CAS is a special category of complex systems that involves modelling of living beings that are capable to adapt to their environment. In models of CAS, dependencies and interactions among the individuals of the system are the main drivers of system behaviour. A wide variety of CAS models are developed to simulate human behaviour in social situations. In this study we focus on models simulating how people belonging to a social network may adapt to certain behaviour caused by social influence from other people in the network. This knowledge is further used to develop an agent-based simulation model for opinion formation in social networks.

Results of the simulation experiments seem to agree well with typical behaviour of complex systems. Emergent, collective behaviour such as group formation and sensitivity to changes in input parameters are observed. The most influential parameters are related to the susceptibility of individuals to change behaviour due to social influence, and to the effect of an external influence field. This field may represent the impact of mass media or propaganda. The network model applied includes individuals with many connections (hubs). These have a central role in controlling the information flow, and thus, for the opinion formation in the network.

Agent-based models of CAS are complementary to other simulation models applied within operational research. They can be used to provide insight into the behaviour of human social systems and how these systems are influenced by different actions.

Modelling of CAS is a relatively immature field of science which has become more popular in recent years, particularly within the defence research community. There are, however, several challenges related to model validation, and data collection and modelling that have to be sorted out to increase the confidence in these models. Thus, further research is required to make CAS models useful as decision support tools on real-world problems.

Sammendrag

Erfaringer fra de militære operasjonene i Afghanistan og Irak har vist viktigheten av å forstå menneskelig atferd. I en effektbasert tilnærming til operasjoner vektlegges evnen til å kunne påvirke menneskelig atferd i en fordelaktig retning i forhold til definerte effekter og mål. Et eksempel kan være å vinne tillit i befolkningen for å sikre støtte til en fredsprosess. Det modellgrunnlaget som finnes for å støtte beslutningstaking relatert til menneskelig sosial atferd er svært mangelfullt. Formålet med denne studien er å bygge opp kunnskap om modellering av komplekse adaptive systemer (eng: complex adaptive systems – CAS) for å kunne vurdere egnetheten av denne type modeller mht. å støtte analyse av komplekse sosiale systemer i konfliktområder.

CAS er en egen kategori av komplekse systemer som involverer modellering av levende vesener. I modeller av CAS er det interaksjon og avhengigheter mellom individene i systemet som i stor grad er styrende for systemets oppførsel. Det er utviklet mange ulike typer CAS-modeller for å simulere menneskelig atferd i forskjellige sosiale kontekster. I denne studien har vi valgt å se på modeller for hvordan mennesker tilhørende bestemte sosiale nettverk kan velge å tilpasse sin atferd på bakgrunn av sosial påvirkning fra andre mennesker i nettverket. Denne kunnskapen benyttes i utviklingen av en agentbasert simuleringsmodell for simulering av meningsdannelse i sosiale nettverk.

Resultatene av de gjennomførte simuleringseksperimentene viser god overensstemmelse med typisk oppførsel observert i komplekse systemer. Spesielt gjelder dette oppdukkende, kollektiv oppførsel som f.eks. gruppedannelse, og sensitiviteten for forandringer i input. De viktigste parameterne i modellen er knyttet til individenes motstand mot å forandre oppførsel/mening og til effekten av ekstern påvirkning som kan ha sitt opphav i eksempelvis massemedia eller propaganda. Nettverksmodellen som benyttes inneholder individer med mange relasjoner. Disse individene spiller en sentral rolle med hensyn til kontroll av informasjonsflyten og vil således også kunne ha stor påvirkning på meningsdannelsen i nettverket.

Agentbaserte simuleringsmodeller av CAS er komplementære til andre simuleringsmodeller som benyttes innen operasjonsanalyse. De kan anvendes til å gi bedre innsikt i menneskelige sosiale systemer og hvordan disse systemene påvirkes av ulike virkemidler og handlemåter.

Modellering av CAS er et relativt umodent forskningsområde som i de senere år er viet større interesse, spesielt innenfor militær forskning. Men, det er flere utfordringer, blant annet knyttet til validering og til innsamling og bearbeidelse av inputdata, som må håndteres for å øke tiltroen til disse modellene. Det er derfor behov for videre forskningsinnsats for å gjøre disse modellene anvendbare som beslutningsstøtteverktøy for reelle problemstillinger.

Contents

1 Introduction

In peace support operations (PSO), and in particular in the stabilisation and reconstruction phase, the emphasis has shifted from traditional ‘physical targets’ to so called ‘behavioural targets’, which means to influence the behaviour of the civil population and adversaries in a favourable manner. To succeed in PSO it is regarded as important to win their ‘hearts and minds’ to ensure support and compliance with the peace process. To achieve this goal it is necessary to influence many parts of the society – political, military, economical, social, infrastructure, and the information system (PMESII) – which requires a broad spectrum of military and civilian means.

A condition for good decision making in this context is an information basis comprising all relevant aspects of the systems one wants to influence. This includes information necessary for developing decision alternatives, and information relevant for assessing consequences of the alternatives. The challenge is to find the decision alternative that most likely gives the desired outcome while simultaneously minimising unintended, negative consequences. This is particularly challenging when dealing with human social systems. Despite this focus, there is a lack of adequate models and methods to help understand how human behaviour is affected by different means in conflict environments.

PSO is about influencing complex human social systems. Complex systems contain many constituents interacting nonlinearly, and it is the relationships and dependencies among the constituents that are the main drivers of system behaviour. In complex adaptive systems (CAS) human beings interacts and influence each other through social relationships, which can result in adaption of certain behaviour. CAS is found to have many properties in common with real human social systems, and thus, models of CAS may be useful tools for analysing social behaviour in conflict environments.

The aim of this study is to review and explore models of CAS and to assess their applicability to support analysis of human social behaviour in conflict environments.

Chapter 2 gives a brief introduction to CAS and the challenges in modelling this kind of systems. In Chapter 3 different models of CAS are presented and discussed. Chapter 4 introduces a model for simulating opinion formation in social networks based on models and theories presented in Chapter 3. In Chapter 5 some results from the opinion formation model are presented. Chapter 6 contains a summary and discussion of our main findings, and in Chapter 7 we present the conclusions of this study.

2 Complex Adaptive Systems

CAS is a category of complex systems which involves models of adaptive living beings [1]. CAS models are usually computational agent-based models where agents represent individuals that are capable of making autonomous decisions on how to adapt to different situations [2;3]. Agents adapt to increase their rate of success. They are also capable of influencing their environment in a favourable direction.

The complexity of a system arises when the dependencies among the elements becomes important. Complex systems are sensitive to changes – removing one element may have large consequences for the behaviour of the whole system. Hence, complex systems are not easily reducible without sacrificing important system behaviour. Models of CAS are to a large extent based on models developed for analysing complex systems. Baranger and Michell highlight some typical properties of complex systems [4;5]. Complex systems contain many interdependent elements interacting nonlinearly. A common feature of nonlinear systems is that only small changes in some parameters may bring about large changes in system behaviour.

Complex systems possess a structure spanning several scales. A human society spans several levels such as the individual, family, social groups, municipality, and national level. At each level we find a certain structure. Complex systems are capable of *emergent behaviour* when shifting focus from one scale to a more coarse scale. Behaviour observed at a certain scale is said to be *emergent* if it cannot be understood by studying, separately and one by one, every constituent of this scale. Emergent behaviour is caused by interaction between the constituents on a particular scale.

Complexity involves the interplay between chaos and non-chaos. If the value of some control parameter is changed, the system may be chaotic for some values and non-chaotic for others. The values for which the system undergoes large changes are often referred to as *critical points*.

Complexity involves interplay between cooperation and competition. Competition on one scale may nourish cooperation on a finer scale, e.g. good cooperation between the players of a football team strengthen their competitiveness as a team, and good cooperation between soldiers in a troop may strengthen their performance and survivability.

3 Theories and models of CAS

This chapter gives a survey of relevant methods and models related to CAS. The main focus is on network models, however, some other important models will be mentioned as well.

3.1 Cellular Automata

Cellular Automata (CA) are probably the most applied class of CAS models. These models consist of a uniform lattice of $N*M$ cells which at time t can be in one of k states. The state of the CA is completely specified by the values of the state variables at each cell. The CA evolves in discrete time steps where the variables in each cell is updated simultaneously based on the value of the variables in its neighbouring cells in the previous time step according to a definite set of local rules. There are different kinds of neighbourhoods, but the most common are the von

Neumann neighbourhood including the four closest neighbouring cells, and the Moore neighbourhood including the eight nearest cells.

CA models have been extensively used for simulation of complex systems in natural science. In recent years they have also been more accepted within social sciences as a tool for studying complex human systems. Using the basic principles of CA combined with more advanced rules for interaction between agents (cells) it is possible to simulate and explore many properties of human societies. One famous example is Axelrod's model of dissemination of culture [6]. This model is based on a regular lattice of cells that are updated at discrete time steps. Each cell represents an agent which is born in a certain state determined by a set of socio-cultural parameters referred to as features. Each feature can take a discrete number of values called traits. The basic premise of the model is that the more similar an individual is to a neighbour, the more likely they will interact, and adopt one of the neighbour's traits. Similarity leads to interaction and interaction leads to still more similarity, and the main question addressed by Axelrod was that if people tend to become more alike in their attitudes and behaviour when they interact, why do not all such differences eventually disappear?

For a more thorough presentation of CA with applications, see [7-9].

3.2 Networks

In a society there usually exist a wide variety of social relationships between individuals giving rise to social networks, e.g. friendship networks, family networks, labour networks, etc. People interact through these networks to exchange information and to influence each others opinions. The consequences of social influence depend on the properties of the agents and the type of relationships among them. Social interaction is regarded as an important mechanism for adaption in societies.

This overview of network models starts by a short introduction to graph theory to explain some basic properties of networks. Further, different kinds of network models will be presented and compared to real-world network models.

3.2.1 Graphs

The construction and analysis of networks is based on graph theory [10-12]. A graph is composed of nodes (vertices) and edges that connect pairs of nodes. In this context a node is synonymous with an agent and edges represent relationships between agents. Graphs can be directed (digraphs), meaning that the relationship between a pair of agents is dependent on the direction, i.e. the relation from agent a to b is in general different from the relation of b to a. In an undirected graph there is no such distinction. Figure 3.1 shows a simple undirected graph with four nodes and edges.

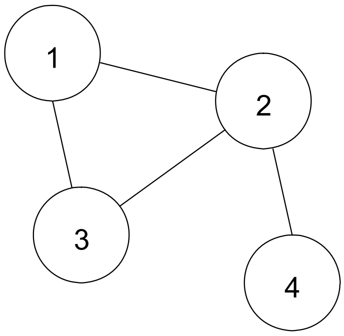

Figure 3.1 A simple undirected graph with nodes and edges

The *degree* of node no. i, k_i, is equal to the number of edges connected to the node. In Figure 3.1, node 1 has $k = 2$ while node 2 has $k = 3$. The distribution of k's, $P(k)$, is an important property of networks, and different networks typically have different distributions. The nearest neighbours to a node are referred to as adjacent nodes. The adjacency matrix, **A**, is a matrix containing the relationships between adjacent nodes. Table 3.1 gives **A** for the network presented in Figure 3.1. For undirected graphs **A** is symmetric, i.e. **A** = **A**'.

Node no.	1	2	3	4
1	-	1	1	0
2	1	-	1	1
3	1	1	-	0
4	0	1	0	-

Table 3.1 Adjacency matrix for the network presented in Figure 3.1

The distances between nodes can be measured by the number of edges between pair of nodes. In the graph presented in Figure 3.1 the distance, $d = 1$ between node 1 and 2 and $d = 2$ between node 1 and 4. In a network there is usually more than one path between pairs of nodes. The *geodesic distance* is a measure of the length of the shortest path between nodes. In addition, the nodes may have a geographical position associated to a world represented by for instance a grid with $n*m$ cells. Agent a_i has position (x_i, y_i), where $x = 1, 2, ..., n$ and $y = 1, 2, ..., m$ that enables calculation of the Euclidian distance between agents. Both these distance measures are important, because the level of interaction between agents usually is dependent on the immediacy of the nodes.

Table A. 1 in Appendix A lists some additional measures that are used to characterize networks. In this study we mainly make use of the *clustering coefficient* C_i, which measures the formation of groups or cliques, the *geodesic distance* $d(n_i, n_j)$ and the *nodal degree* k_i. See e.g. [12] for a more elaborate explanation of these measures.

3.2.2 Network models

There exists a wide variety of network models that share common characteristics with real-world social networks. References [5;11;13-16] highlights some important properties observed in real-world networks:

- They tend to have "small-world" properties, which mean:
    - High degree of clustering, i.e. it is likely that friends of my friends also are my friends; thus the edges of the graph are not distributed uniformly, but tend to form clusters
    - Short average path length between pair of nodes, i.e. short geodesic distances
    - The graphs tend to be sparse; they usually have few connections relative to the theoretical maximum number of connections, which for an undirected graph of N nodes is $N(N-1)/2$.
- Existence of hubs. The degree distribution, $P(k_i)$, follows a power law which allows for nodes with a high connectivity.

Network models are usually constructed to reflect one or more of the real-world properties described above. The most common network models are:

- *Regular networks:* graphs where each node has the same number of neighbours, i.e. the degree of the nodes are constant, $k = const$. An example of this kind of network is a regular lattice where each node has exactly four connections ($k = 4$)
- *Random networks* (the Erdös-Rényi model) [15]: graphs generated by connecting pairs of nodes at random using a uniform probability p. In the one extreme $p = 0$ there will be no connections while when $p = 1$ the graph will be a clique (the clustering coefficient = 1). The expected number of connections are $p*N(N-1)/2$
- *Small-world networks* (Watts and Strogatz model) [14]: graphs based on a regular network where each node is connected to k neighbours. For each link, with a probability p, one end of the link is rewired to a randomly chosen node in the network. When $p = 0$ the network will be regular and when $p = 1$ it will be random. The interesting range of p lies between these extremes. Small-world networks have the small-world properties mentioned above.
- *Scale-free networks* (Barabasi-Alberts model) [13]: graphs that shows all the properties of real-world networks described above. Scale-free networks are further described in Chapter 3.2.3.

In Barabasi et al. [15] the network models are compared to typical properties of real-world networks.

Social network analysis (SNA) comprises a suite of methods for construction and analysis of human social networks [12]. SNA is utilised to collect and store information about relationships between humans. This in contrast to the methods mentioned above to automatically generate network structures with real-world properties. In SNA, networks are constructed by use of qualitative information, but analysed using quantitative methods from graph theory. The objective is usually to identify central actors and important relationships between actors in the networks.

3.2.3 Scale-free networks

The behaviour of scale-free networks is independent of the number of nodes, and the distribution of connections, $P(k)$, follows a power law,

$$P(k) \sim k^{-\lambda} \qquad (3.1)$$

where k may take any value in the interval [0, N-1] and the exponent λ typically takes values between 2 and 3. A power law has a fat tail which mean that there is generally a higher probability for nodes with many connections compared to for instance an exponential or normal distribution. An example of a scale-free network together with $P(k)$ for different network sizes is shown in Figure 3.2.

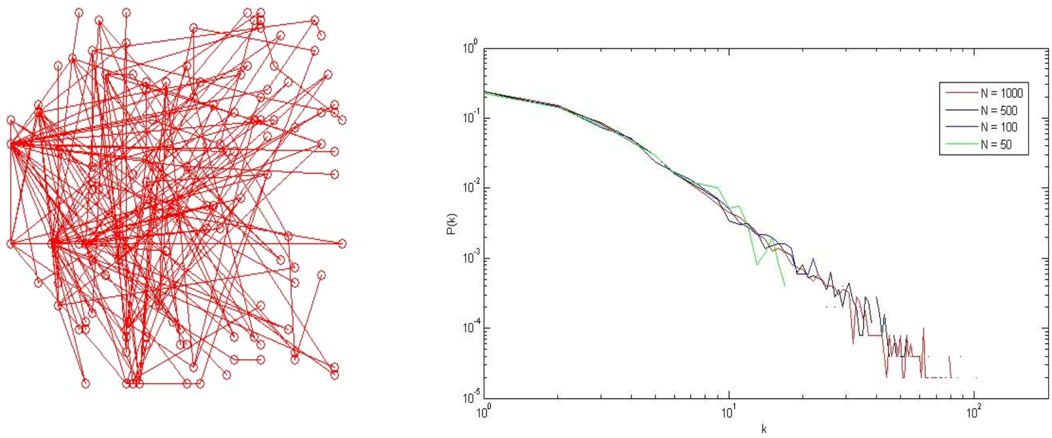

Figure 3.2 | Left: A scale-free network with N = 100 nodes. Right: $P(k) \sim k^{-2.8}$ *for N = 10, 50, 100, 1000 nodes.*

The figure shows that there exist highly connected nodes (hubs) in the network. For N = 1000 nodes with more than 100 connections are observed. The scaling exponent, $\lambda \approx 2.8$, is in line with empirical networks studied in [13]. Using the β distribution with the parameter $\beta = 1$ we can calculate the expected number of connections by,

$$\bar{k} = \frac{1-\gamma}{2-\gamma} \approx 2.2 \qquad (3.2)$$

Scale-free networks are developed by applying a procedure based on preferential attachment. Initially, a few nodes are generated (typically 2 or 3) and mutually connected. Further, new nodes are generated and attached to the nodes in the network depending on how well the existing nodes are connected. Preferential attachment means that a new node is more likely to connect to a well connected node then to a node with fewer connections. The probability that a new node is connected to node i is given by Equation (3.3),

$$P(k_i) = \frac{k_i}{\sum_j k_j}, \qquad j = 1, 2, \ldots, N \qquad (3.3)$$

3.3 Modelling behaviour

Agents are proactive objects representing individuals that are capable of making their own decisions on how to behave. In CAS models agents are allowed to interact and to adapt to their environment through cooperation or competition with other agents. The decision making process is usually rather simple and comprises only the most relevant factors influencing individual decision making. This is the core of CAS models – individual behaviour on smaller scales yield emerging, collective behaviour on larger scales.

Agents perceive their environment through sensors and they exchange information with other agents. The information is interpreted and contributes to forming the agent's intentions which, together with habits and facilitating conditions, may result in adaption – change in behaviour. Triandis has developed a theoretical framework for explaining behaviour [17]. The model comprises casual relationships between important concepts from different subfields within psychology. This framework may serve as a basis for modelling adaption of behaviour. A simplified version of this framework is shown in Figure 3.3.

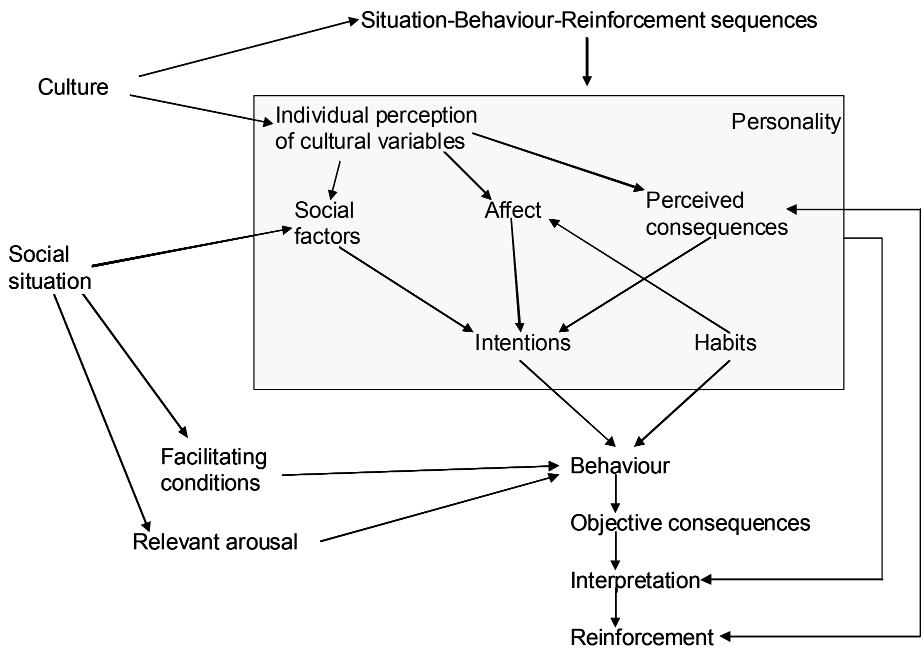

Figure 3.3 A simplified version of Triandis model of human behaviour.

According to Triandis model agent behaviour is determined by habits and intentions which are constituents of the agent's personality combined with facilitating conditions and relevant arousal. Intentions are formed by social factors which are the result of internalization of the particular culture's way of perceiving the social environment including the subjective culture with norms, roles and values. Previous experiences with a particular behaviour result in affect toward the behaviour, i.e. the emotional system is influenced to make an individual feel pleasure or displeasure for some particular behaviour. Behaviour takes place in different social situations that impacts the facilitating conditions and the arousal, which again influence the probability of adaption. Behaviour has objective consequences which are interpreted by the individual giving rise to reinforcement. Reinforcement affects how consequences are perceived – both the value of consequences and the probability of occurrence.

Social influence is one of the main mechanisms driving adaption. Individuals belonging to the same social network influence each other through interactions. This may give rise to changes in individual behaviour, which further can have consequences for the opinion formation in the whole network, e.g. formation of groups (cliques) with similar opinions.

3.4 Modelling social influence

Agents live in societies where they take part in different social networks. The nature of these networks determines the level of interaction between agents in the group and how they influence each other. There are several models developed for simulating interaction and adaption of individuals to societies. Among these are Latané's social impact model [18], Axelrod's model of dissemination of culture [6], Deffaunt's model of consensus formation [19], and artificial societies [20]. In this study Latané's model of social impact is emphasised, because our main focus is on group influence.

3.4.1 Group influence model

In Latané's model of social impact people interact and adapt to their environment through relationships with other humans. People are exposed to influence from sources that support or oppose their current opinion, which may result in, for instance, adaption to the prevailing opinion in the social network.

In social impact theory [18;21] the *social force* experienced by an individual, $I = f(smN)$, is a function of the *source strength* (s), the *immediacy* (m), and the number of sources (N). The *source strength* may depend on factors such as the perceived legitimacy of the source, the age, status in the society, economic status, and on the nature of relationships with other individuals. In a society as for instance in Afghanistan, religious leaders (mullahs), paterfamilias, landowners, and elders traditionally have a high social status, and thus, are expected to have a high level of impact on the opinion formation in the society. Latané distinguishes between two types of source strength – one with respect to the people who share the sources opinion and another for the people opposing the sources opinion.

Immediacy between two agents i and j refers to their closeness in space and is expressed as,

$$m_{ij} = \frac{1}{d_{ij}^{\alpha}} \tag{3.4}$$

where d_{ij} is the distance between agents measured by the *geodesic distance* between pair of agents and α is a decay exponent [22]. In Wagg [7] m_{ij} is extended to include social distances originating from differences in for instance religious affiliation and ethnicity. These differences may have huge impact on the likelihood of communication between individuals. This is in accordance with one of the premises of Axelrod's model which assumes that people sharing similar attributes are more likely to interact and communicate.

The third parameter in *SF* is the number of sources. In [18] the impact of sources is modelled as $I \sim sN^t$, where $t < 1$. This implies that the first source has greater impact than the second and so on.

Individuals are influenced by people supporting or opposing their current opinion. The net social influence on an individual is given as the sum of influences from its neighbours in the network. Usually the individual, to some extent, resists changing its current opinion. This is accounted for by a resistance factor β, reflecting the inclination of an individual to maintain his/her current opinion or the individual's susceptibility to external influence. In principle this factor will vary from person to person and may change over time due to new experiences. However, in this simple model β is kept constant. In [21] an individual is likely to change behaviour if $I_o - I_s > \beta$, where I_o is the opposing social pressure and I_s is the supporting pressure. Karperski et al. [23;24] have developed a model that incorporates all these factors in one equation for the net social influence, I, experienced by an individual,

$$I_i = -s_i\beta - \sigma_i h - \sum_{j=1,\, j\neq i}^{N} \frac{s_j \sigma_i \sigma_j}{d_{ij}^{\alpha}} \tag{3.5}$$

- s_i, s_j is the social status of the agents
- β is the resistance factor (susceptibility to social influence)
- h is an external field such as global preference or effect of mass media
- σ_i, σ_j is the current opinion of agent *i* and *j*. $\sigma = \pm 1$

The last term of this equation corresponds to a linear version of the social force described above. In this model it is only the factor β that is related to the agent's personality, and thus can be directly related to Triandis framework for behaviour described in Chapter 3.3.

The model expressed by Equation (3.5) is rather simple. The net influences on a agent is given as a linear sum of social influences from neighbouring agents in the network together with a uniform external field of influences. If this sum is greater than the product of the agent's resistance factor and its social strength, i.e. $I > 0$, the agent will change its opinion. To introduce some randomness in this decision process Karperski applied the following expressions for the probability of changing opinion at time $t + \Delta t$.

$$\sigma_i(t+\Delta t) = \begin{cases} \sigma_i(t) \text{ with } P(I_i) = \dfrac{e^{-I/T}}{e^{-I/T} + e^{I/T}} \\[2ex] -\sigma_i(t) \text{ with } 1 - P(I_i) = \dfrac{e^{I/T}}{e^{-I/T} + e^{I/T}} \end{cases} \tag{3.6}$$

The parameter T in Equation (3.6) introduces a degree of randomness in the behaviour and may be interpreted as the agent's average volatility. If T is increased we introduce more randomness, and in the limit $T\to\infty$, $P(I) = 0.5$, while when $T\to 0$, $P(I) = 1$ (deterministic limit).

To illustrate the model given by Equation (3.5) we use the network model shown in Figure 3.4.

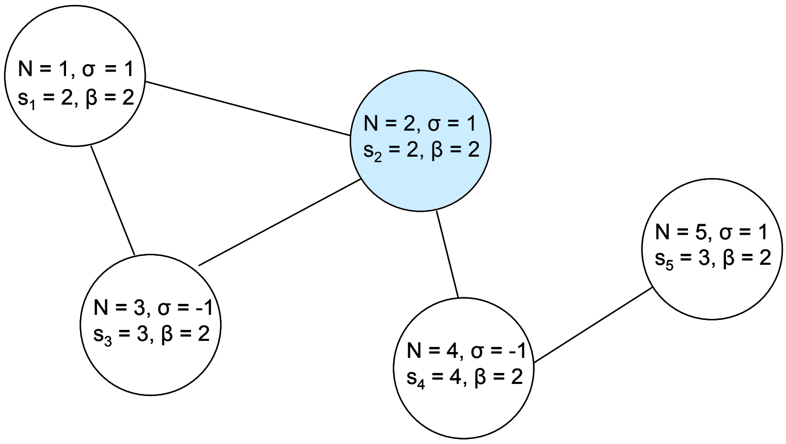

Figure 3.4 A simple graph with five agents (nodes)

Choosing agent 2 as the target and the other agents as sources the social influence I, experienced by agent 2 to change or retain his/her opinion is given in Table 3.2.

Relation	σ_j	σ_2	s_j	d_{2j}	SF_{2j}
1→2	1	1	2	1	2
3→2	-1	1	3	1	-3
4→2	-1	1	4	1	-4
5→2	1	1	3	2	0.75
				Sum	-4.25

Table 3.2 Calculation of social force on agent 2 in Figure 3.4

Using Equation (3.5) with, $\alpha = 2$, $\beta = 2$, the level of social influence experienced by agent 2 is; $I_2 = -2*2 - 1*1 - (-4.25) = -0.75$. Since $I < 0$ it is likely that agent 2 will retain its current opinion. Using Equation (3.6) with $T = 1$ (small randomness) gives a probability of retaining current opinion, $\sigma_2(t+\Delta t) = 0.82$. If T is increased to 10 the probability is reduced to 0.54.

3.4.2 Deffaunt's consensus model

Deffaunt's consensus model is different from the group influence model presented above [19;25;26]. Assume that N agents with opinion x_i participate in a network. At every time step one agent, A, is chosen at random together with an agent, B, from the sites connected to A. If the difference in opinions σ_A and σ_B of agent A and B respectively is less then a constant ε then A and B make contact and exchange information. In this process A and B become more alike by changing opinion by an amount $\delta = \mu(S_A - S_B)$ on a continuous scale where μ is a constant taking values in the interval [0, 1]. A takes the opinion $S_A - \delta$ and B the opinion $S_B + \delta$. Otherwise, if A's and B's opinions differ by more then ε they refuse to talk. For an example of application see [19;27].

4 A model for simulating opinion formation in social networks

The main motivation for developing a model of opinion formation is to gain more experience with modelling and simulation of CAS, and to explore the potential of CAS models to simulate human social behaviour in conflict environments. The model reflects how people's opinions are affected by social influence from other people belonging to the same social network. Social influence is recognised as one of the main mechanisms driving adaption of human behaviour. The model is based on the group influence model described in Chapter 3.4.1 and the scale-free BA model presented in Chapter 3.2.3.

The model may be viewed as a first attempt to model problems related to winning the 'hearts and minds' of a population to ensure support and compliance with a peace process. The diagram in Figure 4.1 depicts some important cause effect relationships between factors that are believed to have impact on whether the population supports the peace process or not.

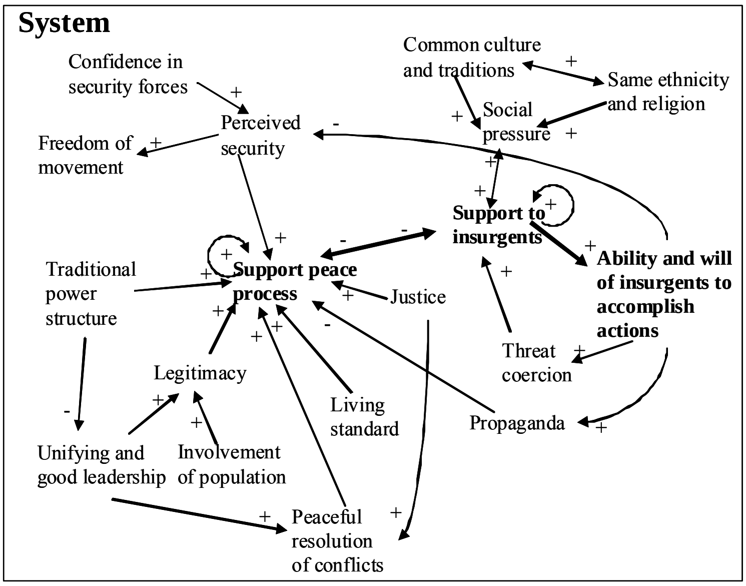

Figure 4.1 A simple causal diagram with factors and relationships having impact on whether people or groups of people support the peace process

This diagram comprises several cause effect relationships which are difficult to determine and quantify. Looking at the individual scale (personal level) several factors included in the diagram may result in adaption of individual behaviour. These factors are included as state variables of the agents in the opinion formation model. The main state variable is x_1, support to the peace process, which is dependent on the state of the other influencing variables shown in Figure 4.1 such as perceived security, living standard, perceived justice, and legitimacy of government.

The main ingredients of the model are:

- There are generated N interacting agents with different properties and opinions to form a society. The agents interact through their social network.
- The agents have several state variables measuring their opinion on certain important issues related to whether they chose to support the peace process or not.
- Every agent is characterized by a set of socio-cultural factors governing its attitudes and the likelihood of changing opinion. Every agent has an associated 'social strength' (social status) that determines its strength of influence on other agents, and the level of impact other agents have on its current opinion.
- The social impact is governed by the social strength and the immediacy between agents. Immediacy is not limited to the physical distance between agents, but may include social separation as well.
- The model has an external uniform influence field that influences all the agents in the society.
- The state variables of the agents are updated at discrete time steps. At each time step an agent is chosen at random and the net social influence from its neighbours are calculated. If the social pressure is large enough the agent will most likely change its opinion.
- The model is stochastic allowing for Monte Carlo simulations.

4.1 Network model

The agents are linked to other agents through a network structure representing social relations. A social network may comprise different types of relations; family, neighbourhood, professional, etc. which are activated with different frequency. For instance, in a village in the northern part of Afghanistan family, religious and landowner networks plays an important role in everyday life. Generating network models that incorporate relevant properties of real-world networks requires good knowledge about social relations and how information propagates. Although the network models described in the previous chapter show many characteristics of real-world networks they need to be adapted to the specific social context they represent. Another possibility is to build empirical networks based on collected data about people and relationships as in SNA.

In our model the preferential attachment of the scale-free BA network presented in Chapter 3.2.3 is slightly modified to generate networks that emphasize small-world properties to a larger extent. This is done by introducing geometrical distances, d_{ij}, between the agent positions in Equation (3.3).

$$P(k_i) = \frac{k_i}{\sum_j k_j} + \frac{1}{d_{ij}^{\alpha}}, \qquad j = 1, 2, ..., N \tag{4.1}$$

α is a decay exponent with default value 2. This expression for $P(k)$ may become larger than 1, and in this case $P(k) = 1$. In Figure 4.2 the distribution of the standard BA network model is shown together with the modified model (green dashed line). The modified BA network has more nodes with degree, k, between 1 and 10, thus, the average number of connections (average nodal degree) for the modified network is higher, $\overline{k}$ = 3.2, compared to the standard BA network where

$\overline{k} = 2.1$.[1] The modified network has a higher *density* $D_{mBA} = 0.013$ compared to standard network where $D_{BA} = 0.008$. The *geodesic distance* between pair of nodes (i.e. the shortest path) is almost equal for the two network models (4.2 for the modified network and 3.9 for the standard network). For definitions of the density measure and the *geodesic distance*, see Appendix A.

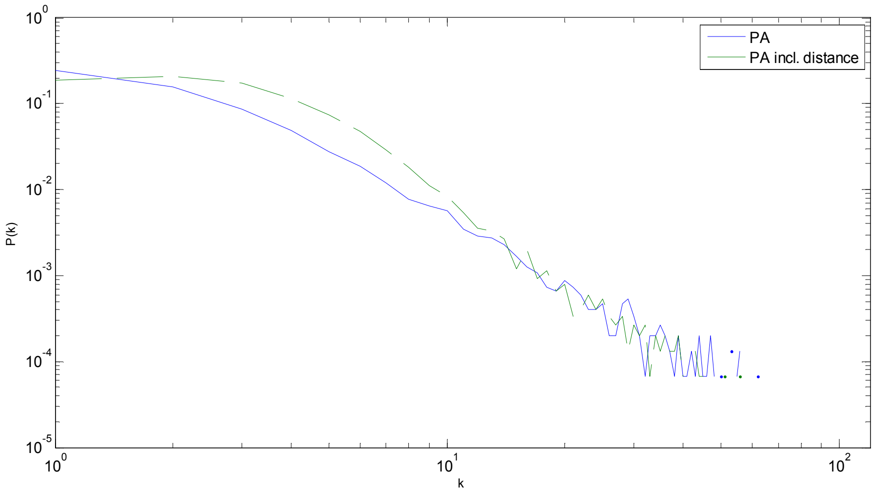

Figure 4.2 P(k) vs. k for the standard BA model and for the modified BA model

The network applied in this model is a simple undirected graph as illustrated in Figure 4.3.

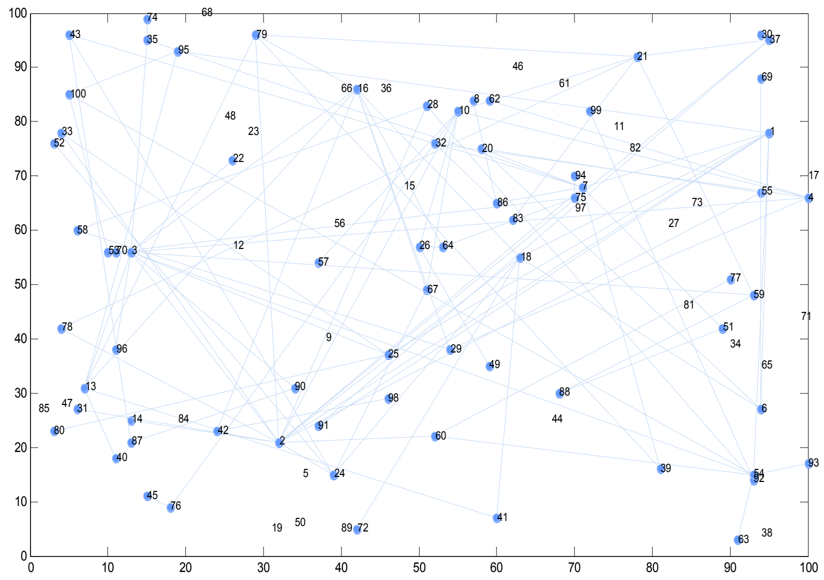

*Figure 4.3 A BA scale-free network with 100 nodes residing in a 100*100 lattice*

[1] This is close to the value $\overline{k} = 2.2$ calculated in Chapter 3.2.3.

4.2 Social influence model

The social influence model is a modified version of the model given by Equation (3.5) in Chapter 3.4.1 to allow for three different states instead of two. The motivation for this extension is that people do not necessary have a binary point of view. They can be uncertain about what standpoint to support and therefore chose to be neutral.

It is assumed that the state variables are discrete and that they can take three different values, $x_i \in [1, 0, -1]$, where 1 = support, 0 = neutral, and -1 = oppose. The state diagram of the variables is given in Figure 4.4.

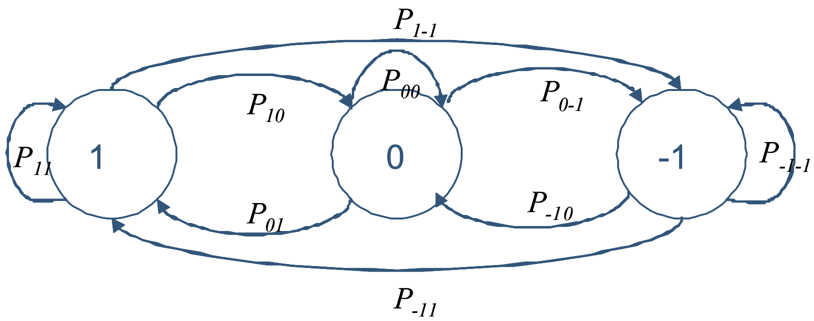

Figure 4.4 State diagram for the state variables with some transition probabilities, P

Every agent in the network is created with a certain combination of values on the state variables (state vector), which depends on factors such as age, gender, geography, religion, ethnicity, etc. The initial distribution of values may reflect the distribution of a real society, e.g. an area in the northern part of Afghanistan.

As explained above, the model for interaction between agents is slightly modified to allow for three states and to include social separation in the expression for the immediacy. The geometrical distance d_{ij} is given as the number of edges between pair of agents, i.e. nearest neighbours have distance, $d_{ij} = 1$, next nearest neighbour, $d_{ij} = 2$, and so on. The social separation is expressed by sd_{ij} which may include various socio-cultural factors such as ethnicity and religion. An example of how social separation can be included by use of the Bogardus social distance scale is given in [7]. The expression for the immediacy is given by Equation (4.2)

$$m_{ij} = \frac{1}{(d_{ij}^{\alpha_1} + sd_{ij}^{\alpha_2})} \tag{4.2}$$

To extend the influence model to include a third, neutral level, a two stage algorithm to calculate the state transitions is introduced. First, the agent has to decide if he should change his current state. Then, if change of state is true, a particular state has to be chosen. Equation (4.3) corresponds to Equation (3.5) in Chapter 3.4.1 except from the last term which accounts for the social force from neighbouring agents. In this three state model the net social influence on agent i is calculated by separating agents supporting A_i's current opinion from those agents opposing it.

$$I_i = -s_i\beta - h_\sigma - (\sum_{\sigma_j=\sigma i} s_j m_{ij} - \sum_{\sigma_j \neq \sigma i} s_j m_{ij}) \tag{4.3}$$

This equation together with the probability for changing state given by Equation (3.6) in Chapter 3.4.1 is used to determine if an agent will change its opinion as a result of social influence. If the model contains more then one state variable it is necessary with one expression (Equation (4.3)) for each of the state variables.

The parameters and variables of the model are explained in Table 4.1.

I_i	Social impact on agent *i*, A_i
σ_i, σ_j	Opinion of agent *i* and *j*
s_i, s_j	Social strength affecting the degree to which agent *i* and *j* is influenced by others and influence others
β	Individual's resistance to change opinion
h_σ	Uniform external influence on A_i
m_{ij}	Immediacy between agent *i* and *j* which depends on the geometrical distance, d_{ij} and the social separation sd_{ij}. Immediacy may be seen as the likelihood of communication between the agents.
d_{ij}	Geometrical distance measured by the number of links/arcs between agents
sd_{ij}	Social separation which is a function of socio cultural factors, e.g. ethnicity and religion
α_1, α_2	Distance decay exponents. Usually α_1, $\alpha_2 \geq 2$

Table 4.1 Parameters in Equation (4.2) and Equation (4.3)

If agent A_i decides to change opinion, he can enter two different new states. To choose which state to enter we apply the probabilities shown in the state transition matrix **T**,

$$\mathbf{T} = \begin{pmatrix} P_{11} & P_{10} & P_{1-1} \\ P_{01} & P_{00} & P_{0-1} \\ P_{-11} & P_{-10} & P_{-1-1} \end{pmatrix}$$

$$= \begin{pmatrix} 0 & w_{10}\dfrac{(N_0+E_0)}{(N_0+N_{-1}+E_0)} & w_{1-1}\dfrac{(N_{-1}+E_{-1})}{(N_0+N_{-1}+E_{-1})} \\ w_{01}\dfrac{(N_1+E_1)}{(N_1+N_{-1}+E_1)} & 0 & w_{0-1}\dfrac{(N_{-1}+E_{-1})}{(N_1+N_{-1}+E_{-1})} \\ w_{-11}\dfrac{(N_1+E_1)}{(N_1+N_0+E_1)} & w_{-10}\dfrac{(N_0+E_0)}{(N_1+N_0+E_0)} & 0 \end{pmatrix} \tag{4.4}$$

Every element of **T** corresponds to a state transition probability, P, shown in the state transition diagram of Figure 4.4. N_1, N_0, N_{-1}, represent the number of agents in state 1, 0, -1 respectively, and E_1, E_0, E_{-1} the strengths of a possible external field. It is assumed that the transition probabilities are proportional to the number of agents in each state. In addition, the probabilities are given weights to allow for adjustments of the transition probabilities. For instance it may be more likely to change to a neighbouring state than to a more distant state. The diagonal is zero because it is already decided to change state.

The opinion formation model developed in this chapter comprises three sub-models; a social network model, a social influence model, and a behaviour model. Initially, agents are created and placed at a random position in an $M*M$ matrix. Further, every agent is given specific properties based on the value of the input parameters and connected to other agents by the preferential attachment procedure. This network of agents constitutes the starting point of the simulation. At each time step an agent is chosen at random and the social influence model is applied to calculate the net social influence on the agent. If the net social influence to change opinion exceeds the agents' resistance against change, it is likely that the agent will change its opinion. This model only makes use of one state variable. A further development of the model may include more interdependent state variables, e.g. make, say x_1, dependent on the state of the other state variables as shown in the causal diagram of Figure 4.1. A change in perceived security from state 0 to 1 may result in an increase in the agent's support to the government x_1, i.e. $x_1 = f(x_2)$.

5 Results

The model for opinion formation described in Chapter 4 has been implemented to a simulation model using MatLab. Only one state variable, x_1 – support to peace process, is included in the simulation model to avoid complexity.
The agents can be in one of three different states; state = 1, support peace process (blue – B), state = 0, neutral (green – G), and state = -1, oppose (red – R). The experiments are performed by varying the parameters of Equation (4.3). Four different experiments were performed:

- What are the consequences of changing the initial distribution (densities) of opinions; $(n_{B0}, n_{G0}, n_{R0}) = (N_{B0}, N_{G0}, N_{R0})/N$
- What are the consequences of varying the resistance parameter (the susceptibility for social influence), β_i
- What are the consequences of changing the distribution of social strengths, s_i:
  - By introducing a strong leader, i.e. an agent with much higher social status than the other agents
  - By removing the strong leader from the network
- What are the consequences of varying the uniform external influence field, h_σ

The default parameter setting is given in Table 5.1.

Monte Carlo iterations	30
Size of lattice	100*100
Number of agents, N	500
Initial distribution of opinions	$n_{B0} = 0.3$, $n_{G0} = 0.4$, $n_{R0} = 0.3$
Social strength s_i,	$s_i = 0.8*k_i + 0.2*age_i$. s_i is a function of the number of connections (degree) and the age of the agents
Age agent i	$Age_i = uniform(15,70)$. Uniformly distributed between 15 and 70 years
Resistance to change, β_i	1
External influence, h_σ	0
Exponent, α_1,	2
Volatility factor T	5
Weights for transition probabilities in **T**	All weights are set to 1

Table 5.1 Default parameter setting for the simulation experiments

The results are presented using two different measures:

- The distribution of opinions, (n_B, n_G, n_R)
- The size of the largest cluster, $\frac{\langle S_{\max} \rangle}{N}$

S_{max} is the size of the largest cluster of one of the opinions. To be included in S_{max} the agents have to be part of the relational network and to share the same opinions as their neighbours. There are also other measures that can be utilised to characterize the simulation results, see table A.1 in Appendix A. However, these two are found to be sufficient for communicating the results of the simulation experiments. An example of output from a simulation is given in Figure 5.1.

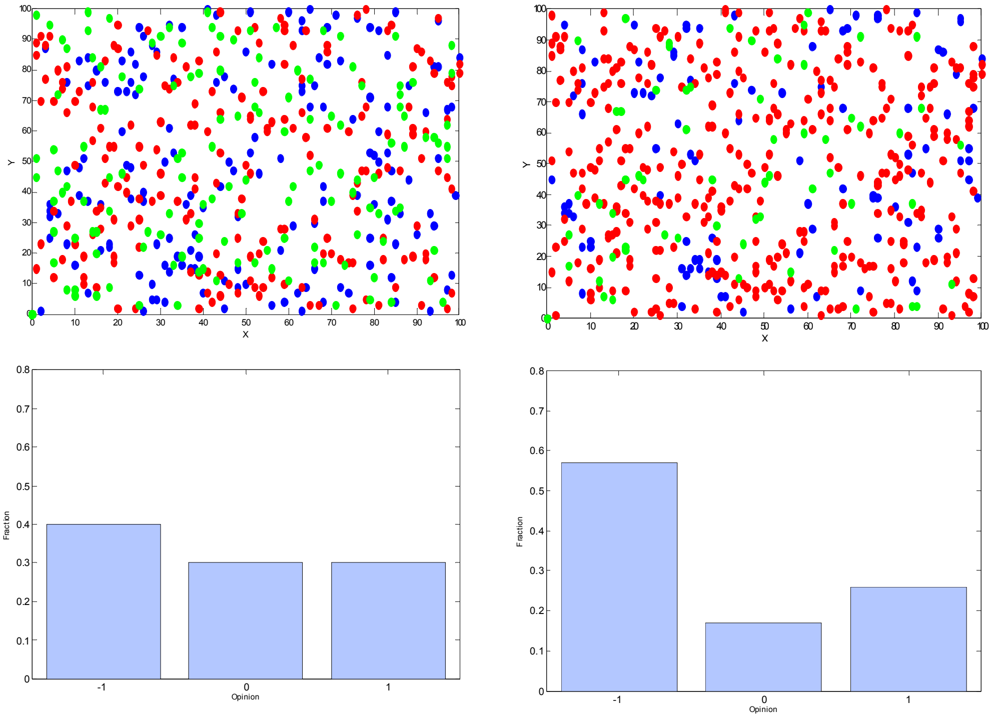

*Figure 5.1 Typical results of a simulation on a 100*100 network with 500 agents. The left part shows the initial distribution of agents and the right part the simulation result.*

The upper part of the figure show the distribution of agents, (n_B, n_G, n_R), on a 100*100 lattice (the relationships between agents are not shown to avoid making the figure too complex). The left part of the figure shows the initial distribution and the right part the results of the simulation after 3000 time steps. The lower part of the figure displays the mean fraction of agents after 30 Monte Carlo (MC) iterations. It is apparent that the small initial advantage of the red agents, $n_{R0} = 0.4$, results in red dominance, $n_R = 0.57$.

5.1 Distribution of opinions

How does the initial distribution of *B*, *G*, *R*, (n_{B0}, n_{G0}, n_{R0}), influence the simulation results? It is expected that the initial distribution of agent opinions is important, because if an opinion is predominant it is likely that this dominance will increase through the simulation. However, it is not expected that we will obtain a global opinion (complete conformity) due to the fact that some of the agents are not part of the network. This in contrast to CA models where a global opinion is more common [9].[2] Figure 5.2 gives the results of using different initial distributions of *R* agents, between 0.1 to 0.7, while the fraction of *G* and *B* are equal, $(1 - n_R)/2$.

[2] The reason for this is the lattice structure and updating rules of CA models, see 3.1.

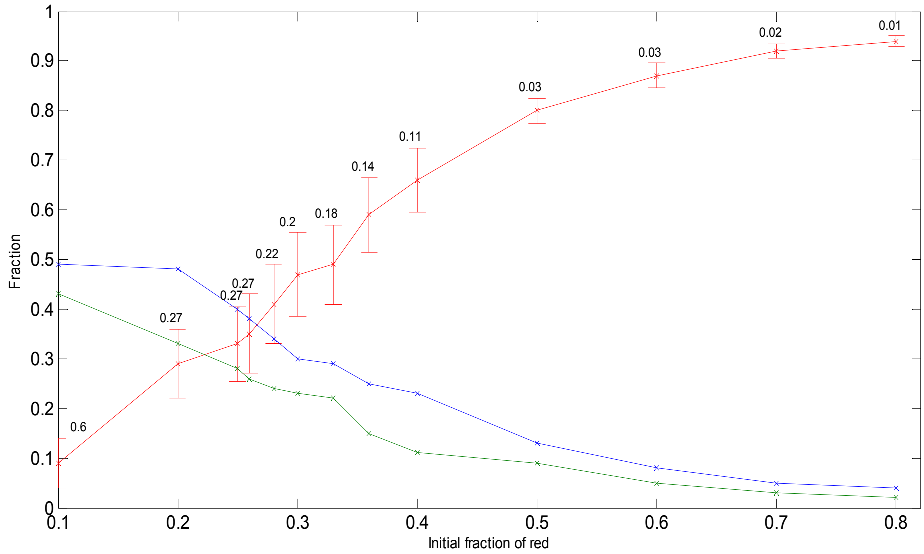

Figure 5.2 Simulation results for different initial distributions of red agets

The results show how the fraction of R agents increases non-linearly with the initial fraction of agents. When n_{R0} is in the interval [0.1, 0.4] the curve of n_R has its largest slope, $\Delta n_R/\Delta n_{R0} \approx 2$. Above this interval the slope is less then 2, and when $n_{R0} \rightarrow 1$, $dn_R/dn_{R0} \rightarrow 0$. We also observe that n_R is not likely to reach 1 as expected. The red agents start to dominate when the initial fraction of red exceed 0.3.

Figure 5.3 shows the results when the initial number of neutral agents (G) is set to 0, i.e. there are only R and B agents present in the simulation. The curves intersect approximately at $n_R = n_B = 0.5$, and the slope of the curves are steeper in the vicinity of the intersection point.

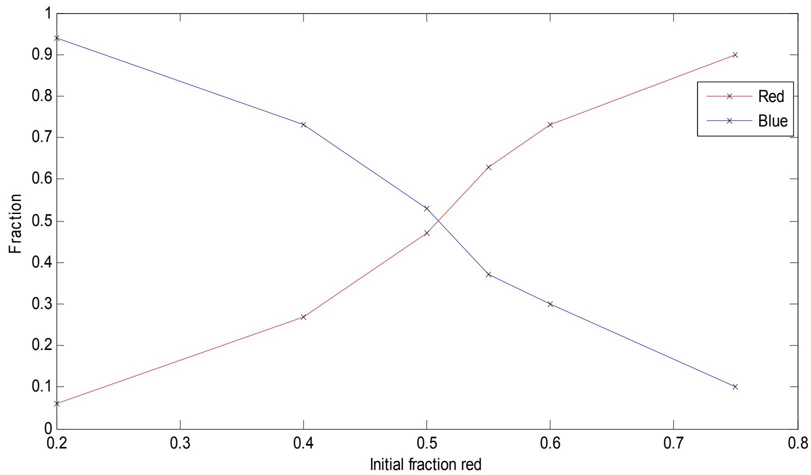

Figure 5.3 Simulation results when the inital number of green agents is set to 0, $n_{G0} = 0$

Another feature of complex systems is apparent in Figure 5.2. The variation of n_R for different values of n_{R0} is given with error bars in each point. The variation of n_R is large for small values of n_{R0} and decreases when n_{R0} starts to dominate. This becomes particularly clear when we look at the relative uncertainties which are given by the numbers above the error bar. This indicates sensitivity for initial conditions in the region where n_{R0} doesn't dominate. This is a characteristic feature of non-linear complex systems, which makes the results of single runs at least as interesting as the average results of MC simulations. In Figure 5.4 and Figure 5.5 the variation of n_R and $<S_{max}>/N$ is plotted together with their initial values for every MC iteration. The default parameter setting is applied.

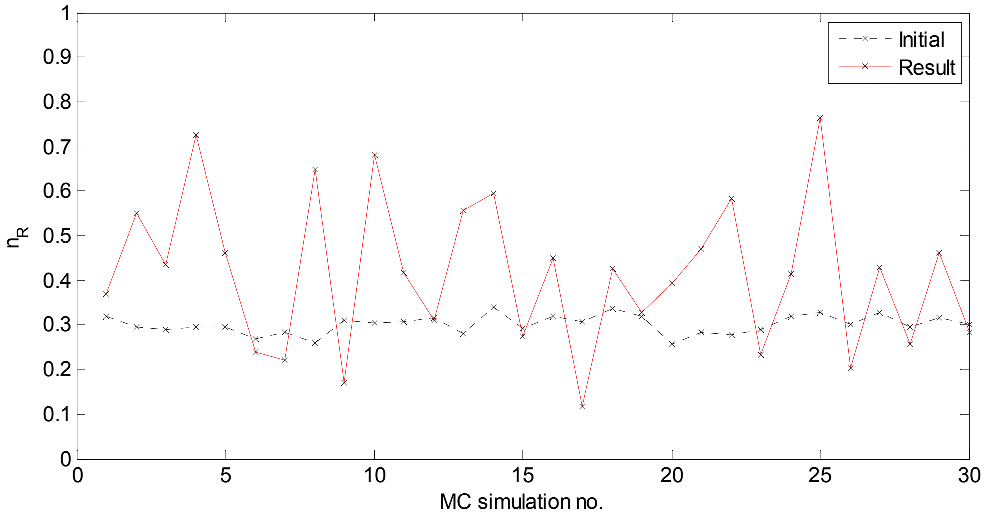

Figure 5.4 Variation in the density of red agents (nR) before and after simulation for each of the 30 MC iterations

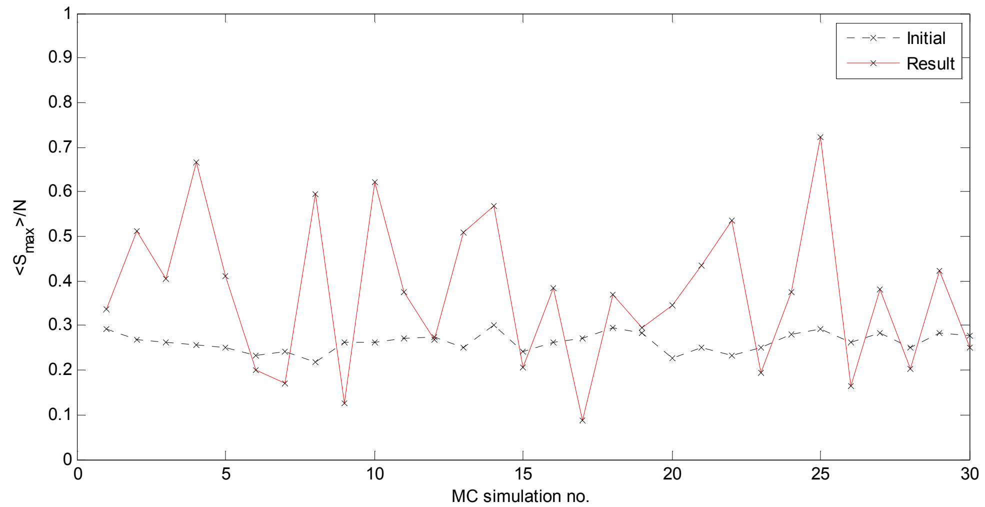

Figure 5.5 Variation in the largest red cluster size, <Smax>/N, before and after simulation for each of the 30 MC iterations

It is apparent that only small variations in input can give large deviations in output. The resulting fraction of *R* varies from 0.12 in iteration no. 17 to 0.77 in iteration no. 25. It is therefore appropriate to stress that only considering the average results of MC simulations – we risk losing a lot of information about the behaviour of the systems.

5.2 Susceptibility to external influence

The resistance factor β is expected to have a significant impact on the simulations. It represents the individual agent's susceptibility to influence from external sources. In the impact model (Equation (4.3)) β is multiplied with the social strength of the agent and the total external influence has to be larger than this product to obtain $I_i > 0$, and thus, increase the probability for changing state (Equation (3.6)). The results by varying β are summarized in Table 5.2.

Resistance, β	n_B	n_G	n_R
0,5	0,24	0,26	0,5
1,0	0,19	0,32	0,49
5,0	0,29	0,41	0,31
10,0	0,3	0,4	0,3

Table 5.2 Variations of the resistance factor β

Almost no change in the state is observed when β exceeds 5, i.e. everybody hold their initial opinion. This behaviour is expected, because the product of the agents average social strength, which is approx. 12 (see Figure 5.6 below), and β is approx. 60. This is more than twice as much as the expected social influence from the neighbouring agents, which is approx. 26 assuming that the average number of neighbours is 2.2, and that the neighbouring agents have the opposite opinion. Using Equation (3.6) to calculate the probability of changing state gives a result close to 0. However, if $\beta = 1$, the probability increases to approx. 1.

5.3 Social strength

Social strength is another important parameter in the influence model. Each agent in the network is created with a static social influence factor based on a weighted sum of the agents' connectivity and age (see Table 5.1). The higher k_i (degree factor) the more prominent is the position of A_i in the network. This rather simple model gives a distribution of social strengths in the network as shown in Figure 5.6.

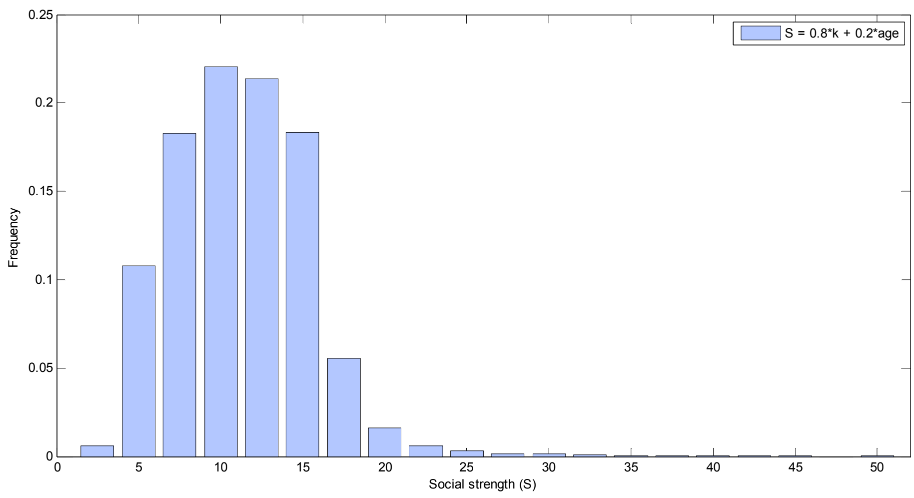

Figure 5.6 The distribution of social strength, s, from 30 MC iterations

It is apparent that most of the agents have s between 5 and 15 with an average of approx. 12. However, there are some agents with social strengths up to 50 present in the network. In order to complete the study, different normal distributions of s were tested, $N(5, 1)$, $N(5, 5)$ and $N(10, 10)$. The results show only small changes in output for variations in the initial distribution of social strength. The fraction of red, n_R varies from 0.4 to 0.51 for $N(10, 10)$ and $N(5, 1)$ respectively. This is as expected, because the resistance factor which by default is set to 1 will be less dominating in the latter case where most of the agents (≈ 70 %) have a strength 5 ± 1.

A particularly interesting case is when a strong leader is introduced in the network. The red agent with most connections (largest k) is selected and given an increased social strength, while the strength of the other agents remains the same. The results of the variation of s for one strong red leader are given in Figure 5.7.

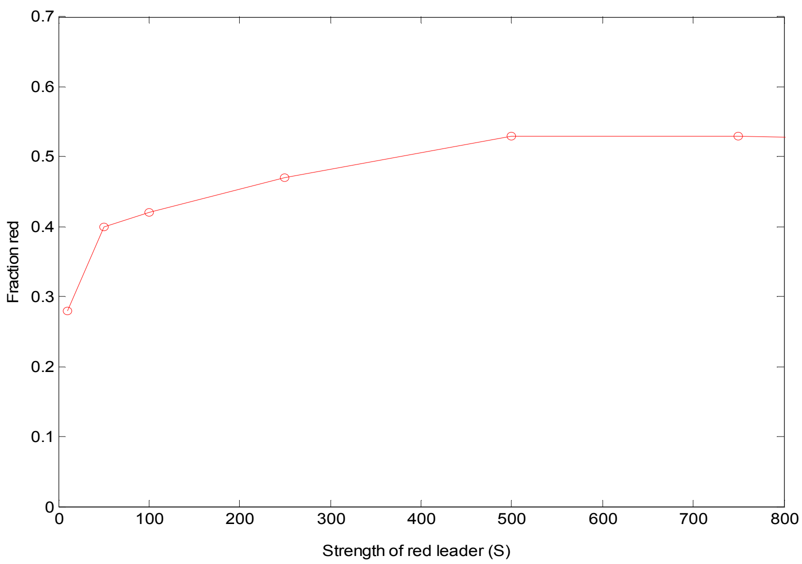

Figure 5.7 Fraction of R (n_R) for different values of s for a strong leader

It is apparent that the largest increase in n_R is for s values below 50 – an increase of more than 40 % is observed when s increases from 10 to 50. For s values above 50 the increase is smaller. This behaviour can be explained by the fact that the agents' strengths are distributed as shown in Figure 5.6, where the average social strength is approx. 12. When the strength of the leader becomes larger than this value the leader starts to dominate his neighbouring agents.

Figure 5.8 shows the resulting fraction of red agents as a function of the initial fraction of red agents for three different experiments. The curve at the top represents the situation where the most connected red agent is given a strength s = 1000. The curve in the middle depicts the situation where a strong red leader (s = 1000) is chosen at random among the agents in the network, and the curve at the bottom shows the situation when the strong leader is removed from the network.

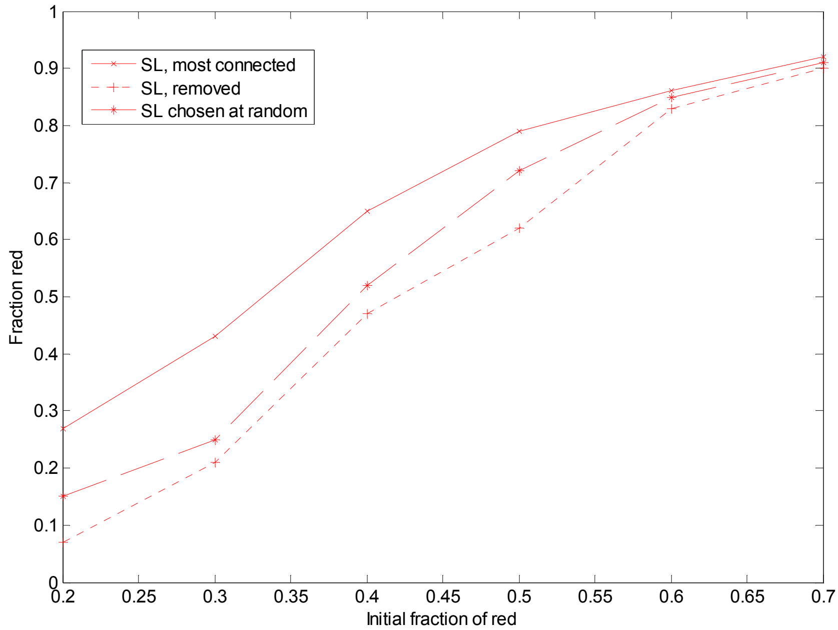

Figure 5.8 The importance of a strong leader (SL)

It is apparent that the effect of removing the strong leader is most prominent when the initial fraction of red agents is small. If the leader is operating in a network where most of the agents share his opinion, the consequences are rather small, only a 4 % reduction is observed for n_{R0} = 0.6. This result can be explained by the fact that there are other well connected agents in the network sharing the strong leader's opinion which will compensate for some the loss. If, on the other side, the strong leader is a part of a network where only 30 % of the agents initially support his opinion the consequences are larger, an average reduction up to 50 % is observed. The cluster of red agents is thus more vulnerable when the initial fraction of red agents is small. The reason for this is that when n_{R0} is small there is probably no other agent that can replace the strong leader. This observation indicates that a small group of supporters are more dependent on their leader than a larger group, which appears as more robust to changes in the leadership.

Figure 5.9 shows the dependency between the resulting fraction of red agents and variations in the volatility factor T in Equation (3.6) for the situations with and without a strong leader present.

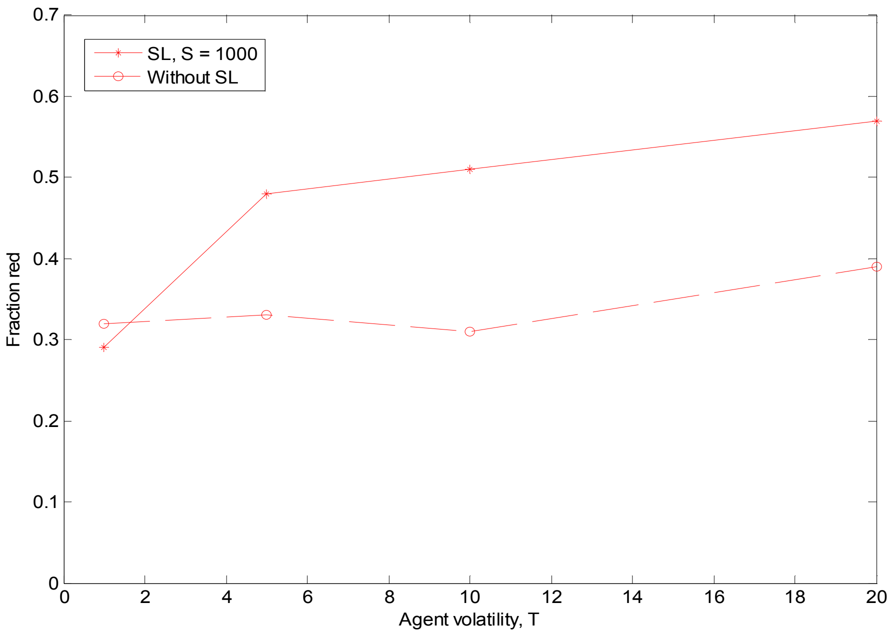

Figure 5.9 The resulting fraction of red agents as a function of agent volatility (SL = strong leader)

The figure shows that a leader has greater impact when the agents are more volatile. This kind of system behaviour may be interpreted as, when the situation becomes more volatile, the strong leader becomes more influential.

5.4 External influence field

The uniform external influence field of Equation (4.3), h_σ, represents a global preference supporting one of the opinions and which can be stimulated by mass media, politics, threats, propaganda, etc. This kind of influence is assumed to have a relatively high impact on the opinion formation in the network. The effect of this field depends on the resistance to change opinion, β, and the social strength, s, of the agents. It is more likely that an agent with low social status and low resistance change opinion due to influence of the external field than an agent with large s and β.

Figure 5.10 shows the resulting densities of B, G, R for variations of the external influence field. The default parameter setting is applied and the external opinion is set to R. As can be seen, the field strength has a rather huge impact on the opinion formation. In this situation the density of red agents, n_R approaches 1, because the uniform field reaches all the agents, even those which do not take part in the network.

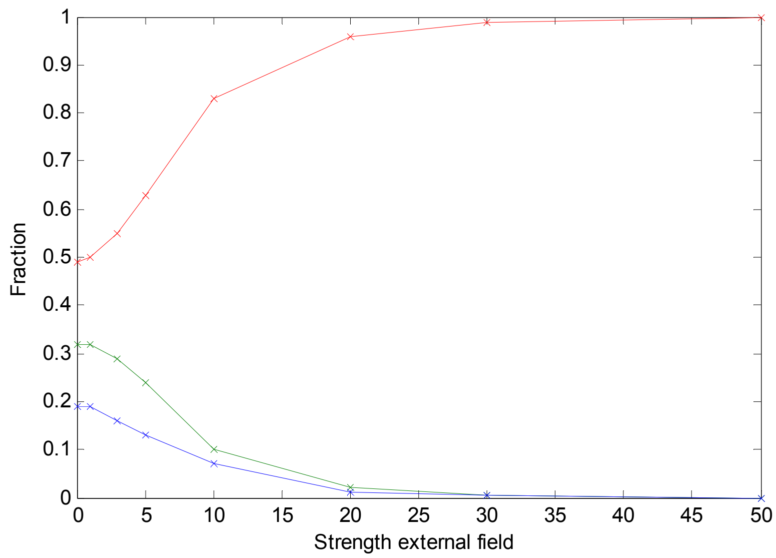

Figure 5.10 The resulting densities of agent opinions as a function of external field strength

The relative importance of the external field can be balanced by increasing the resistance of the agents to change opinion or by introducing a strong leader with an opposing opinion.

In Figure 5.11 the distribution of agents is plotted against the resistance for two different values of the external field. The opinion of the external field is *R*, and it is apparent that the resistance parameter has large impact on the final distribution of *B*, *G*, *R*. In both cases (external field strength 10 and 20) the largest changes are observed within the interval [0, 5].

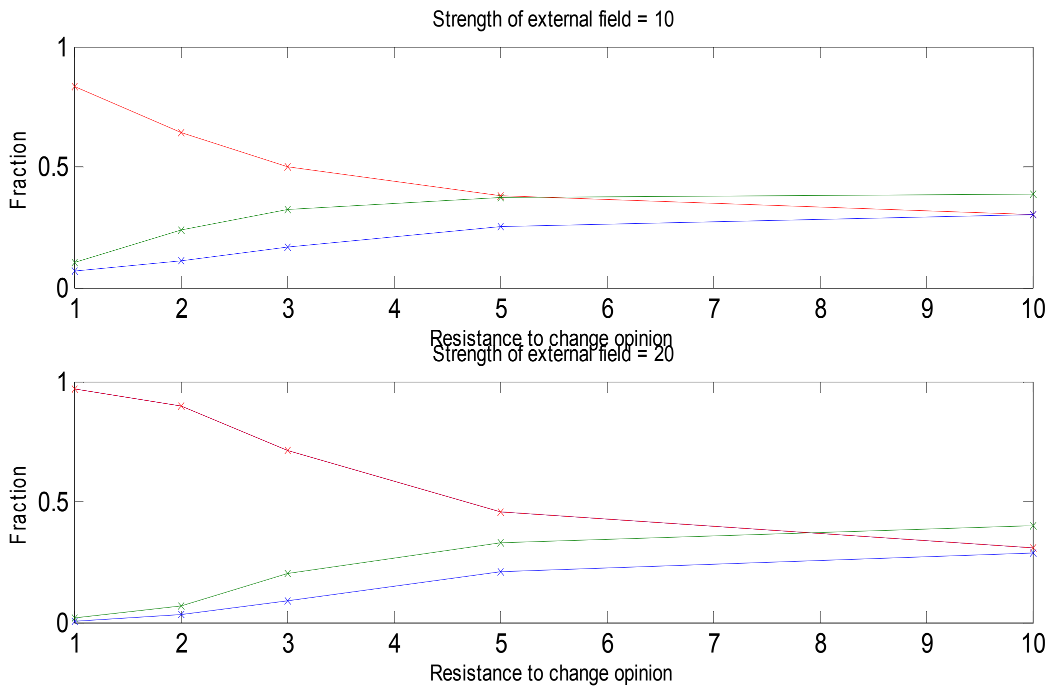

Figure 5.11 The opinion densities as a function of resistance for different values of the external field strength

6 Discussion

The aim of this study is to review and explore CAS models and to assess their applicability to model human social behaviour in conflict environments. Currently there is a lack of models to quantify effect achievement on ‘behavioural targets’ even though these targets are recognized as particularly important for achieving success in PSO. The CAS models explored in this study focus on relationships between individuals and how social influence through interaction gives rise to adaption of individual behaviour which further may lead to emergent, collective behaviour on a courser scale.

6.1 Models and results

The model described in Chapter 4 consists of three sub models:

- Network model
- Behavioural model
- Social influence model

The network model applied is based on a scale-free BA network which has many features observed in real-world social networks. The degree distribution of this network, $P(k)$, follows a power law, which is a fat tailed distribution that allows for agents with high connectivity, i.e. existence of hubs. These agents play a prominent role in the networks because they have high influence on the information flow, and thus, they may also have great impact on the opinion formation. The existence of hubs has consequences for the vulnerability of the networks. If the information flow depends on a few agents only, the redundancy/robustness of the network is usually low. Removing these agents may cause the network to collapse, or more likely, it breaks into smaller parts (clusters). The network model applied is extended with a factor that rewards short geometrical distances between agents. This results in more dense networks with more connections between agents close to each other than in standard scale-free BA networks.

Human beings are modelled as agents. Agents have the ability to make their own decisions based on input from their environment. In the real-world there are many factors that influence individual behaviour, but in our model the representation of human behaviour is rather simplified. Agents are created with a certain opinion on whether to support the peace process or not. Each agent is equipped with a resistance factor that determines its susceptibility to change opinion. The social influence model is based on Latané’s work on social impact theory [18] and Kacperski et al’s model of social influence and opinion formation [23]. This simple linear model given by Equation (4.3) comprises factors that are important for determining the level of social impact. Even though the model is simple it gives interesting non-linear behaviour such as emergent, collective behaviour when applied on a complex network of agents. The external influence experienced by an agent is of two types; the influence from other agents in the network with supporting or opposing opinions, and the influence from a uniform external field which may represent some common policy in the society. Every agent is initially given a certain social strength which depends on its role and status in the society. If the level of opposing external influence exceeds the product of the agent's resistance factor and social strength, the agent is likely to change opinion.

In the simulation experiments the parameters of the social influence model were varied to explore the behaviour of the model on the modified scale-free BA network. The initial distribution of red agents was varied from 0.1 to 0.8. The most interesting behaviour was observed in the vicinity of the point where the agent opinions initially were distributed evenly, (n_{B0}, n_{G0}, n_{R0}) = 0.33. In this region the largest changes in the resulting distribution, (n_B, n_G, n_R) were observed. Also, the variations in the results of single simulations were huge in this region. In one experiment the resulting red distributions varied from 0.12 to 0.77. This kind of behaviour indicates sensitivity to initial conditions, i.e. small changes in the input may give rise to large deviations in output.

The most influential parameters seem to be the level of resistance and the strength of the uniform external field. Small variations in these parameters cause large variations in output. In this simplified model the resistance parameter, β, is equal and constant for all agents during the simulation. To make the model more realistic this parameter can be made dependent on the social status of the agents, i.e. an agent with a high social status is more likely to hold on to his opinion than one with a lower status. Another factor that may contribute to the resistance is whether the agent has changed his opinion earlier, and because of this will more likely change its opinion in the future as well. The influence of the uniform external field is balanced by the level of resistance combined with the agents' social strength. If the external influence field originates from different sources it is possible to make the resistance factor dependent on the nature of the source.

The model does not seem to be very sensitive to the distribution of social strength. Several distributions were tested with only small changes in output. However, by introducing a strong leader in the network we observed a 40 % increase of the group supporting the strong leaders view. Removing this leader has large consequences for the distribution of opinions, in particular when the initial group of people sharing the leader's opinion is small. A reduction of approx. 50 % in the largest cluster was observed. The main reason for this is that the cluster disintegrates into smaller parts.

6.2 Applicability to operational research

Although the models explored in this study do not pretend to simulate human social behaviour in real societies it is our opinion that multi-agent models of CAS have the potential to address several important problems related to human social behaviour in conflict environments.

CAS have many properties in common with real social systems, and thus, they may serve as models of such systems. For a more elaborate discussion of the applicability of CAS to model real social systems, see for instance [1], Chapter 12. The results of the simulation experiments presented in Chapter 5, reflects typical behaviour of CAS. Emergent, collective behaviour such as group formation were observed in the system arising from the adaptive behaviour of interacting agents in a complex social network. An individual is likely to change its opinion if the external social pressure to do so exceeds the individual's resistance against change. The model shows non-linear behaviour and sensitivity to initial conditions even though the equation of social influence is linear (Equation (4.3)). Non-linear behaviour is a premise for emergent behaviour.

To succeed in PSO it is regarded as important to win the 'hearts and minds' of the civil population. To achieve this goal it is necessary with a thorough understanding of the social system and how social behaviour can be influenced in a favourable direction by various actions. From an OR perspective CAS models can be used to support knowledge development related to various aspects of human social behaviour in conflict environments. More traditional simulation techniques applied in OR are not capable of simulating the behaviour of human systems very well. CAS models are complementary to these models, and thus, can be useful to provide a more complete decision basis. CAS models may give insight into the behaviour of social systems and important factors driving system behaviour. Further, they may also be applied to explore possible effects of different actions carried out to impact social behaviour. However, these models do not have the level of accuracy necessary to calculate consequences in an absolute manner, but they may be useful to narrow the range of plausible behaviour outcomes in certain situations.

To make a CAS model useful to a specific operation it is necessary to adapt it to the situation of interest. The purpose of the present model is not to simulate opinion formation in a real society, but to explore the potential of multi-agent simulation models to simulate CAS. However, in principle it should be possible to model for instance the support to the peace process in an area in the northern part of Afghanistan. Here people participate in various networks determined by for instance family, religious, and ethnical affiliations. Some of these networks are governed by strong leaders such as landowners, religious leaders (mullahs), and warlords, which traditionally have a high status and hence a large impact on the opinion formation in the society. People's susceptibility for external influence depends on their social status, cultural factors, the security situation, living standard, and the social situation. Triandis framework of human behaviour (Chapter 3.3) may serve as a guide for modelling these factors. Accessibility to data of sufficiently high quality about all relevant aspects of the system is necessary to be able to build realistic and credible models of social behaviour. Thus, it is necessary to emphasise data collection and data modelling (see [28]).

Although CAS models seem to have potential to support analysis of various aspects of human social systems there are still significant challenges to sort out. This kind of simulations is an immature field of science, but a growing interest within the defence research community is observed.[3] A major challenge is to obtain confidence in the model and its results. This is a general problem faced when developing models, but it seems to be particularly hard for models involving human systems. The process of validation is performed to convince ourselves and others that the model is a good and sufficient representation of reality, i.e. its correctness and completeness. We may get confidence in the model if it is capable of mimicking typical

[3] Both our partners within the ANNCP collaboration, dstl (UK) and TNO (Nl), are doing work within this field. Dstl seems to put emphasise on using CAS in relation with models of command and control (C2), while TNO are looking at different ways to exploit CAS, among others in decision trainers.

behaviour of human systems that are exposed to similar scenarios. The models may be validated if the results of the simulation experiments can be explained by empirical studies and/or by sound theoretical models. There exist empirical studies supporting the sub models used in this report, see for instance [13;29] for the scale-free BA network model, [17] for the Triandis model and [18] for the social impact model. However, when the goal is to simulate opinion formation in a real society, e.g. in Afghanistan, there is a lack of adequate empirical studies and theories that can be used to validate the model. In this case a minimum of confidence may be established through combining available data with expert opinions and testing the models on different real-life situations.

6.3 Further work

The present model is relatively simple and some suggestions for further development of the sub models are discussed in Chapter 6.1. Different models of agent interactions and behaviour should be explored to assess their applicability to study real human systems. For instance Deffaunt's consensus model and Axelrod's model of dissemination of culture (described in Chapter 3.4.2 and Chapter 3.1) are combined behaviour and impact models that can easily be implemented and studied on the scale-free BA network.

Artificial societies are more advanced models of human societies where agents are allowed to move around on a landscape with resources where they interact and act to meet their design goals [20]. In this case the networks are dynamic and agents may decide to establish or abolish relationships with other agents to satisfy their goals.

In order to strengthen the confidence in the model described in Chapter 4 it should be applied to a real case, for instance related to the ISAF operations in Afghanistan. The success of such an exercise is entirely dependent on the access of relevant and reliable input data.

7 Conclusions

The aim of this study is to explore and assess the applicability of complex adaptive systems (CAS) models to model human social behaviour in conflict environments. This study gives only limited insight into the wide field of CAS models, but based on our findings and review of relevant literature we conclude that multi-agent simulation models of CAS seem to be applicable for exploring human social behaviour in conflict environments.

A premise for good decision making in a complex environment is a decision basis containing information on all relevant aspects of the systems one wants to influence. Currently there is a lack of operational research (OR) models to support decision making on 'behavioural targets', even though these targets are emphasised as particularly important to achieve success in peace support operations (PSO). Based on the discussion in the previous chapter (Chapter 6), we conclude that simulation models of CAS are complementary to other simulation models applied within OR, and that they can be used to provide insight into the behaviour of human social systems and how these systems are influenced by different actions. Examples of possible areas of application are:

- Give insight into underlying mechanisms driving system behaviour, and thus, help identifying factors that have large influence on human social behaviour
- Explore the likely range of outcomes of different actions.
- Help identifying risks
- Explain observed behaviour of human social systems

However, to make CAS models applicable to support real-world decision problems it is necessary with further research to gain more experiences with this kind of models. Applying CAS models to simulate human social behaviour is an immature field of science. But, a growing interest is observed which also include the defence research communities. One major challenge is to find suitable and acceptable methods for validation, maybe by looking at how methods and models are validated in social sciences. Acquiring relevant data of sufficiently high quality is another important challenge.

Further work should focus on applying CAS models to simulate human social behaviour in real conflicts, for instance in Afghanistan. There exist a lot of theories, models, and methods that can be used, but there is a lack of applications on real systems. A future study may develop models that are able to recreate observed social behaviour. The success of such models is dependent on the accessibility of relevant and reliable input data, which may be problematic due to the limited access to reliable data sources in areas of conflict.

Further work on applying CAS models would profit from collaborating with other international military research institutions, e.g. within the Angelo, Netherland, Norwegian collaboration program (ANNCP) or within the NATO Research and technology organization (RTO).

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Abbreviations

ABMS	Agent-based modelling and simulation
BA	Barabasi-Alberts
CA	Cellular automata
CAS	Complex adaptive systems
COA	Courses of action
MC	Monte Carlo
OR	Operational research
PMESII	Political, military, economical, social, infrastructure and information
PSO	Peace support operations
SNA	Social network analysis

Appendix A

Table A. 1 gives an overview of different measures used to characterise networks.

Clustering coefficient	The average probability that two neighbours of a given node are also neighbours of each other. Measures the degree of cliquishness.	$C_i = \frac{2E_i}{n_i(n_i-1)}$, E_i = actual number of links in neighbourhood of i n_i = Number of neighbours to node i.
Geodesic distance	Length of shortest path between two agents	$d(n_i, n_j)$
Average path length	The average distance between pairs of nodes in the network	$l_{av} = \frac{\sum_{ij} d(n_i, n_j)}{N(N-1)}$
Density of network	Number of dyadic arcs to the total possible number of dyades	$D = \frac{2\sum_i \sum_j k_{ij}}{N(N-1)}$
Nodal degree		$k_i, \bar{k}$
Degree centrality	Measures the degree to which a node connects to all other nodes	$C_D(n_i) = \frac{\sum_{j=1, j\neq i}^{N} x_{ij}}{N-1}$
Closeness	Measures how near a node is to the other nodes. Inverse of the sum of geodesic distances between agent i and the other N-1 agents	$C_c(n_i) = \frac{1}{\sum_{j=1, j\neq i}^{N} d(ni, nj)}$
Betweenness	Measures the extent to which other agents lie on the geodesic path between pairs of agents in the network	$C_B(n_i) = \frac{2\sum_{j<k} g_{jk}(n_i)}{g_{jk}(g-1)(g-2)}$ g_{jk} (n_i) is the number of geodesic paths between node j and k that contain node i
Cliques	Every agent is connected every other agent in the network	

Table A. 1 Different measures used to characterise networks