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Modelling consumer behaviour

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3 A methodology of modelling

In this chapter, we will focus on the methodology that is being used in scientific models. We will first present an inventory of the metaphors that underlie scientific models. These form the necessary basis to describe the various modelling paradigms that are being used in the social sciences. Because agent-based modelling offers a methodology to model the dynamics of interacting agents, we will focus on the conceptual tools that are being used in that modelling paradigm. This chapter will conclude with a discussion on the application of models.

In Chapter 1 we stated that scientific models can be conceived as formal descriptions of systems. The development of scientific models usually proceeds through isomorphisms. These isomorphisms can be considered as general metaphors, which implies that the modelling of a certain system is based on the formal description that is available of another system (e.g., Khalil, 1992). For example, a better formal understanding of chemical processes also triggered the development of analogous economic models. On the basis of formal models it is possible to develop simulation models that to a certain extent behave like real-world systems. Doran and Gilbert (1994) argue that the technique of computer simulation is an appropriate methodology to study social phenomena that are not directly accessible for research in the classical tradition, as is the case with man-environment interaction. Such a lack of accessibility may be due to the complexity of a phenomenon, which does not allow for understanding it on the basis of observational data, or because the phenomenon in question does not exist anymore, as is the case with historical processes.

Modelling as a metaphor

Considering a simulation model (computerised or not) as a metaphor of a real-world process yields the question 'To what extent can a certain metaphor capture a real-world process?' To answer this question, it is first necessary to realise that different types of metaphors exist, and that the type of metaphor underlying a simulation model has consequences for the applicability and outcomes of simulations with it.

According to Khalil (1992) there are at least four types of metaphors. The *superficial metaphor* refers to an observed similarity but is not meant to indicate any functional likeness. An example is 'He's got a head like a potato'. Superficial metaphors may be used as illustrations, but, because they do not refer to a deeper similarity (e.g., at the functional level), it is not recommendable to use them in a scientific context.

The *heterologous (or analogous) metaphor* refers to a similarity of analytical functions. Khalil (1996) mentions as an example the comparison of the wings of a bat with the wings of a butterfly, which perform the same function but which have totally different (evolutionary) origins. The previously mentioned example of economic models that were developed analogous to chemical processes is one example of this type of metaphor that is being widely used in science.

The *homologous metaphor* designates a similarity from the resemblance of contexts. An example is the similar origin of the forelimbs of the bat and the mouse, which have the same origins but have different functions. This type of metaphor may be describing the similarity between e.g., fighter-jet training simulators and flight-simulator games, which have the same origin, but have been developed to fit very different functions. This type of metaphor is hardly relevant for the formalisation of scientific models.

The *unificational metaphor* expresses similarities arising from the same law. For example, Newton's law of gravitation can be understood as a metaphor that expressed celestial movement (Kepler's laws) and terrestrial gravity (Galileo's laws) in terms of the same law or principle. The genetic algorithms used in simulating processes of adaptive behaviour (e.g., Holland, 1975) can also be understood as an unificational metaphor, being isomorpheous to the principles underlying the genetic recombination of DNA (Watson and Crick, 1953), which explains the laws of heredity as formulated by Mendel (1865).

Regarding the degree to which a scientific model captures real-world processes the relevant question becomes 'What type of metaphor underlies a particular simulation of a real world system?' Regarding the development of scientific simulation models, we concluded that both the *heterologous* and the *unificational* metaphor play an important role, whereas the *superficial* and *homologous* metaphors are unimportant. In developing simulation models, scientists may use different theories, laws and appropriate insights as metaphors to formalise a system to be studied. It should therefore come as no surprise that various modelling approaches exist. Whereas all these approaches use some basic common concepts, such as a mathematical basis, they differ regarding the theories and procedures for constructing and testing models. These differences can partly be attributed to the metaphors used in modelling. A major source of metaphors is provided by the natural sciences, a discipline that was among the first to apply mathematics in practical settings. According to Meadows and Robinson (1985), all mathematical models share a general biased starting point by assuming that the world is not only knowable by a rational process of observation and reflection, but is also assumed to be controllable. Of course, this holds in different degrees for various modelling approaches, as system dynamical models are assuming a much larger controllability than e.g. models of adaptive systems using genetic algorithms. Because these differences stem from different (implicit) assumptions of how the real world system works, these various modelling approaches seem to fit the concept of paradigm (Kuhn, 1970). New insights in principles of system behaviour may cause a paradigmatic change, thereby disqualifying an 'old unificational metaphor' as a heterologous metaphor. This implies that the scientific usefulness of metaphors depends on one's paradigmatic perspective. In the following section some important modelling paradigms and the underlying assumptions will be discussed.

Metaphors as modelling paradigms

The developments in the natural sciences influenced the number and nature of modelling paradigms to a large extent. The start of mathematical modelling can be dated to the 17th century, in which physical science developed a mechanistic, reversible, reductionistic and equilibrium-based explanation of the world. This proved to be very successful in calculating trajectories of moving objects (e.g. cannon balls) and predicting the positions of celestial bodies. Especially the work of Newton, culminating in the *Principia Mathematica*

Philosophiae Naturalis (1687), was and still is very influencing. The associated rational and mathematical way of describing the world around us was also applied in social science, economics and biology. Despite the fact that later developments in the natural sciences seriously constrained the applicability of the mechanistic paradigm, its relative simplicity had a large appeal on scientists from various disciplines working with models. However, despite the wide-spread use of this approach, the mechanistic paradigm becomes increasingly criticised. The foundations of the mechanistic view: reversibility, reductionistic, equilibrium-based and controllable experiments fade away in the light of a number of 'new' scientific insights.

First, the discovery of the Second Law of Thermodynamics brought down the notion of reversibility. The Second Law states that the entropy of a closed system is increasing. This means that heat flows from hot to cold, so that less useful energy remains. One of the consequences of the Second Law is the irreversibility of system behaviour and the single direction of time. Changes within systems cannot reverse back just like that (irreversible). This is in contrast to many mechanistic models, in which the time can easily be reversed to calculate previous conditions.

Second, the equilibrium view on species was brought down by Darwin's (1859) book on the origin of species. The static concept of unchanging species was replaced by a dynamic concept of an evolution by natural selection and adaptation of species, thereby fundamentally changing our view of nature. Natural systems are in continuous disequilibrium, being interdependent and constantly adapting to changing circumstances.

Third, the theories of quantum mechanics confronted us with a fundamental uncertainty regarding knowledge about systems, especially on the level of atoms and particles. Well known is the uncertainty theorem of Heisenberg (1927), stating that it is impossible to simultaneously measure the position in space and momentum (mass times velocity) of any particle. The statement by Laplace (1805 –1825) that if every position of every atom was known, the future might be predicted exactly, became therefore a lost illusion. Moreover, the notion of fundamental uncertainty implied that fully controlled experiments are strictly spoken not possible.

Notwithstanding the fact that the just described developments in the natural sciences changed our perception of the world, mathematical models are still mainly based on a mechanistic view on systems. However, the rapid growth of computing power and the increase in simulation research has also yielded a new modelling paradigm and associated tools. This new paradigm uses the metaphor of the organism, including notions of adaptability and learning. Whereas the computer is a typical product of the mechanistic worldview, it allows to model irreversible, non-equilibrium, unpredictable and uncontrollable processes that are typical for organic systems. Because no organic counterpart of mechanistic mathematics exists, special tools have been developed to simulate organic processes using mechanistic model rules. Agent-based modelling, which implies formalising a multitude of relatively autonomous agents that interact, proved to be a successful approach within this organic modelling paradigm. The associated notion of distributed intelligence is being used in a rising number of simulations of complex adaptive systems.

For further reading on the gap between mechanistic and organic views on systems, see e.g., Allen (1990), Toulmin (1990), Geels (1996) and Janssen (1998). In the following section various modelling approaches that are used nowadays within integrated modelling will be discussed.

Multiple regression models

Many scientists in the social sciences are developing models using the statistical technique of multiple regression analysis to discover systematic patterns of relations in large data sets. In this line of modelling, scientists describe the system of interest in terms of simultaneous equations, linear relations, many exogenous driving variables, and observable statistics. The multiple regression model is based upon the significant relations that have been found between variables, emphasising the $p < .05$ criterion of chance occurrence. Empirical data are rigorously used to determine model parameters, while frequently less effort is spent on estimating the relevance and representativeness of the data. For example, often the reliability of (historical) data is unknown. Because of the correlational basis of the multiple regression modelling approach, no causal relations can be inferred between variables. Often theoretical models (or less formalised mental maps) are being used to interpret relations between variables as a means to introduce causality in the models.

Multiple regression models can be used to extrapolate tends of past developments. Despite the fact that quite complex extrapolation techniques have been developed, the fact remains that the relations between model variables are treated as static, whereas in the real world these relations may be dynamically changing. This implies that multiple regression models are not capable of reflecting the dynamical processes of real world systems. Because multiple regression models do not allow for assessing processes of structural changes or adaptation, the use of most multiple regression models is limited to the short-term precise forecasting of developments and the exploration of possible future developments in scenarios. Because multiple regression models do not capture real world dynamics, it can be said that multiple regression models constitute a heterologous metaphor of real world systems.

Optimisation

Models that involve the optimisation of behaviour are widely used in economics, as has been noted in Chapter 2. In this modelling approach, rational agents are assumed that have perfect foresight and that are maximising their discounted sum of utility of consumption. Hence, the question is one of how much to consume now, and how much to invest in capital goods to increase consumption later. Maximising such a single utility function over finite time reflects the supposed existence of a single generation, or even a single individual, which exists forever. Regarding the modelling of human behaviour, the general critique on using optimisation models is that real people do not always optimise their outcomes, but rather use more simple heuristics to manage their limited cognitive resources. Consequently, the optimisation approach does not deal with behavioural processes such as habit formation, imitation and social comparison. Gintis (1998) mentions four postulates on rational-actor behaviour and explains why this approach entails a limited description of human behaviour. First, the rational-actor approach postulates that people have outcome-regarding preferences, which apply to the quantity of goods and services that are produced, consumed and exchanged. However, people also have process-regarding preferences, which are related to the distribution of these goods and services (thinking about fairness, reciprocity).

Second, the rational-actor approach postulates that self-regarding preferences reflect the potential contribution of opportunities to the own level of need satisfaction. However, people are also other-regarding, deliberately performing behaviour to affect the wellbeing of other persons, which also relates to the concept of social value orientation

(see Chapter 2 on personal factors influencing behaviour in a dilemma). For example, rewarding and punishing other people may go against one's self-interest.

Third, the rational-actor approach postulates that the well-being of an individual depends on the degree to which his/her preferences are satisfied. However, often people perform behaviours that decrease their level of need satisfaction, for example, drug abuse and obsessive status seeking. Also people may change their preferences to obtain a higher level of need-satisfaction. This can be considered as changing ones perspective on what is perceived as satisfying.

Fourth, the rational-actor approach postulates that the preferences are exogenous, which implies that peoples' preferences are not determined and affected by economic policy and institutions. However, the preferences of people are often affected by their own experiences, by what other people do (e.g., high-status examples) and by other social forces such as advertisement (endogenous preferences).

Because the optimisation approach describes the principles of deliberate decision-making (outcome optimising), this approach can be considered as an unificational metaphor. The optimisation approach is also being used to explain non-outcome-optimising behaviours that save cognitive effort, such as habit formation, imitation and social comparison. These strategies are aimed at balancing the outcomes of the behaviour and the amount of cognitive processing. Optimisation often correctly describes the outcomes of such behaviour, provided that large groups of people are taken into consideration. However, the fact remains that the processes that guide the behaviour of real people differ from the rational actor being formalised in the model. As such, when applied to the non-outcome-maximising behaviours as mentioned above, the optimisation approach can be considered to be a heterologous metaphor. Many discussions between mainstream economists and psychologists who study behavioural processes originate from the use of different types of metaphors about human behaviour.

System Dynamics

In the system-dynamic modelling paradigm, processes of the real world are represented in terms of conglomerations of interacting feedback loops. Stocks of material and information and flows between these stocks are being modelled using non-linear equations and time-delays. This implies that a model gives a precise description of a system's behaviour, which can be compared with the behaviour of the real world system. An example is the use of Lotka-Volterra equations to simulate a predator-prey system (Lotka, 1925; Volterra, 1931). Lotka and Volterra independently developed the necessary manipulation of logistic equations that constitute one of the stock phrases of ecological modelling.

Many natural processes involve flows of materials, which can be adequately described using a system dynamic approach. This holds that the same mechanism underlies both the real world processes and the model, implying that the model constitutes an unificational metaphor. However, the (adaptive) processes that govern human behaviour (and many ecological systems involving behaving organisms) can not be captured fully in terms of stocks and flows. Therefore, behavioural (economic) models that are based on a system dynamical framework can be considered as heterologous metaphors. In many situations the behaviour of the real system can be mimicked quite well using a system dynamical model. However, because the laws and principles that lie behind

the real world and the simulated system differ, this type of simulations can hardly be used to test hypotheses regarding the laws and dynamics of the simulated system[3].

Because system-dynamic models are very suitable for studying long-term system behaviour, this approach is frequently being used to model issues like population growth, biochemical cycles, economic processes, land-use and ecological systems. Moreover, in integrated assessment models, simple versions of such expert models are being integrated in a system-dynamic framework (see also Chapter 1 on Integrated models).

Despite the fact that more realistic simulations of e.g. fish stock systems may be available, many researchers prefer to use system dynamical simulations because they guarantee efficient programming and they offer a good experimenting tool to study e.g., the way in which people manage resources. In such experimenting tools the processes behind the simulation are not important for the research, as long as the output is mimicking the real world system in a convincing manner. Consequently, within such a 'mimicking context' simulations are being used as an experimental tool, not as an object of scientific study in themselves.

In the development of system dynamical models, usually much effort is spent on the development of a model structure that resembles the stocks and flows in the real world. Here, the multiple regression of empirical data can be helpful in validating the outcomes of system dynamical models. The estimation of parameter values in the model often gets less attention. This is partly due to the difficulty of formulating parameter values on the aggregated level of a model on the basis of disaggregated, not suitable or even missing data.

Important studies employing a system-dynamical modelling approach are the Club of Rome models of the early seventies (Forrester 1971; Meadows, Meadows, Randers and Behrens, 1972; Meadows, Behrens, Meadows, Naill, Randers, and Zahn, 1974). Some models include insights from psychology/cultural anthropology to include adaptive agents (Bossel and Strobel, 1978), although these more advanced descriptions of behaviour remain exceptions. Later integrated assessment models using a system-dynamic framework are IMAGE1 (Rotmans, 1990) and TARGETS (Rotmans and De Vries, 1997).

Stochastic simulation models

Due to the complexity of the real world, many processes are unpredictable, and hence uncertain. To capture this notion of uncertainty in simulation models, system dynamical models have been equipped with stochastic variables. Instead of using fixed values to describe certain relations in the model, events and/or parameter values are being formalised as probability distributions. These distributions are frequently based on empirical data or educated guesses from scientists. The introduction of a stochastic element in a simulation model implies that model-runs that start with identical initial settings may yield very different outcomes. Therefore, usually many runs are being performed, and means and reliability intervals are being reported.

Because a 'stochast' is being used to model the unpredictability following from the complexity of real world systems, it can be said that the stochastic simulation approach is a heterologous metaphor. Instead of studying system characteristics, this modelling

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[3] However, this type of simulations may be useful to demonstrate the behaviour of a system, as is clearly demonstrated with e.g., the relation between predators and prey described by Lotka-Volterra equations.

approach is mostly fit to develop research tools as mentioned under system dynamic simulation models.

Agent-based models

Many macro-level processes that can be observed in social systems, such as crowding, over-harvesting and stock-market dynamics, emerge from the interactions between a multitude of individual agents. Here, an agent is being considered as a system that tries to fulfil a set of goals in a complex, dynamic environment, and 'agent' thus may refer to e.g., bacteria, plants, insects, fish, mammals, humans households, firms and nations. Agent-based modelling implies that agents are being formalised as making decisions on the basis of their own goals, the information they have about the environment and their expectations regarding the future. The goals, information and expectations an agent has are being affected by interactions with other agents. Usually, agents are adaptive, which implies that they are capable of changing their decision strategies and consequently their behaviour.

The multi-agent simulation approach allows formalising several interacting agents in a model, and thus provides a tool to study how processes at the micro-level may affect macro-level dynamics. Many multi-agent simulations have been developed, which are focussed on a variety of social processes (see e.g., Conte, Hegselmann and Terna, 1997). These simulations differ with respect to the level of detail in the agent rules. Many researchers apply very simple agent rules to study how macro-level behaviour emerges from very simple micro-level rules. An example is the 'Tit-for-Tat' rule (Axelrod, 1980a, 1980b) that is being used to study the emergence of cooperation in large-scale prisoners' dilemmas (see Chapter 4 for examples). Simulations using such simple agents are being used to formulate (mathematical) theories on social system behaviour. However, it is often questioned to what extent such theories are validly describing real-world processes, because they are based on agent rules that lack psychological validation. Yet, these theories are aimed at describing the basic micro-level processes that guide the macro-behaviour of real world systems, and consequently such models constitute a homologous metaphor.

If the simulated processes are not intended to resemble a real world process, the simulation forms a world in itself, and there is no metaphor at all. However, sometimes such simulations lie at the basis of the discovery of new laws that appear to be valid in both the simulated and real world systems. Phenomena that were observed in simulations as well as in the real world, e.g., swarms, self-organisation, emergent behaviour, then appear to be understandable from the same principle. Here, simulations of artificial societies that were not (directly) meant as metaphors for real world processes helped to discover laws and principles that hold both in real and in simulated worlds. Examples of such laws and principles are the importance of diversity (e.g., why is a 'rich' forest more viable in times of change), how lock-in effects work (e.g., how VHS video became the standard, why most people use Microsoft software) and the importance of contingency (e.g., small causes may breed large effects, and the fundamental unpredictability of complex systems). It is important to realise that these dynamics are not programmed explicitly in the simulation as laws or principles, but emerge from the simulations. Once such laws and principles have been identified, they often can be recognised in real world systems. With respect to the discovery of such 'laws of complex systems', the unificational metaphor adequately describes the relation between a simulation model and the real world

Researchers that develop more complex agents clearly consider their simulations as a metaphor, as their goal is to enhance the mundane realism and hence the practical relevance of their simulation models. Here, it is important that the rules of the agents are being modelled after valid theory or data, so as to obtain at least some valid resemblance with the behaviour of real world social systems. This usually results in a more complex set of agent rules. Ernst (1998), who employs theory on attitude formation in developing agent rules, provides a representative example of such a simulation. This example will be discussed in the next chapter. Here, the agent rules are carefully designed on the basis of valid behavioural theory. However, because of the lack of suitable meta-models of behaviour, many simulation models lack such a theory-based validation of agent rules. This causes many simulation models to lack ecological validity, which makes them less convincing tools for studying real world systems.

Conclusions

It appears that several modelling approaches exist, and that questioning the appropriateness of these approaches for developing a simulation model directly relates to the goals one has with simulation. In general it can be stated that if the purpose of a simulation model resides in the study of how people or agents interact with it, it is sufficient that the simulation model mimics the behaviour of the real world system, e.g. a fish-stock. The simpler the model, the better it is, as this makes the model easier to program and to work with. A researcher may prefer a system dynamical approach to simulate a fish stock as a tool to investigate people's harvesting behaviour, being aware of the fact that a multi-agent model would more correctly describe the dynamics of a real fish stock. However, if one is mainly interested in mimicking the natural fluctuations of a fish stock, it may even be the case that a simple equation-based model yields more realistic outcomes than a badly formalised multi-agent model. A more realistic modelling of the processes does not guarantee that the outcomes of the model are more realistic as well. However, if one intends to use simulation techniques to study the behavioural dynamics of a system, it is essential to choose a paradigm that is capable of capturing the processes of interest. For example, in modelling a macro-economic system it seems appropriate to use a system-dynamical modelling framework, whereas the modelling of processes that involve social interactions requires a multi-agent framework.

This monograph is focussing on human behaviour in changing environmental systems. Although the modelling approach will contain elements of all the above-mentioned paradigms, it will mainly be based on elements from agent-based modelling and system dynamics. Being focussed at the behavioural dynamics that affect the resource management of agents, it is necessary to use a multi-agent modelling approach to allow for the simulation of interdependent agents in a commons dilemma situation. Moreover, this multi-agent approach is also necessary to allow for the simulation of processes such as social comparison and imitation. The agents' behaviour will be studied in a changing environment. The agents' activities may change the environment, which in turn may change the abilities and opportunities of the agents. The system-dynamical approach will be used for the modelling of the environment the agents behave in. As such, the resulting integrated model combines modelling techniques originating from different paradigms.

Because the modelling of behaviour is the central issue of this monograph, the next section will be focussed at the tools that are being used in agent-based modelling.

Conceptual tools for agent-based modelling

The modelling of autonomous agents has become increasingly popular in the last decade. Along with this increase, also the variety of tools to model such agents by software (computer-programs) and hardware (robots) has increased. The tools that are currently being used in this field are neural networks, cellular automata, fuzzy logic, genetic algorithms, cybernetics, artificial intelligence and sets of non-linear differential equations (chaos and catastrophe theories). Within the scope of this monograph it is not possible to discuss all these tools in detail. Therefore, only the tools that are most common in social-scientific research are being discussed: genetic algorithms, cellular automata and artificial intelligence. Those readers interested to learn more about other kinds of modelling tools are referred to, e.g., Langton (1989; 1995), Holland (1995), Goldberg (1989), Rietman (1994) and Sigmund (1993).

Genetic Algorithms

In the sixties John Holland and colleagues developed the concept of genetic algorithms by means of trying to abstract and explain the adaptive processes of natural systems (e.g. Holland, 1975, 1992a, 1992b, 1995; Goldberg, 1989). The basic notion is to consider each agent in a population as a solution to a problem. Technically, a binary bit string of fixed length represents an agent. The sequence of 0s and 1s can be recoded into decimal numbers that represent a solution, for example, the value of a decision variable of a problem. The bit-string length depends on the number of possible solutions taken into consideration. The relative success of each agent to solve the problem is considered to be its fitness. A higher fitness increases the chances that the agent produces offspring that constitutes the next generation. This offspring (child) is identical to the parent agent, as graphically depicted in Figure 3.1.

Figure 3.1: Identical offspring

This rule follows the principle of natural selection (survival of the fittest), and causes that an original population, consisting of many agents differing in abilities and fitness, will in a number of generations result in a much more homogeneous population. A major risk here is that when the circumstances change, it may be so that other abilities become important, and these may have been lost in the natural selection process. A homogeneous population lacks the adaptive capacities that are required to cope with changing environments. The identical offspring population lacks the necessary capacity to adapt.

To include adaptation, and to prevent a population to end up with a small set of unchangeable solutions, the mutation rule can be included. This rule implies that in the reproduction process each bit has a small chance of flipping, as is depicted in Figure 3.2.

Figure 3.2: Mutation

The process of mutation can produce new genetic information and is a powerful operator in finding ways to adapt to a changing environment. Even if a homogeneous population exists, the mutation rule guarantees that new types of solutions will emerge, which, if their fitness is high, may be very successful in reproducing.

However, the mutation rule is working randomly, and is relative slow in finding successful solutions. A much faster strategy is provided by sexual reproduction, where the principle of crossing-over is being used to create new kinds of solutions. Here, the bit-string of two parent agents is being cut at a random point, which is the same for both parents, and the two fitting pieces are being pasted in the child, as is depicted in Figure 3.3.
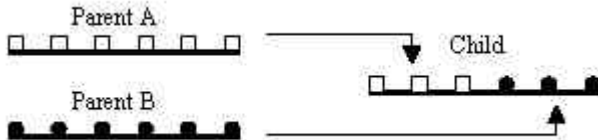

Figure 3.3: Crossing-over

Combination of crossing-over and selective reproduction on the basis of fitness yields a powerful tool to find effective solutions in a very complex environment. However, to avoid the risk of ending up with a homogeneous population it remains necessary to include a small chance of mutation.

Examples of integrated models that employ the genetic algorithm tool are the work of Janssen and De Vries (1998a) and Janssen and Carpenter (1999), who developed a model for the climate change issue with agents that change their behaviour if their observations differ significantly from what they expect, and Janssen and Martens (1997) who assess the integrated impact of changes of climate and policy control on the malaria problem.

Cellular Automata

A cellular automaton consists of an array of cells in which each cell can assume one of a predefined number of discrete states at any one time. Figure 3.4 shows such a small checkerboard type of cellular automaton, in which the black automaton in the centre can only observe its eight direct neighbours (Moore environment), which are coloured grey. Each cell in the grid represents an agent.
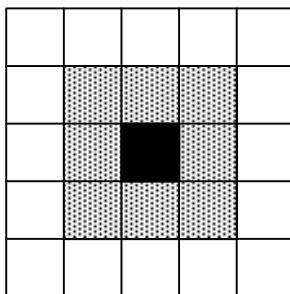

Figure 3.4: A small cellular automaton consisting of 25 cells

When the checkerboard is formalised so that the edges are fixed, the world is a so-called island model. This kind of 'world' is very suitable to represent a physical environment such as a square or a region. When the checkerboard is formalised so that the edges are being pasted together (e.g., moving left from the left border brings you to the right border), the resulting world is a torus, as is being shown in Figure 3.5. The torus shape is very suitable for the study of more abstract systems, because possible disturbing effects caused by the fixed border can be ruled out.
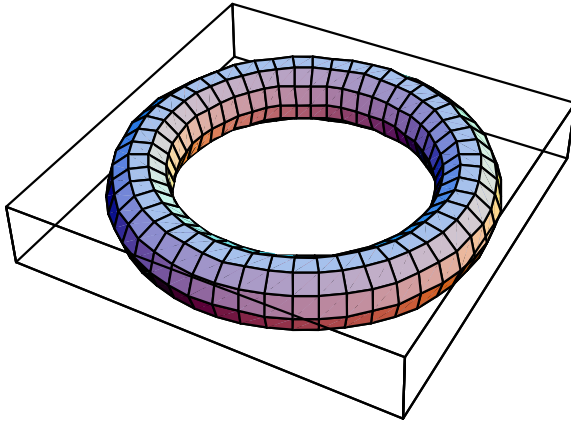

Figure 3.5: A cellular automaton with the edges pasted (Hegselmann and Flache, 1998)

In a cellular automata-based simulation, time progresses in discrete steps, and all cells change state simultaneously. The changing (or not) of the cell state depends on the specific function underlying the cell state. Usually, this function consists of a specified set of transition rules that use historic information on the own state together with the states of the neighbouring cells (e.g. Gardner, 1970; Tobler, 1979). A famous example that uses very simple rules is the LIFE algorithm (Gardner, 1970). Consider a torus-like world. Each cell has eight neighbours, and a cell has only two states: empty or occupied. If a cell happens to be empty, it remains empty in the next generation (i.e. time-step), except if exactly three of its neighbouring cells are occupied: in that case, it will be occupied in the next generation. Conversely, if a cell happens to be occupied already, then it remains occupied whenever two or three of its neighbours are occupied. If not, the cell becomes empty in the next generation. This simple set of rules already leads to processes of self-reproduction and complex self-organising structures.

Applications of the cellular automata in the field of sustainable development involve more complex rules, and more possible states of the cells. The cellular automata tool is very suitable to model issues in which spatial relations play a role. Examples are the ISLAND model (Engelen *et al.*, 1995), which is a demonstration version of a framework capable of modelling a complete island or part of a coastal zone in an explicitly dynamic and spatial manner, and Sugarscape (Epstein and Axtell, 1996), which will be discussed in Chapter 4.

Artificial Intelligence

Currently, the autonomous agents research or behaviour-based artificial intelligence (AI) dominates the study of Artificial Intelligence. This approach, which is highly inspired by biology (e.g., Wilson, 1991), studies the behaviour of adaptive autonomous agents in the physical world (robots) or in cyberspace (software agents). The phenomena of interest are those traditionally covered by biology and ecology (in the case of plants and animals) or

psychology, sociology and ethnology (in the case of humans). The agents are usually equipped with sensors to perceive the environment (e.g., constructing a map of the environment). In order to behave efficiently, the agents are equipped with intelligent functions such as perception, planning, and learning. This approach is usually being used to study the dynamics following from the interaction between agents and environment. Here, researchers have a powerful tool to experiment with a wide variety of characteristics and processes of both the agents and the environment.

The use of several interacting agents is a recent development within the study of artificial intelligence (Bond and Gasser, 1988). For an overview of this field see for example Steels (1995) and Maes (1995). Research employing such a 'distributed artificial intelligence' approach is focussing on the properties of sets of communicating agents existing in a common environment. This research pursues different goals. First, it may be aimed at studying the properties of such systems in an abstract way. An example is the work of Steels (1995, see also Chapter 4), who studies emergent behaviour in a group of electric-powered robots that 'live' together in a physical environment and that have to cooperate every now and then in order to reload energy. A second aim is to design systems of immediate practical use, such as expert systems or training simulations for the management of complex environments. An example is the Driving Simulator of the Centre for Environment and Traffic Psychology (Van Wolffelaar and Van Winsum, 1996, see also Chapter 4), which contains a traffic system consisting of a multitude of interacting cars. A third aim is the development of a programmed multi-agent system as a model of a human or other real-world system. This third aim is the central aim of the model that is being developed and applied in this dissertation.

The aims that one has with a simulation model also confront the researcher with the application of the model. Sometimes very sophisticated models are being built, but hardly being used because the researchers did not deliberated much on the use of the model. The next section is focussed on the use of simulation models.

The application of models

Simulation models are frequently being used in a passive way, presenting only the results of experiments performed with the model. Regarding the application of a model on a well-defined topic this may be a good strategy. Here, presenting a series of experiments leading to a set of clear conclusions may be a good strategy to make a convincing point. However, when the simulation models are being used as a common language to exchange knowledge from different disciplines, it is usually better to use models in a more active manner, letting people experiment with the settings of the model themselves. Especially when the topic of research involves a complex system, which implies that the predictive value of a model is very low, people who experience the system dynamics will yield a better understanding of the model than people who more passively read about a series of experiments. Therefore, gaming and policy exercises are being developed and used to communicate the knowledge of the researchers on the processes which they put into the model. This requires the models to be relatively simple.

Policy exercises have the goal to let people experience the problem in a virtual world, thereby offering a situation to learn about the complexities that determine the developments in the real world system. In a simulation game like Fishbanks (Meadows,

1989) the different interdependent players in the game make decisions about fishing strategies (how many boats and of what type) and the computer computes the fish catch. Therefore, a computer model represents the environment of the players, and the players have only limited control over the state of the environment. Another game is SusClime (De Vries, 1998) where different players representing governments control two or more countries. Climate change may occur as a consequence of their decisions. The countries have to negotiate what kind of control strategy to implement. Here, the players are confronted with a commons dilemma, in which the consequences of their behaviour refer to climate change in a computer simulation model of the world climate. Another interactive model in the climate change debate is the Interactive Scenario Scanner developed by Berk and Janssen (1997). They built a very simple model around the key issues of the climate change negotiations and held interactive sessions with policy makers where the software functions as a communication tool to facilitate discussion.

Another way of interactively using computer models is the use of microworlds to study how people achieve control over some aspects of a complex system (Brehmer, 1992; Brehmer and Dörner, 1993; Dörner and Schaub, 1994). The computer simulations provide interactive and dynamic scenarios of complex problems that allow for repeated and detailed observations. These simulation models of real world systems condense time such that the participants are being confronted with the long-term effects of their decisions. Consequently, the players have to cope with the emotional strains of failures and have to adjust their strategies. This kind of studies performed by applied psychologists may help to discover systematic mistakes and biases that affect human decision-making in complex situations.

The simulation model of human behaviour that is being developed and tested in this monograph is being presented in a rather passive way. A large number of experiments have been performed with the simulation model, and the results are presented in graphs and tables. When it comes to validation of the simulation model this presentation has some advantages, as it is possible to systematically present results in comparison to other experiments that have been performed. However, when the behavioural model is being applied in the context of an integrated assessment model, it would be worthwhile to let various scientists and policy makers work with the model. This would provide them with more knowledge regarding the behavioural dynamics behind environmental issues. Moreover, it would confront them with outcomes that are relevant in the context of human existence, such as level of need satisfaction and (in)equality, instead of focussing at macro-level indicators of economy and ecology.

Chapter 4 will provide an overview of a number of representative simulation models that are being used within psychology.