Understanding crowd behaviour

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Chapter 4

Simulation to Understand Crowd Behaviour

Computer-based simulation is a type of modelling or, in other words, a way of understanding the world (Gilbert & Troitzsch, 2005). Simulation introduces a way to think about and look at phenomena that is especially suitable for complex systems, i.e. a total of changing, interconnected parts that exhibit properties that are not obviously given the properties of the individual parts (emergence) (Wilson & Keil, 1999). In general, the use of simulation can have two purposes: *understanding* and *prediction*[1]. Using a simulation for understanding aims to uncover the underlying rules of behaviour patterns, whereas using a simulation for prediction aims to reproduce the dynamics of certain behaviour. Note that the underlying rules do not have to match reality, only the outcome should match reality. In this thesis, simulation will be used as a tool and method for understanding. More specifically, it will be used to gain a better understanding of the mechanisms that underlie the emergent patterns of crowd behaviour.

The behavioural dynamics of a crowd is regarded as a complex system: the multitude of factors that are of influence plus the interplay between the internal and external world of an individual, give rise to the complexity of behaviour and the behavioural patterns that can be observed. In the interaction process, behavioural patterns are the result of interactions between individuals, an emergent process (bottom-up). The patterns themselves will in turn affect the behaviour of the individuals. This downward causation is a top-down influence. The multi-level influence and the continuous dynamics give rise to a complex phenomenon where it is difficult to derive cause and effect due to the multitude of influences and their directions. In a crowd, the social environment adds an extra dimension to the complexity, because the social environment is not only different for each individual in terms of what is perceived, but also in terms of the way it is perceived, as this depends on the person and the situation. This heterogeneity and context dependency make crowds a good example of a social complex phenomenon. In the previous chapters, the importance of the

[1] A simulation can also have the purpose of entertainment. Even though they have no scientific goal, real-life games can be similar to the models that aim for understanding or prediction, as they have to be real enough for the gamer, i.e. believable.

individual level of agency in understanding crowd behaviour patterns was addressed. This has resulted in a multi-level study with the cognitive level as the level at which behaviour will be described. These multiple levels are represented by: the group level where behaviour patterns emerge; the individual level at which behaviour is exhibited; and the cognitive level to represent the individual in a crowd. A multi-level analysis (i.e. micro-macro analysis) will relate the group level patterns with the level at which behaviour is chosen and affected. The approach to relate the group and individual level is considered the way to gain better understanding of the underlying dynamics. To represent these important notions of interaction, multi-levelness and the cognitive level of description, a multi-agent simulation will be used. In this way, crowd behaviour patterns will be generated, representing a crowd as multiple computational individuals, i.e. agents, that interact.

In crowd research, like in most studies, scholars all have their own traditions in the methods they use. Crowd research is part of the social sciences where observation and experimentation are common methods to answer research questions and develop theories. These methods are limited in their ability to answer questions such as: "What gives rise to behavioural patterns in crowds?" or "How does a certain type of behaviour arise?". The explanations of traditional crowd research methods, such as observation studies, media studies and post-incident research, are limited. Media studies only focus on specific outcomes of crowd behaviour in terms of riots or emergencies. Post-incident research is similarly restricted, as it looks for answers after an incident, of course relating preceding events to the incident. Observational studies however, do not have knowledge of the outcomes like post-incident research. This results in valuable descriptions of crowds and of the kind of behaviour and behavioural patterns that are displayed, regardless of the outcomes. However, observational studies cannot answer *why* and *how* behaviour patterns arise. It is only possible to look at individuals and groups from the outside, while the internal decision-making process remains a black box. Normally, the next step would be to conduct experiments, relating relevant factors or testing a potential explanation for the why and how questions. However, it is almost impossible to perform experiments in crowds. The factors that play a role are numerous, which makes it difficult to control the circumstances and create an experimental setting. In addition, an ethical issue would arise, as the safety of the subjects cannot be guaranteed.

Computer-based simulation is a method that is not bothered by these limitations. It allows for the exploration and manipulation of each setting that is incorporated in the computational model, and is thus able to investigate the underlying mechanisms in crowd behaviour by studying the formation of behavioural patterns (see chapter 1). Therefore, in this thesis, simulation will be used to gain better understanding of a social phenomenon (Gilbert & Troitzsch, 2005), i.e. social simulation). The strengths of the following relevant fields will be combined: knowledge of human behaviour from the social sciences, knowledge of both human information processing and computational modelling from the cognitive sciences and artificial intelligence. With that, the resources are available to explore the dynamics of crowd behaviour.

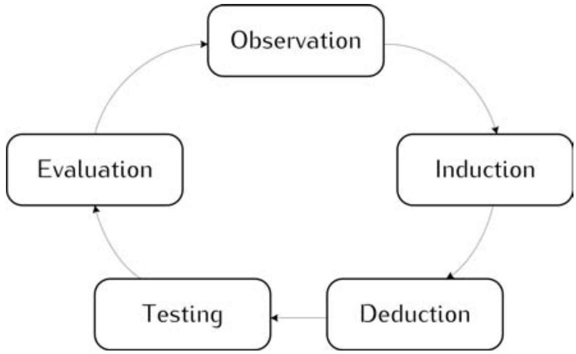

Figure 4.1: The empirical cycle of science (Groot, 1961).

4.1 The scientific cycle

Science aims to explain phenomena by systematically analysing the subject of interest. The cycle of proposing and then evaluating an explanation to come to new proposals is known as the *empirical cycle*. Figure 4.1 visualises this cycle.

All scientific studies implicitly or explicitly make use of models. "A model is a simplification - smaller, less detailed, less complex, or all of these together - of some structure or system" (Gilbert & Troitzsch, 2005, p. 2). Models, both theoretical and computational, are based on the assumption that the comparison between the input and output of the model with data from the real world will say something about the value of one's model for the real world. In figure 4.2, derived from Gilbert & Troitzsch (2005), the logic of simulation as a method is represented. The *target* represents the subject of study, for instance, a social process. Next the researcher develops a *model* and provides a description based on observations, empirical data, theory or other sources. This covers the observation, induction, and deduction steps. The model is then used to generate data in a simulation model, data will be derived in a theoretical model or data data will be predicted in a statistical model. These data can be compared to data collected by traditional methods. The comparison closes the loop and the explanatory power of the model can be assessed. Depending on the goal of the research the data do not have to be an exact match of reality to establish the explanatory power of the model. If the goal is to gain an understanding of the underlying mechanisms, reality can be different while the processes are still comparable. The evaluation of the model can be used as input to adapt the model, improving it making it more specific or broadening it.

The simulation research conducted in this thesis will follow the empirical cycle and make use of a computational model. However, the design of a computational model follows the steps of the so-called regulative cycle,which overlaps with the empirical cycle. The *regulative cycle* represents the systematic way of solving real-life problems using both a theoretical framework and models with a design-perspective that are used in engineering and computer science (Helmhout, 2006). When compared to the empirical cycle, the development of a simulation requires several additional steps which are common for the development of a simulation in an empirical domain.

These steps are incorporated in the life cycle of a simulation, visualised in figure

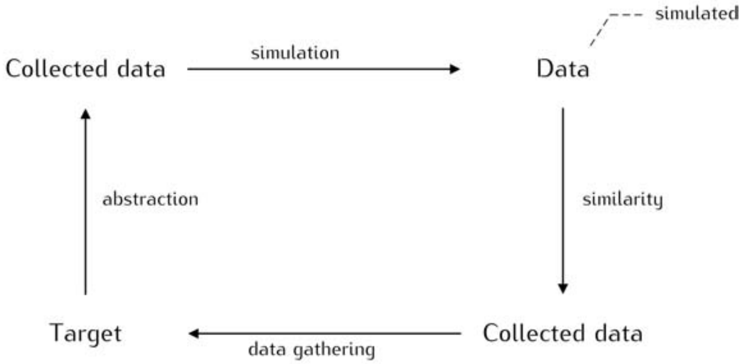

Figure 4.2: The logic of simulation as a method, derived from Gilbert & Troitzsch (2005).

4.3. The life cycle of a simulation can be divided into five phases that describe moving: 1) from the real world to a theoretical model[2] (conceptual modelling); 2) from a theoretical model to a computational model (formalising and coding); 3) from a computational model to an experimental model (experimental design); 4) towards understanding the model (experimentation); and 5) towards understanding the real world (redefinition). The transition from one phase to another always involves a verification and validation step. *Verification* involves checking whether the model represents what it is supposed to represent. For example, the theoretical model should incorporate all assumptions, whereas the computational model should not have any bugs. *Validation*, on the other hand, involves checking whether the model is a good model. A model is a good model when the descriptions of the processes in the conceptual model are theoretically or empirically sound, when the coherence is maximised (Thagard & Verbeurgt, 1998), or when the behaviour of the computational model corresponds to reality. In order to meet the objectives of the study, the model should allow to explain or predict (Law, 2007; Gilbert & Troitzsch, 2005; Balci, 1998).

4.2 How can simulation be used to understand crowd behaviour | the phases of the CROSS model

The following sections will describe the development of the CROSS simulation model of crowd behaviour for each phase. The phases involve the development of, the implementation of and the experimentation with the CROSS model. Ech phase in the simulation cycle will be described, addressing both the main decisions made with regard to the CROSS model as well as the verification and validation of the model.

[2] In computational modelling, the term conceptual model is often used. In this thesis the notion of theoretical model will be used as this fits the jargon of the social sciences better. However, both terms imply the same here.

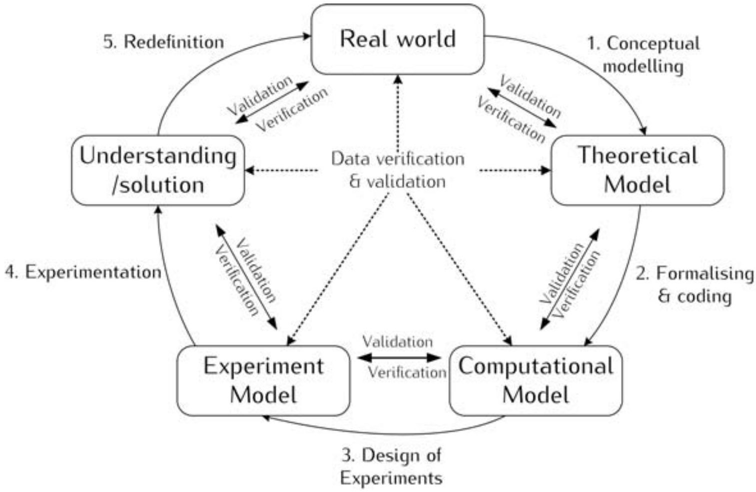

Figure 4.3: Life cycle of simulation research in an adapted version of (Balci, 1998), derived from (Helmhout, 2006).

4.2.1 Phase 1 - from the real world to a theoretical model

In the first phase, the theoretical model is developed, which corresponds to the first three chapters of this thesis. It is the phase in which "one starts by identifying a ‘puzzle’, a question whose answer is not known and which it will be the aim of the research to resolve" (Gilbert & Troitzsch, 2005, p. 18). In this thesis, the emergence of behaviour patterns was identified as the ‘puzzle’ and target of the investigation (chapter 1). In moving towards a model, current crowd research was studied, serving as a base (chapter 2). Other theories from the social and cognitive sciences were included on the base of existing knowledge of behaviour in crowds (chapter 3).

The major choices at this point evolved around the question *What to include and what to exclude?* In fact, in modelling crowd research, the latter remark "what to exclude" is very important, as there is a multitude of factors playing a role in crowd dynamics. The choices made in this thesis have been guided by the combination of the modern foundation of crowd research (section 2.1.3) and the level of detail that is considered necessary for the development of a simple yet sufficiently rich model. Crowd behaviour is generated by the individuals constituting the crowd, where their behaviour is the expression of a continuous interplay between the external and internal world. This approach results in a model that integrates different sources of influence, including the physical and social environment as well as the physiological and mental parts of the intra-individual, rather than in a model that aims at incorporating all the relevant aspects of one type of influence.

At this level, verification only involves checking whether the theory represents what it is supposed to represent. The CROSS model integrates multiple theories. It is important to verify that the different subtheories are represented in the way their developers intended to represent them. For instance, if a theory describes that perceiving high-density levels will increase the arousal level, the verification step checks whether this increase is really represented in the model.

Table 4.1: An overview of the assumptions on which the CROSS model is based. The right-hand column shows the source from which the assumption originates.

Assumption	Source
Crowd behaviour is generated by individuals	Social sciences (e.g. McPhail (1991), Adang (1998))
Crowd behaviour is situation dependent	Social sciences (e.g. Adang (1998), Reicher (2001))
Crowd behaviour is a social phenomenon	Social sciences (e.g. Couch (1968), Adang (1998), Reicher (2001))
Crowd behaviour is dynamic	Social sciences (e.g. Adang (1998))
Individuals are information processing systems (= cognitive systems)	Cognitive sciences (e.g. Newell (1990))
Individuals are situated (= embodied and embedded)	Cognitive sciences (e.g. Lindblom et al. (2002))
Behaviour is goal-directed	Cognitive sciences (e.g. Kendrick et al. (2005))

Validation, on the other hand, involves determining the correctness of the theories and assumptions underlying the model. It also involves determining whether the structure, logic and causal relationships of the model are 'reasonable' (Sargent, 2000). The CROSS model's assumptions are empirically based. From regarding behaviour in crowds as generated by the individual to incorporating the role of the social context as well as the dynamics, all are entirely based on the insights of crowd research that were obtained by systematic observation studies (chapter 2). Table 4.1 provides an overview of the relevant assumptions of the CROSS model. The influence factors and the way these factors are embedded in the structure of the individual are selected on the basis of crowd research literature and social theories concerning the effect of these influence factors on behaviour (see table 4.2). The structure representing the internal world of an individual is also based on the structures used in cognitive architectures that are empirically validated. The elements that form the model can all be justified by being either context-related or evidence-based (see table 4.3).

4.2.2 Phase 2 - from a theoretical to a computational model

The second phase represents the translation of the theoretical model into a computational model, i.e. the formalisation. There are several ways to computationally model social phenomena. For the purpose of this thesis, the CROSS model must meet several criteria to be able to represent crowd behaviour: 1) it must allow for multiple levels; 2) it must describe behaviour at the cognitive level; and 3) it must allow for the dynamics that represent the continuous interaction between individuals and their context. The phase of formalisation deals first and foremost with formalising each aspect into code.

Table 4.2: An overview of the influence factors used in the CROSS model. The right-hand column shows the source from which the factor originates.

Influence factors	**Source**
Point of interest {bar,toilet,stage}	Context related
Density	Inherent to crowds
Friends	Observation studies (e.g. Aveni (1977), Kemp et al. (2004, 2007))
Leaders	Record analysis (e.g. Arts et al. (2009))

Table 4.3: An overview of the elements in the cognitive structure that are specified in the CROSS model. The right-hand column shows the source on which the specification is based.

Cognitive structure elements	**Source**
Physiology - Architecture	
Arousal	Social sciences - Mere presence (Zajonc, 1980; Sanders et al., 1978)
Bladder & Stomach	Inherent to the festival scenario & Consequence of embodiment
Limited perception	Consequence of embodiment
Memory - Representations	
Goals {Identity,Social,Safety,Subsistence}	Social sciences - Needs (Max-Neef, 1993; Maslow, 1943)
Facts	Knowledge-based on context
Behaviour facts {walk,run,dance}	
Person facts {leader,friend}	
Rules	Knowledge-based on context
Behaviour rules {walk,run,dance}	

There are different ways to model social phenomena (Gilbert and Troitzsch (2005) give an overview). For instance, system dynamics (SD), cellular automata (CA) and multi-agent systems (MAS) are widely used approaches for the computational modelling of social phenomena. A major difference between the approaches concerns the aim of the research: prediction versus understanding. In the event of prediction, a model should produce a certain type of behaviour. The description of that behaviour does not necessarily have to be valid, as long as the outcome is. System dynamics is typically a method that is used to design models for prediction. A target system, e.g. a social phenomenon, is described as a system of equations, usually differential equations deriving a future state from a particular current state (Gilbert & Troitzsch, 2005). These models remain at the macro level. In the social sciences, and especially in this thesis, the focus usually is on *understanding*, which involves the inclusion of the valid underlying processes at the individual level for crowd research. This highlights the need for multi-level models, as both the level at which behavioural patterns emerge and the level at which behaviour is generated are involved. Both cellular automata and multi-agent systems allow for multiple levels. Cellular automata models incorporate two levels[3]. They are represented by a grid of cells, where each cell can only have a small number of states. In accordance with rules, the states of a cell can change depending on the states of the neighbouring cells. These dynamics then give rise to changing patterns. Cellular automata are useful in modelling social interaction, for instance, in the spread of gossip (Gilbert & Troitzsch, 2005) or in segregation (Schelling, 1971). The advantage of the simplicity of cellular automata is at the same time its drawback: they are not practical for a description at the functional (i.e. cognitive) level. In cellular automata behaviour rules and states must be quite simple and influences are bound to be local. As has been argued in this thesis, to achieve a richer description of the internal world as well as the inclusion of the environment, an approach is needed that allows for multiple levels (i.e. more than two) and a more complex description of behaviour. This need for interaction between a more complex world and more complex entities leads to multi-agent systems.

Multi-agent systems convey an approach that involves the design, analysis and implementation of complex adaptive software systems (Jennings, Sycara, & Wooldrigde, 1998). They are characterised by the involvement of multiple levels (> 2), more complex individuals, and agents designed to interact 'intelligently' with their environment. Multi-agent systems are systems composed of multiple interacting computing elements, known as *agents*[4]. An agent is a computer system that is capable of independent action on behalf of its user or owner (Wooldridge, 2002). There is no generally agreed definition of an agent, although many have been proposed (Franklin & Graesser, 1996). As Helmhout (2006, p. 21) puts it: "Understanding the field of MAS starts with the understanding of the agent as the main component of the system". In this thesis, a general definition of an agent will be used, adapted from Wooldrigde and Jennings (1995) by Wooldridge (2002, p. 15):

> An agent is a computer system that is *situated* in some *environment*, and that is capable of autonomous action in this environment in order to meet its design objectives.

[3]Unless this CA is build out of CA's: in that case there are more more levels.

[4]The term actor is also often used instead of agent to denote an human or agent that is (represented as) a cognitive system

Two general uses of 'agent' are distinguished by Wooldridge and Jennings (1995), namely having a *weak* or a *strong* notion of agency. The notion of agency refers to the properties of an agent, but also to the level of abstraction that is used to describe the agents. The weak notion of agency implies that an agent has the properties of autonomy, social ability, reactivity and pro-activeness. *Autonomy* refers to the behaviour of an agent that has some kind of control over its actions and internal state, without the direct intervention of human beings or others (Castelfranchi, 1995; Gazendam & Jorna, 1998). *Social ability* refers to the capability of interacting with other agents in order to satisfy its design objectives. *Reactivity* indicates that an agent perceives and responds to changes in its environment in a timely fashion. *Pro-activeness* indicates that an agent does not only respond to the environment (i.e. is reactive), but also shows goal-oriented behaviour. The other use of the term agent[5] has a more specific meaning. In addition to the properties described above, agents are conceptualised or implemented using human-like characteristics, such as mentalistic notions (i.e. representations or states), attributes, etc. These agents can be defined in more detail at the intentional or functional level (Helmhout, 2006). In this sense, the CROSS model is a strong model, as the description it provides of individual behaviour in a crowd at the functional level is more precise. The notion of agency steers the design of an agent. To distinguish between strong and weak agents, the properties and differences appear in the description of the internal world of an agent. A common method describing the mind of an agent distinguishes between perception, action and cognition, which corresponds to the CROSS model description. However, to describe an agent in a crowd context, an agent must be situated. More specifically, it must be socially situated. Carley & Newell (1994) describe what is needed to develop a social agent in what they call the 'Model Social Agent':

> The Model Social Agent has information-processing capabilities and knowledge. Agents' information-processing capabilities are goal-oriented. They control the agents's ability to handle information. Agents exist within an environment that is external to handle processing capabilities. The agents' knowledge is to an extent dictated by the external environment in which it is situated. The Model Social Agent exist in a particular situation (both physical and social). This situation is the environment perceived by the agent, but how the agent encodes it, and how much of the environment is encoded by the agent, is an open issue. The agent has a goal. The agent enters a situation with prior knowledge. The agent may have an internal mental model of the situation that differs from that held by other agents in the same situation. Throughout, we take the agent as having the typical human sensory and motor devices to sense the environment and affect the situation. (Carley & Newell, 1994, p.223)

The situated agent in the CROSS model closely matches this view. As indicated before, it is necessary for an agent to be embodied as well as embedded. The interplay with the external environment refers to the physical and social situation. Being embodied can relate to the sensory and motor devices of the body. In the CROSS model, embodiment implies limited perception, as well as not being able to

[5] Particularly in the field of artificial intelligence.

walk through walls. To be able to differentiate within and interact with the environment, the agents in the CROSS model must have a mental representation of the world and behave in a goal-oriented manner. Each agent has a unique internal state and perception of the world, which leads to heterogeneity. The description of the Model Social Agent stresses the same important points that are emphasised in the CROSS model. However, there is one major difference: Carley & Newell's (1994) aim is to understand cognition, whereas this thesis is concerned with understanding crowd behaviour. Implicitly in Carley & Newells's (1994) MSA represents a complex cognitive architecture from a cognitive sciences perspective. They start from rich complex descriptions of cognitive systems that focus on the internal world of agents, indicating what is needed in terms of knowledge and what are the limitations in terms of processes when moving to agents that must be able to show social action. The CROSS model takes a different approach, incorporating elements from the social and cognitive sciences that are necessary to understand crowd behaviour. Its approach is problem-driven (*"Which mechanisms underlie crowd behavioural patterns?"*) and does not presuppose nor need the full richness of an exhaustive cognitive architecture.

After deciding to design the computational CROSS model in accordance with a multi-agent systems perspective, the actual building could start. To support the development of an agent-based simulation, an MAS toolkit was selected for software development. A toolkit supports the building of sound models and saves development time. There are a huge number of agent-toolkits[6] available and choosing one requires a set of demands. Studies that compare toolkits, e.g. (Bitting, Carter, & Ghorbani, 2003; Shakshuki & Jun, 2004; Nikolai & Madey, 2009) support the formation of a useful list of criteria. For the CROSS model, in addition to comprising a Graphical User Interface (GUI), 2D/3D visualisation and an experimental setup, it was important that the toolkit would allow for 'heavy' or more complex agents. Furthermore, the programming should be object-oriented and in a language that is commonly used, like Java. The tool itself should contain good user support, i.e. documentation, tutorials and a community that stimulates further development by actively providing support. In addition, it is considered an enormous advantage if the toolkit has distinguished itself in the social simulation field, for instance by providing packages to define the social environment or supporting the performance of experiments. Lastly, an open source tool would be appreciated. After a rough selection primarily based on discussions with other social simulation researchers, the visualisation and available documentation resulted in four potentially suitable toolkits that were compared: Jade, Mason, Netlogo and Repast[7]. Jade, Mason and Repast appeared to be suitable to model complex agents. Netlogo did not allow for these complex agents to be modelled, but was used for preliminary versions of the CROSS model and for the exploration of several conceptual ideas. Netlogo showed strong advantages in terms of visualisation, simplicity, development speed and experimentation support. The choice between Jade, Mason and Repast was based on less crucial issues. All use a living language Java, and therefore allow object-oriented programming, which thus provides the freedom to develop any type of agent. Jade is especially suitable for distributed simulations and thus scalability, which was, however, not considered a

[6] See the survey of Nicolai and Madey (2009) for an overview .

[7] The websites of the toolkits (agent Development Toolkits: An Evaluation, ; Jade, ; Mason, ; Netlogo,) can be found in the references.

criterium for the current model. As Repast specifically contains support for behaviour models (i.e. social simulation) as well as an experimental set-up, it was decided to use Repast as it meets all the criteria.

Verification of the computational model must then ensure that both the computer programming and the implementation of the theoretical model are correct (Sargent, 2000). This includes making sure that there is no systematic behaviour that should not occur, so-called artefacts[8]. The use of Repast, or any other toolkit for that matter, makes verification easier, as the adopted parts of Repast are already verified because the verification step is part of software development. To test whether the CROSS simulation model is free of error, a pragmatic approach was chosen and scenario tests were performed. In a scenario test, the expectations of the behaviour of the computational model are tested. In this way, errors are easily identified. With regard to the CROSS model, this involved a test of the major functions: *perception* and *behaviour selection*. By testing these processes, the adequacy of the underlying functions is also tested. The perception test checks all aspects of perception over time. This involves checking whether agents situated in a certain location perceive their surroundings and are affected by it. More specifically, this test is conducted for the perception of points of interests (POIs), other agents and behaviour. In the CROSS model, the perception of a POI, e.g. the bar, toilet or stage, that is situated at a festival should result in a physiology update as well as a goal satisfaction, i.e. memory update. To perceive others, concerns updates of goals or facts, depending on whether the agent is co-audience, a friend or a leader. The perception of behaviour should result in a behaviour rule being primed. The behaviour selection test works in a similar way. Each simulation time step (i.e. tick), one agent is chosen randomly, and the chosen behaviour is then compared to the other behavioural options `{walk,run,dance}`. This comparison is based on the activation level of the chosen behaviour, which should be either higher than or equal to the activation of the behavioural options, or on the the fact that the utility is higher than the other behaviour options[9].

The validation is the most important part of this phase, as it indicates whether the simulation is a good model of the target, i.e. crowd behaviour. The validation of the computational model involves not only the translation of each relationship and concept into a specific function or variable (formalisation), but also the overall behaviour of the computational model. The validation with regard to formalising is realised by choosing the functions or variables. These are either related to reality, i.e. derived from observation studies or case studies, or relative values that represent the theorised behaviour. The validation of the CROSS model as a whole is carried out by means of *event validity*, *comparison with other models*, and *animation*. Data validation, i.e. gathering empirical data to compare the simulation outcome with data from real world settings, will not be applied[10]. Event validity concerns the "events" occurring in the simulation model that are similar to the target events (Sargent, 2000). During a festival, typical events include people going to the toilet, bar or moving towards the stage. These can also be observed in the simulation, see the screen captions

[8] For example, at one point, the agents repeatedly formed a diagonal across the screen. Apparently, the calculation of the heading of the agents did not work properly, which caused this strange result. This is called an artefact.

[9] For the details see the code of CROSS on openABM and SourgeForce.

[10] This does not fall within the time and topic scope of this project, but would nonetheless be a strong validation technique.

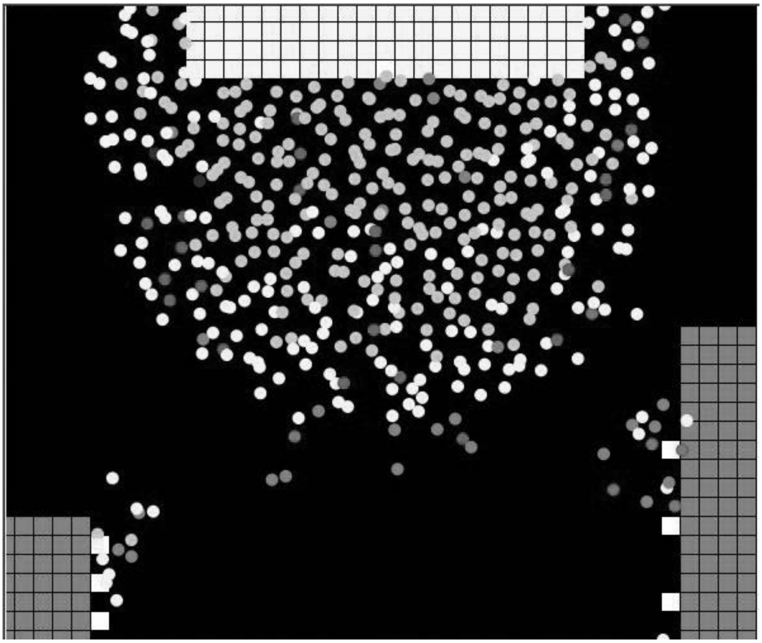

Figure 4.4: A screen capture of the CROSS model in a festival scenario, visualising the typical arc pattern around a stage.

of the simulation in figures 4.4, 4.5 and 4.6. In addition, people at a festival go to the bar together, which will be shown in the simulation as well. The validation technique of the comparison to other models is related to other simulations that are in itself validated (Sargent, 2000; Law, 2007). The CROSS model can be compared to other models based on movement patterns (e.g. arcs, rings, lanes) that are simulated and validated by using empirical data (Helbing, Buzna, Johansson, & Werner, 2005) and observation studies (Tucker, Schweingruber, & McPhail, 1999).

These key observations of patterns in a crowd (i.e. arcs, rings, companion clusters, and lanes) can be related to the notion of 'stylised facts' that is used in economics [11]. The last part of the validation at this level concerns animation. The operational behaviour of a model is displayed graphically as the model changes over time (Sargent, 2000). Not only is this an effective way to find invalid model assumptions but also to enhance the credibility of a simulation model (Law, 2007).

In addition to the usual tests of verification and validation, this phase also involves a sensitivity analysis. Sensitivity analysis gives an impression of the sensitivity of the model to changes in the parameter settings and the initial settings. Not all goals are, for instance, sensitive to the initial settings, only the subsistence goal is fully dependent on the bladder and stomach state that is set. However, also the extreme settings were explored, resulting for instance in a maximum of people that could be placed in the grid. Overall, the behaviour of the model remained stable throughout this visual inspection.

[11] A stylised fact represents the simplified presentation of an empirical finding (Kaldor, 1961).

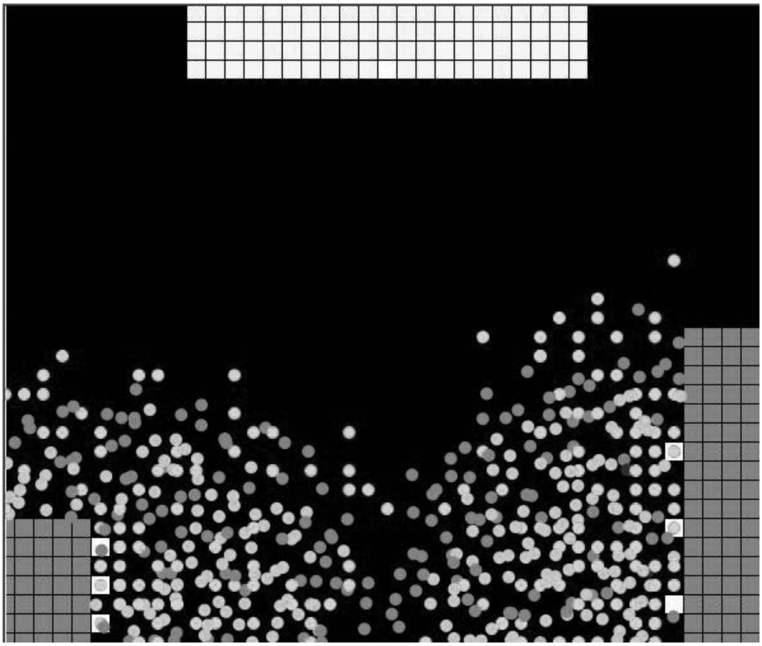

Figure 4.5: A screen capture of the CROSS model in a festival scenario, visualising the typical arc pattern around the toilets and the bar.

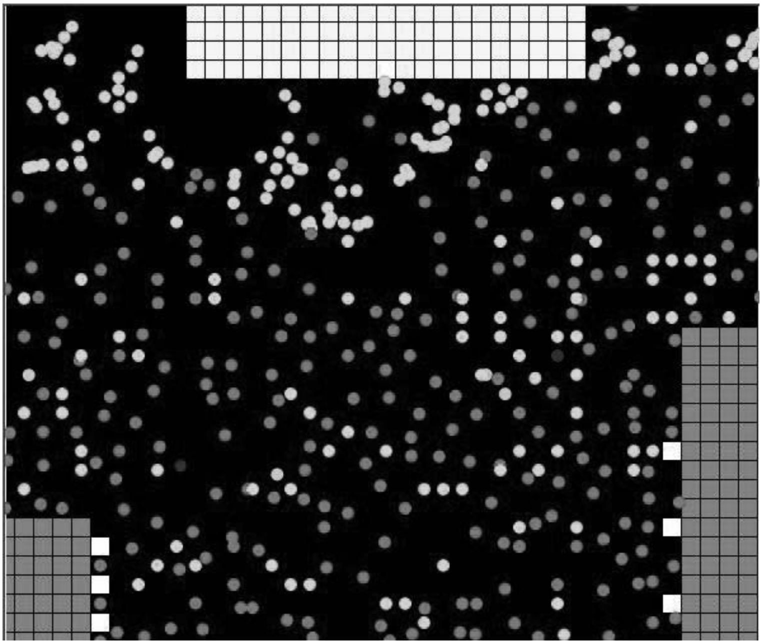

Figure 4.6: A screen capture of the CROSS model in a festival scenario, visualising the typical companion cluster patterns at the festival terrain.

4.2.3 Phase 3 - from a computational to an experimental model

Phase 3 prepares the computational model for experimental usage, i.e. the experimental design. The variables for experimentation are specified and the simulation is adapted in such a way that the relevant input settings can be assigned and that the output variables are written into an output file. Special attention will be paid to the output measure at the group level, and to relating the group level to the underlying levels. The CROSS model has been built around the main aim to gain a better general understanding of crowd behaviour by understanding the behavioural patterns. The research question: *"Which mechanisms underlie crowd behaviour patterns?"* and the role of the physical and social context in behaviour drive the two experiments that will be discussed in this thesis (see chapter 6 and 7). What is meant by behavioural crowd patterns? As discussed in chapter 1, behavioural patterns are patterns of movement, e.g. arcs, rings, lanes, companion clusters (see figure 1.1), but they also include patterns of clusters of people performing similar behaviour, e.g. dancing, talking, drinking. In this thesis, *behaviour clustering* is used as an output measure. Behaviour clustering describes the behavioural pattern of identifiable subgroups of agents exhibiting the same behaviour at a particular moment in time. It is difficult to define a group measure because what is it that defines the boundary of a group? Therefore, the choice was made to define a group on the basis of the behaviour that is shown and the distance between agents. At a dyadic level, agents are ‘connected’ in that sense. The more overlapping dyadic connections, the larger the group. Behaviour clustering will capture the overall behavioural characteristics by indicating the amount or size of the identifiable subgroups in a number. It is an aggregate notion of what the agents do (i.e. individual level → group level)[12]. At the group level, statistical analyses (ANOVA) will be conducted to check the effect of a manipulation. In addition to the classical design of an experiment at one level of description and the use of statistical analysis to find causality, the understanding and explanation is sought by relating the group level to the individual level, i.e. the micro-to-macro emergence (Sawyer, 2003). To be able to explore this relationship, so-called *life histories* will be used. They are represented by the behaviour and internal states of the individual agents. Life histories show the internal dynamics and state of an agent and provide insight into *why* and *how* a certain behaviour is chosen.

Verification of the experimental model concerns a test to see whether the additional experimental settings are set correctly and whether the output is written correctly into an output file. This is an obvious functionality to prevent false causalities or explanations.

Validation concerns the choices made in the manipulation of the experiment. The experiments conducted with the CROSS model concern density and leadership, which will be discussed in chapter 6 and 7. In the density experiment, the levels of density are varied as well as the way density is perceived by the individual in a crowd. In the leadership experiment, the percentage of individuals in a crowd that is regarded as a leader is varied. The choices in the manipulation of the experiments are given in table 4.4. The table indicates that the selected levels of density relate to reality. However, the other choices are based on the interest in exploration driven by the hypotheses.

[12] Behaviour clustering is formalised as the amount of dyads that show the same behaviour at the same time-step, while being in the physical vicinity of each other (see the (pseudo) algorithm 6.2 in chapter 6).

Table 4.4: An overview of the independent variables used for experimenting with the CROSS model. The right-hand column shows the reasoning behind the choice of the manipulation. Details concerning these variables and experiments are discussed in chapters 6 and 7.

Experiment manipulation	Source
Density levels {low,medium,high}	Estimation, Safety management guidelelines (e.g. Fruin (1971), Weidmann (1993)
Safety perception distribution {low,medium,high}	Choice of exploration with the assumption of normality
Leader ratio {0,10,25,100}	Choice of exploration

4.2.4 Phase 4 - from experimental model to understanding the real world

In the fourth phase, the CROSS model is used to explore the research questions by actually conducting the experiments. To be able to run the experiments, several decisions must be made concerning the duration of a run and the amount of runs. There is no rule of thumb for the duration of a simulation that would adequately reflect an event of about five hours. The duration should just be long enough to generate a sufficient amount of information about the behaviour of the model. There are models that reach a kind of equilibrium indicating an endstate. However, the CROSS model does not intend to reach such a point, as there are continuous dynamics. To decide on a cut-off point in terms of the length of a simulation run, the simulation was run with several different durations (`50, 100, 1000 and 5000` ticks) in order to compare the outcome of behaviour clustering. Figure 4.7 clearly demonstrates that `50 ticks` does not provide sufficient information about the general behaviour of the model. There appears to be an onset effect that is negligible when looking at the runs of a duration `>1000 ticks`. Therefore it was decided to use a `runlength` of `1000 ticks` as this would incorporate sufficient richness in information to describe the behaviour of the model. A simulation with `5000 ticks` did not seem to contribute to more understanding, but would just take more time to run the experiments.

The number of runs represents the iterations (i.e. repeated experiments) that are needed to distinguish whether the outcome of a manipulation is relying on chance or not. In the experiments described in this thesis, the number of runs is set to 30. The significant results of the experiments justifies the number of repetitions (see chapters 6 and 7).

Verification of this phase involves a check on whether all the initial settings of the manipulations are correctly set.

Validation in this phase would concern the actual link with the real world and is realised by exploring the behaviour of the model. There are three ways of comparing the model and the real world according to Sargent (2000): 1) graphs of the model and system behaviour data, 2) confidence intervals, and 3) hypothesis testing. In this thesis graphs and hypothesis testing are used in which another level of explanation is

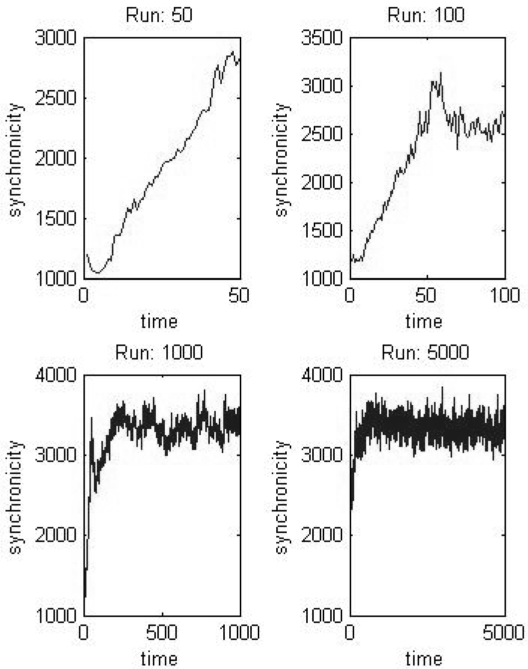

Figure 4.7: The visualisation of the output for various simulation run lengths.

added by using the life histories.

4.3 Conclusion

In this chapter simulation was described as a tool for understanding crowd behaviour. By addressing the four phases a simulation must go through, the choices and justification were made explicit. In developing a theoretical model (phase 1), assumptions and influence factors of the CROSS model discussed in Chapter 3 were summarised and linked to their theoretical and/or empirical foundations. In the development of the computational model (phase 2) the choice for a multi-agent system approach in order to model crowd behaviour was discussed. This choice was made in accordance with the requirements that the design of a multi-level model of a crowd composed of situated agents must satisfy. To be able to use the model for experiments (phase 4), the adaptations of the model for the density and leadership experiments were described in terms of the specifications and the choice for output measures and initial settings. It is good practice to *verify* and *validate* (V&V) before moving on to the next phase, hence every phase involves V&V.

As the first phase (i.e. from the real world to a theoretical model) has already been discussed in the preceding chapters, the remainder of this thesis will deal with phases 2, 3 and 4, i.e. the description and use of the computational model.