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Our work includes tackling flooding and pollution incidents, reducing industry's impacts on the environment, cleaning up rivers, coastal waters and contaminated land, and improving wildlife habitats.

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Science at the Environment Agency

Science underpins the work of the Environment Agency. It provides an up-to-date understanding of the world about us and helps us to develop monitoring tools and techniques to manage our environment as efficiently and effectively as possible.

The work of the Environment Agency's Science Group is a key ingredient in the partnership between research, policy and operations that enables the Environment Agency to protect and restore our environment.

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- **Setting the agenda**, by identifying where strategic science can inform our evidence-based policies, advisory and regulatory roles;
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- **Delivering information, advice, tools and techniques**, by making appropriate products available to our policy and operations staff.

Steve Killeen

Head of Science

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1 Introduction

This document reports the results of Work Package 4 (WP4) of the Environment Agency science project FDB(05)01 – Risk assessment for flood incident management: Phase 1. Activities within this work package are set out in *Table 1.1*.

Table 1.1 Activities of Work Package 4.

WP4 activity	Title	Description
4.1	Literature review and analysis of data	Review literature and collect data and/or information to identify the key properties and behaviour of all 'sources–pathways–receptors' system components, including the influence of different drivers for flood incidents and different responses for flood incident management (FIM)
4.2	Application of risk assessment and complex systems methods	Identify and evaluate different risk-assessment methodologies and 'complex system' models and analyse the appropriateness for wider FIM
4.3	Conceptual framework	Propose elements for the conceptual methodology to be developed, with a focus on systems and component failures that could have the greatest probability and impact, as determined by analysis of their causes and consequences in the whole complex system, including organisations and individuals involved in FIM
4.4	Requirements document	Formulate requirements for complex systems simulation models that capture the essential characteristics of the systems involved and are able to produce the emergent behaviour of the whole system; this will focus on simple frameworks that reflect the human and operational, rather than physical, FIM system
4.5	Report	Stand-alone work package report. This will include sections that report in detail on each of the above work package activities, together with scoping recommendations for Phase 2

This report covers the outputs of all activities of WP4. Chapters in this report correspond to work package activities as follows. Chapter 2 describes outputs of activities 4.1 and 4.2, chapter 3 describes outputs of activity 4.3 and chapter 4 describes outputs of activity 4.4.

2 Application of risk assessment and complex systems methods to flood incident management

This chapter analyses the application of risk assessment and complex systems methods to flood incident management (FIM) on the basis of a review of literature on the key properties and behaviour of system components. This literature deals, on the one hand, with the influence of different drivers for flood incidents and different responses for FIM, and on the other hand with a representative sample of complex systems approaches.

2.1 A complex systems approach to flood incident management is necessary

Complex systems can be defined in many ways (see, for example, Mitchell 2003). At a minimum, complex systems consist of entities that interact with each other to produce the behaviour of the system as a whole (see, for example, Bar-Yam 1997, p. 1). An important characteristic of a complex system is that the properties and/or behaviour of the whole are emergent, that is they cannot be inferred in a straightforward way from the properties and behaviour of the components (see, for example, Bar-Yam 1997, p. 10, Holland 1998). Many relatively simple entities interact in relatively simple ways to give rise to emergent phenomena that could not have been predicted easily from the definition of the entities and their interactions. To understand the behaviour of a complex system, we must not only understand the composing entities and their behaviour, but also how they interact and self-organise to determine the emerging state and behaviour of the whole (for example, Bar-Yam 1997, p. 1, Lam 1997, p. 359, Holland 1998).

The above implies that a complex system consists of a minimum of two levels, that of its parts and that of the whole system. Often there are more levels, in the same way that reality as a whole can be thought of as consisting of a series of different levels, with entities of each higher level composed of entities of the next lower level (see, for example, Salthe 1985, O'Neill *et al*. 1986, Allen and Hoekstra 1992). Examples of such levels are, from the lower to higher levels, atoms that consist of elementary particles, molecules that consist of atoms, cells that consist of molecules, organisms that consist of cells and ecosystems that consist of organisms. This hierarchy is extremely simplified and only illustrative, as many more intermediate levels, or alternative hierarchies, can be imagined.

2.1.1 Flood incidents emerge from properties and behaviour of complex systems

Flood incidents are one category of natural catastrophes, disasters or emergencies. The occurrence of emergencies is determined by the operation of complex systems. The principal characteristic of a complex system is that it is composed of many interacting entities. Results of the interaction of these entities are hard to understand and predict. In the case of natural disasters this is already apparent at the highest level of system description, where a system that produces disasters is described as only two interacting subsystems, determining, respectively:

- extreme natural events (for example, floods, earthquakes, landslides);
- society's risk taking and vulnerability.

There are different views of the interaction of these subsystems to produce casualties and damage, summarised by Alexander (2000, pp. 227-228) as follows:

extreme natural events *act upon* human vulnerability and risk taking *to produce* casualties and damage	society's risk taking and vulnerability *interact with* extreme natural events *to produce* casualties and damage	human risk taking and vulnerability *produce* casualties and damage *when there are* extreme natural events

It is already apparent that emergencies are produced in complex systems in which it is far from obvious how to define unequivocal cause and effect relations.

2.1.2 Flood incident response systems are complex systems

Both the management of and response to emergencies are determined by the operation of complex systems. Flood incident response systems are one kind of emergency management system. An incident may be defined as an occurrence, caused by either humans or natural phenomena, that requires action to prevent or minimise loss of life or damage to property. Emergency management has been based in the past on a rigid hierarchical structure of authority, but more emphasis is now given to adaptability, for example, in the incident command system used in the USA (Alexander 2000, pp. 164-165). This is a standardised on-scene all-hazard incident management system that allows its users to adopt an integrated organisational structure to match the complexities of emergency management. Such an adaptable system must be:

- expandable from the scale of minor emergencies to that of full-scale disasters;
- based on the procedures used by existing agencies;
- simple enough to be inexpensive and easy to learn;
- adaptable to new technologies;
- able to handle a wide variety of different types of emergency;
- functional both for single and multiple organisations and jurisdictions.

Emphasis is placed on coordination through consultation and flexibility, on the constitution of task forces to deal with problems as they arise and on consensus as to the goals to be achieved by a process of delegation, participation and mutual involvement (Alexander 2000, p. 165).

In addition to order and central planning, improvisation is vital for emergency management, and there will be emergent groups, emergent norms and emergent social structure (Alexander 2000, p. 166).

The incident command system is an example of the current trend in thinking about emergency response, which acknowledges that emergency response systems are complex systems. This trend is also exemplified in current British government regulations on emergency preparedness and response, as described in *Emergency Preparedness: Guidance on Part 1 of the Civil Contingencies Act 2004*, and its associated Regulations and non-statutory arrangements, and *Emergency Response and Recovery: Non-statutory guidance to complement Emergency Preparedness*. These government regulations are the context in which the work of the Environment Agency is carried out.

2.1.3 Integrated flood risk management requires a systems-based approach

Hall and Dawson (2005) clearly demonstrate the necessity of a systems based approach in a note for discussion at the third meeting of the urban flood risk assessment working group in Exeter on 9 June 2005, as:

> flooding may have positive or negative impacts on any part of the natural or built environment. Integrated flood risk management considers all these different aspects of the flooding system and their influences on each other.

They confirm that ‘a key methodological advancement to enable integrated flood risk management (IFRM) is the development of a unified systems-based flood risk analysis methodology’ (Hall and Dawson 2005).

2.1.4 Conclusion

A complex systems-based approach is necessary for effective FIM because:

- flood incidents emerge from properties and behaviour of complex systems;
- flood incidents and procedures for flood incidents are complex systems;
- emergent behaviour of these systems may not be obvious from more simplified modelling – complex systems modelling allows emergent behaviour of the system to be identified;
- it is essential to assess not only the probabilities and consequences of the failure of individual components, but the impact on the whole, complex system of individual component behaviour;
- such an approach will help to decide how to mitigate or manage the risk and uncertainties inherent in the whole system of FIM.

Many approaches to modelling and analysis of complex systems have been proposed, and it is not immediately clear which particular methods are most appropriate for an application area such as FIM. In Section 2.2 we quickly review what complex systems are.

2.2 Complex systems methodologies

The study of complex systems requires methods of analysis and simulation with characteristics such as (Bar-Yam 1997, pp. 8-9):

- looking at parts of a system in the context of the whole system and its environment, using adapted experimental tools, theoretical analysis or computer simulation;
- not assuming that a system is smooth and uniform, as is assumed when a system is described by differential equations and local details do not matter for larger scale system behaviour;
- taking into account that the behaviour of complex systems depends on many independent pieces of information and not on just a few parameters.

A number of widely used methodologies for the study of complex systems are listed in *Table 2.1*.

In the remainder of this section typical complex systems methodologies are reviewed with respect to their application to risk assessment in FIM.

Table 2.1 Methodologies used to study complex systems.

Methodology	Remarks	Examples
Artificial life	Field of scientific study that attempts to use computer simulation to discover general principles of life by creating artificial organisms that capture the essential characteristics of real organisms	Emmeche 1994, Bonabeau *et al*. 1995a, 1995b, Adami 1998
Bayesian networks	Systematic analysis of situations with many components that involve risk and uncertainty; in a graphical representation of a Bayesian network nodes represent variables and arcs represent probabilistic relationships between the variables	Charniak 1991, Negnevitsky 2002
Cellular automata	Very simplified models of system components and interactions; appropriate to demonstrate abstract general principles; can easily capture spatial aspects, especially in two dimensions, but in principle also in three dimensions	Wolfram 2002
Computational complexity theory	Theoretical approach mainly relevant for computer scientists	Bar-Yam 1997
Emergent models	Complex systems simulation methodology suitable to study multiple hierarchical levels in a system	Stolk 2005
Evolutionary computation	In computer science evolutionary computation is a subfield of artificial intelligence (more particularly, of computational intelligence) that involves optimisation problems; it provides a very general method to solve problems that involve approximately optimal solutions	Holland 1975, 1998, Koza 1992, Stolk 1992, Bäck *et al*. 2000, Luke 2002, Stolk *et al*. 2003, Stolk 2005
Game theory	Branch of applied mathematics that studies strategic situations in which players choose different actions in an attempt to maximise their returns	Holland 1998
Genetic regulatory networks	Application area of complex systems methods	Kauffman 1993, De Jong 2002, Stolk 2005
Hierarchy theory	Theory on relationships between hierarchical levels, especially in ecology	Allen and Hoekstra 1992

Methodology	Remarks	Examples
Individual-based modelling	Modelling ecological systems starting from individual organisms	DeAngelis and Gross 1992
Markov processes and chains	Mathematical approach to risk and uncertainty	Stroock 2005
Multi-agent simulation	Systems components and interactions can be modelled with arbitrary detail	Wooldridge and Jennings 1995, Weiß and Sen 1996, Weiß 1997, Ferber 1999, Ciancarini and Wooldridge 2001, Davidsson 2001, D'Inverno *et al*. 2002, Gimblett 2002, Wooldridge 2002, Wooldridge *et al*. 2002, Ferber *et al*. 2003, Luck *et al*. 2004, Stolk *et al*. 2003, Stolk 2005
Network analysis and graph theory	Demonstration of abstract and general principles related to network architecture	Buchanan 2003
Neural networks	Interconnected group of artificial neurons that uses a mathematical or computational model for information processing based on a 'connectionist' approach to computation; the complex global behaviour is determined by the connections between the processing elements and the parameters; typical applications include pattern recognition and classification problems	Rumelhart *et al*. 1987, Bar-Yam 1997, O'Reilly and Munakata 2000
Non-linear dynamics	Methods to study systems based on mathematical equations	Bar-Yam 1997

2.2.1 Non-linear dynamics and iterative maps

The classic way to study non-linear dynamics is differential equations. This approach assumes that the behaviour of the system under study is basically smooth and uniform, in other words that local details do not matter for larger scale system behaviour. Differential equations are therefore less adapted to the study of complex systems.

Iterative maps are another general way to describe dynamic systems (Bar-Yam 1997, p. 35). An iterative map f is a function that describes the evolution as a system as (Bar-Yam 1997, p. 19):

$$s(t) = f(s(t - \partial t))$$

where:

$s(t)$ = state of the system at time t

This approach to dynamic systems is a very general one. Thus, a FIM system could, in principle, be described by it, assuming that enough information about the state variables of the system is available. To define an iterative map, it is necessary to have complete information about the state of a system at time t and about the function f that relates the state at time $t - \partial t$ to the state at time t. This is an unrealistic assumption in the case of FIM systems. A dynamic systems approach could be suitable for parts of a FIM system, such as hydrological or climatological models to describe the environmental conditions that lead to flooding, but it is unrealistic to expect insight into the whole system using dynamic systems modelling alone. The dynamic systems approach is also a deterministic one and thus not suited to risk assessment.

For the description of the whole system a more qualitative approach is needed to capture essential behavioural characteristics without being overwhelmed by too great a mass of detail. It is also necessary to adopt a stochastic approach.

2.2.2 Stochastic iterative maps and Markov chains

Stochastic iterative maps can be used to describe systems for which the values of system variables at the next time step cannot be predicted with certainty from the present values. Such stochastic systems can be described as an iterative map using a probability distribution of random variables to describe system states, as (Bar-Yam 1997, pp. 38-39):

$$P_s(s^{'}(t);t) = \sum_{s^{'}(t-1)} P_s(s^{'}(t) \mid s^{'}(t-1)) P_s(s^{'}(t-1);t-1)$$

where:

$P_s(s^{'}(t);t)$ = probability distribution at time t that describes the likelihood that random variable s has the value $s^{'}$ at time t

$P_s(s^{'}(t) \mid s^{'}(t-1))$ = transition probability, or the probability distribution of s at time t given a particular value $s^{'}(t-1)$ at the previous time

$P_s(s^{'}(t-1);t-1)$ = probability distribution at time $t-1$ that describes the likelihood that random variable s has the value $s^{'}$ at time $t-1$

This description assumes that the probability distribution of system variable s only depends on the value of the system variable at a previous time and that the transition probabilities do not depend on time. A stochastic system that satisfies these conditions is a Markov chain.

Stochastic iterative maps and Markov chains have the potential to alleviate some of the problems of differential equations and iterative maps. Full information on the system state at a given time is no longer required, but information about the probability distribution of states is. However, this can still be a formidable requirement.

Despite this, the use of probability distributions could inspire possible approaches to risk analysis in the context of complex systems. However, stochastic iterative maps and Markov chains as described here assume, like ordinary iterative maps, exhaustive and exact information about the system. Such information is not available in the case of the Environment Agency's FIM system. Therefore, stochastic iterative maps and Markov chains could not be realistically applied to it. In the case of the FIM system it is necessary to use an approach based on probability that can take into account not only objectively defined probability distributions, but also subjective probability estimates.

2.2.3 Neural networks

A neural network is an interconnected group of artificial neurons that uses a mathematical or computational model for information processing based on a 'connectionist' approach to computation. Global behaviour is determined by the connections between the processing elements and parameters. In most cases a neural network is an adaptive system that changes its structure based on external or internal information that flows through the network. A simple example of a neural network is an attractor network or Hopfield network (Bar-Yam 1997, p. 300-301), schematically represented in *Figure 2.1*.

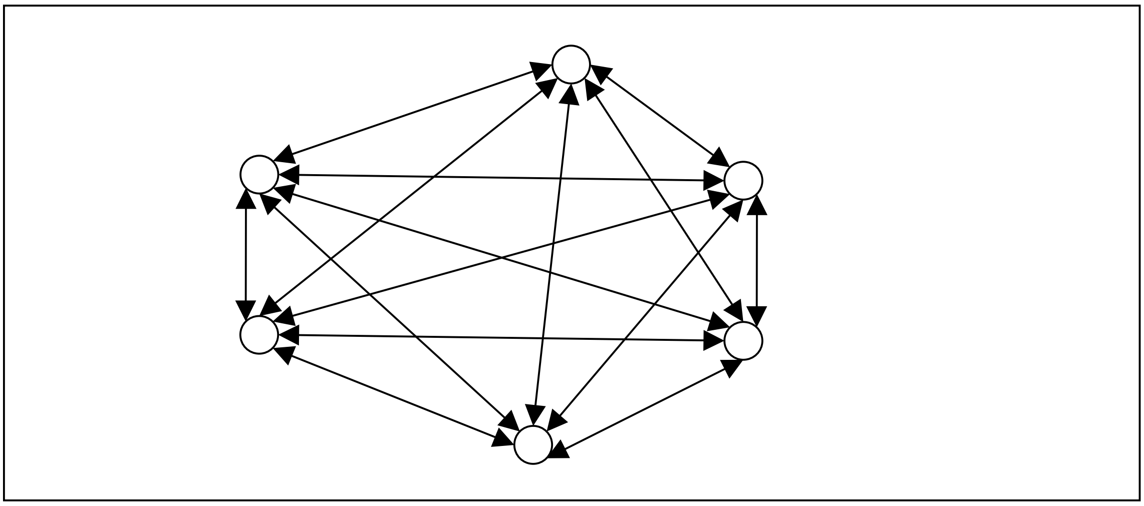


Figure 2.1 An attractor neural network with six neurons.

It consists of *N* neurons (*N* = 6 in *Figure 2.1*) and potentially all their connections, or synapses. The possible states of the neurons are described by binary values $s_i = \pm 1$ $(i = 1,...,N)$. A connection between two neurons is characterised by a value or weight that determines how they interact. The first neuron activates the second neuron if the weight is positive (that is, the second neuron becomes active if the first neuron is active). If the weight is negative, the first neuron inhibits the second one. Activation and inhibition can be weak or strong, reflected in the numerical value of the weights.

Neuron states are updated at each time step by the functions:

$$s_i(t) = sign(\sum_j J_{ij} s_j(t-1)$$

where:

J_{ij} = matrix of synaptic weights

This network can work as a memory. Training with a particular pattern of neuron states can set the weights J_{ij} to such values that the network can reconstruct a particular pattern from only a part of the pattern. The pattern has become an attractor state of the network.

This is a property of the network as a whole, and not of any subset of neurons or synapses. Therefore, it illustrates well the emergent behaviour of a complex system. The system as a whole exhibits a behaviour that is not present in its components, which is also true of organisational systems in general and FIM systems in particular.

However, a description of the FIM system as a neural network would, like an iterative map, require a precise definition of all elements of the system in terms of activation and inhibition functions. This is not feasible in the case of a FIM system, for the same reasons as cited in Sections 2.2.1 and 2.2.2.

2.2.4 Graph theory and complex networks

Graph theory is the mathematical study of graphs. A graph is a set of objects called 'points' or 'vertices' connected by links called 'lines' or 'edges'. Assigning a weight to each edge of the graph can extend a graph structure. Weights can be used to represent several different concepts (for example, the length of a road network).

Complex networks are networks with irregular and complex structures that evolve dynamically in time. The main focus of research in complex networks has recently moved from the analysis of small networks to that of systems with thousands or millions of nodes, and with a renewed attention to the properties of networks of dynamic units (Boccaletti *et al*. 2006).

Graph theory used to study complex networks attempts to capture the global properties of systems composed of a large number of highly interconnected dynamic units. The first approach to such systems is to model them as graphs with nodes that represent the dynamic units, and with links that stand for the interactions between them. This approach aims to cope with structural issues, and so reveal the unifying principles that are at the basis of real networks, and develop models to mimic the growth of a network and reproduce its structural properties. Other questions arise when studying complex networks' dynamics, such as learning how a large ensemble of dynamic systems can behave collectively (Boccaletti *et al*. 2006).

On the whole, these approaches focus on structural properties of the networks under study. They have been applied to information and communication networks, such as the internet and social networks, and could, in principle, be applied to organisational networks, such as a FIM system. Some results already obtained might be interesting for the design of an effective system. For example, it was shown that the coupling architecture has important consequences on the network functional stability and response to external perturbations, such as random failures (Boccaletti *et al*. 2006, p. 178).

Thus, graph theory and complex networks analysis could be applied to a FIM system to the extent that fundamental restructuring of the existing system is considered an option.

2.2.5 Computational complexity theory

Computational complexity theory is the branch of the theory of computation that studies the resources or cost of the computation that is required to solve a given computational problem. The cost is often measured in terms of abstract parameters, such as time and space, called computational resources. The time represents the number of steps that it takes to solve a problem and the space represents the quantity of information required or how much memory it takes.

This kind of theory of information and computation treats complexity in the context of mathematical objects, such as character strings or computer programs (see, for example, Bar-Yam 1997, pp. 703-781). The complexity of a system is defined as the amount of information necessary to describe it (Bar-Yam 1997, p. 703).

It is mainly a descriptive approach that makes possible the characterisation of systems in terms of quantitative measures of complexity. While potentially useful to compare different systems, it does not offer a practical methodology to define or develop real systems such as those required for FIM.

2.2.6 Cellular automata

A cellular automaton is a discrete model studied in fields such as computability theory, mathematics, theoretical biology and geography (see, for example, Wolfram 2002). It consists of an infinite, regular grid of cells, each in one of a finite number of states. The grid can be in any finite number of dimensions. Each cell can be in a number of different states. The cellular automaton is updated during a number of time steps, each cell being updated at each time step according to a rule that relates the state of the cell at time t to the state of the cell and its neighbouring cells at time $t - 1$.

Cellular automata are a useful description of complex systems that enables the study of many interesting properties of such systems. In particular, because of the focus on relationships between neighbouring cells or system components, spatial questions can be studied in a natural way.

For FIM systems a cellular automata technique could be used as a flood mapping method to model spatial aspects of flooding. However, a FIM system consists of system components with interactions that are not readily described as cellular automata rules and it is not obvious how a cellular automata approach could be used to assess ‘weak links’ in a FIM system.

2.2.7 Game theory

Game theory is a branch of applied mathematics that studies strategic situations in which players choose different actions in an attempt to maximise their returns. In game theory a game is described by the set of possible states of the game (see, for example, Holland 1998, pp. 33-42). Possible states can be reached from the initial state by executing moves, or state transitions, according to the rules of the game. The rules impose constraints on possible moves. Players execute moves to try to reach their objective, such as winning the game or maximising their pay-off.

To describe a FIM system in terms of game theory, we could consider all actors involved as players who observe the state of the game and determine their next moves. Their strategies would consist of rules for choosing moves that correspond to all possible states of the system. Then we could try to determine which set of strategies would result in desirable behaviour of the whole system.

In practice, game theory could not be used to model the Environment Agency FIM system because not enough data are available about all the participants in the FIM system to allow it to be described as a system of players with well-defined strategies.

2.2.8 Artificial life

Artificial life is a research area that studies the biology of the possible by synthesising life-resembling processes or behaviour in computers or other media (see, for example, Emmeche 1994). It is assumed that artificially created components can exhibit behaviour just as genuine as that of real-life organisms, because life is a process and the form of this process, not the matter, is the essence of life. Some artificial life researchers even claim to create life forms that are just as alive, but differ from life on earth as we know it. Like exobiology, which studies life that supposedly exists on other planets, artificial life is a 'biology of the possible' (Emmeche 1994). Its objective is to discover the general principles of life, and not be restricted to any particular instance of life. Artificial life is constructed using a bottom-up method that leads to processes executed in parallel with self-organising, emergent behaviour (Emmeche 1994). Some researchers conceive life as an emergent property of an artificial computational chemistry (Adami 1998).

Artificial life offers obvious possibilities to analyse relationships of emergence between levels. Indeed, numerous articles on emergence have been written by artificial life researchers, such as Cariani (1989, 1991), Baas (1994, 1997), Bonabeau *et al*. (1995a, 1995b), Bedau (1997), Rasmussen *et al*. (2001), Kvasnička and Pospíchal (2002) and Kubik (2003).

This research on the definition and significance of emergence is relevant on a conceptual level for FIM systems, regarded as complex systems, as emergent behaviour can arise from the behaviour and interactions of the components of these systems. To be relevant to the Environment Agency's FIM system, a practical approach is needed that makes use of the concept of emergence.

2.2.9 Evolutionary computation

In computer science evolutionary computation is a subfield of artificial intelligence (more particularly, computational intelligence) that involves optimisation problems. Evolutionary algorithms are general problem-solving algorithms inspired by the evolution of organisms, interpreted as an optimisation process. They utilise the reproduction, random variation, competition and selection of contending individuals in a population to find an optimal, or nearly optimal, solution to a problem (Fogel 2000). In general, evolutionary algorithms do not find globally optimal solutions, but only approximate solutions.

In an evolutionary algorithm each individual in the population typically represents a potential solution considered for a given problem. Randomised processes of mutation, or erroneous self-replication of individuals, and recombination, or exchange of information between individuals, generate descendants of individuals. Individuals are evaluated according to a fitness measure related to the problem in a selection process that favours the reproduction of better individuals (Bäck *et al*. 2000).

Various kinds of evolutionary algorithms have been developed, such as evolution strategies (Bäck *et al*. 2000, pp. 81-88, Schwefel 1995), evolutionary programming (Bäck *et al*. 2000, pp. 89-102), genetic algorithms (Bäck *et al*. 2000, pp. 64-80, Holland 1975) and genetic programming (Bäck *et al*. 2000, pp. 103-113, Koza 1992). Evolutionary algorithms are often a good tool to solve system identification problems. System identification aims to identify the essential characteristics of a system, so an approximate fit to given data is an advantage, as an exactly optimal fit to probably noisy data is undesirable. For example, evolution strategies can be used to find approximately optimal parameters of a function that describes some part of the system to be identified. Similarly, genetic programming is a method to find, in general, a computer program or function that solves a given problem, such as to describe the system to be identified.

To design an optimal, or at least good, FIM system is a system identification problem, so evolutionary algorithms could be usefully applied to it. To do this, first we would have to define what is to be optimised, for example to minimise loss of life, minimise damage, maximise appropriateness of flood warnings or some combination of these and/or other success criteria. Further, it would be necessary to define a set of possible changes that could be made in the FIM system, for example to improve reliability of forecasts, decrease risk of communication failure, etc. If it is possible to evaluate for each change what the impact is on the success criteria, evolutionary algorithms can be applied to select the most appropriate changes to be made in the FIM system.

2.2.10 Genetic regulatory networks

A genetic regulatory network can be considered to be similar to multi-cellular organisms with many cells that contain the same set of genes. However, these cells are very different, because the genes are not expressed in the same way in each of them. Gene products, not the genes themselves, determine cell architecture and behaviour. Genes can regulate the production of gene products by other genes in such a way that not all genes are expressed in all cells all the time (Ptashne and Gann 2002, p. 3). A set of genes and gene products, together with their regulatory interactions, constitutes a genetic regulatory network. A model of such a network describes interactions between deoxyribonucleic acid (DNA), ribonucleic acid (RNA), proteins and small molecules in an organism through which gene expression is controlled (De Jong 2002).

Various formalisms have been proposed to model genetic networks, including directed graphs, Bayesian networks, Boolean networks and their generalisations, stochastic master equations, ordinary and partial differential equations, qualitative differential equations, stochastic master equations and rule-based formalisms (De Jong 2002, p. 69). These formalisms all have gene expression and gene product levels that are represented as nodes, and their interactions as links in a network.

For example, in a Boolean network (Kauffman 1993, De Jong 2002) the state of a gene is described by a Boolean variable with value true, or 1, for an active gene (gene products present) and value false, or 0, for an inactive gene (gene products absent). Interactions between genes are represented by Boolean functions that calculate the state of a gene which results from activation and/or inhibition by other genes. When the evolution of a Boolean network is calculated during a number of time steps, an attractor – steady state or state cycle – is typically reached.

Differential equations have also been used widely to model genetic networks (De Jong 2002, pp. 77-89). Levels of gene products are modelled more realistically than in Boolean networks, as real values. Regulatory interactions, such as activation or inhibition, between gene products are modelled by rate equations.

In the same way as does a genetic network, a biochemical network models interactions in an organism between molecules that are not directly related to its genes. A genetic or biochemical network consists of interacting elements and can be considered a complex system. In a genetic network the micro-level consists of DNA, RNA and protein molecules that interact with each other in excitatory or inhibitory ways (Bower and Bolouri 2001). The macro-level is that of the organism's phenotype as determined by the expression of its genes.

Therefore, a genetic or biochemical network can be simulated in a straightforward way as a multi-agent simulation that represents genes and gene products as interacting agents on the micro-level. These interacting agents model a genetic and/or biochemical network, which can describe the properties and behaviour at a higher level of a cell, an organ or a whole organism.

Methods used in genetic networks are basically methods applicable to any complex system that can be described as a network, and thus potentially to FIM systems. Genetic networks are themselves an application area of complex systems methods, rather than a particular method, so their study can serve to sharpen intuition about the application of complex systems methods, but it does not provide in itself a method applicable to a FIM system.

2.2.11 Individual-based modelling and simulation

This section examines individual-based simulation modelling in ecology as a methodology for complex systems simulation, and focuses on its potential to elucidate emergence in ecological systems. While multi-agent simulation has been developed in the tradition of artificial intelligence research, individual-based simulation has been developed in that of ecological research.

In ecology it has been recognised since the 1980s that many simplifying assumptions used in mathematical models are not compatible with the reality of ecological systems (see, for example, DeAngelis and Gross 1992). One of the most important of these unrealistic assumptions was that individual members of populations can be aggregated into a single state variable that represents population size, neglecting individual differences. A response to this inadequacy of models has been to develop models based on processes at the level of individual organisms, a number of which are reviewed in DeAngelis and Gross (1992). In many of these models local interactions of individuals with their nearest neighbours are considered. Some also take into account the hierarchical structure of ecosystems (see also Ehleringer and Field 1993).

Individual-based simulation in ecology is really the same as multi-agent simulation and is discussed in a separate section only because it has been developed in a different research tradition. To model processes at the level of an individual as well as interactions between individuals and then build a computer simulation on the basis of that model amounts to nothing else than developing a multi-agent simulation of a natural system.

An FIM system is a system of interacting individuals, so relevant ideas could be gleaned from the literature on individual-based modelling and simulation. Multi-agent simulation is recommended in this report as a method applicable to the development of a better FIM system and Chapter 3 details how this method could be used.

2.2.12 Bayesian networks

In general, Bayesian networks describe systems in which elements in a situation can be causally connected, with conditional probabilities associated with the connections. They can be used to determine the probabilities of particular states of events in the described situation, when some part of the situation has been observed. A detailed discussion is given in Section 3.3.

Influence diagrams are an extension of Bayesian networks suitable for decision support. An example is reproduced in *Figure 3.5*. Most nodes are the same as those in a Bayesian network, with added decision nodes (rectangles) and a value node (rounded rectangle). The network can be used to calculate the probable impact of a decision (for example, make a tactical warning) on the value, that is the final result of the network on something desirable, such as life or economic value.

Bayesian networks appear to offer a particularly relevant formalism to describe probability and risk aspects of a FIM system because:

- they offer an intuitive way to define probabilities of different outcomes at the level of individual system components;
- these probabilities need not to be defined objectively, but can be based on the judgement of experts and Environment Agency staff with practical knowledge of the system;
- they offer a method to integrate component-level knowledge in the outcome at a whole-system level.

2.2.13 Multi-agent simulation

In multi-agent simulation active entities in the world and their behaviour are represented in a computer as software entities called agents. This simulation method makes it possible to represent a phenomenon as the result of the interactions of a set of autonomous agents (for example, Ferber 1999, p. 36, Holland 1998, pp. 116-118, Ferber 1999, p. 36, Wooldridge 2002). It can be applied to any system composed of individual entities.

Multi-agent simulation is a special case of multi-agent systems, which were developed in the field of distributed artificial intelligence in computer science. A multi-agent system is a computing system of artificial entities in an environment or space. Agents and other objects are situated at positions in the environment. Relations link these agents and objects to each other. Agents can perceive, produce, consume, transform and manipulate objects. The reactions of the world to agents' actions, or the 'laws of the universe', are also represented (Ferber 1999, pp. 4, 11).

An agent is an entity with tendencies or objectives it tries to satisfy by acting in an environment and communicating with other agents, using its resources and skills. Its actions depend on its perception and representation of the environment, and on communications it receives (Ferber 1999, p. 9). In other words, an agent is proactive, with a goal-directed behaviour, and takes the initiative to satisfy its objectives. It is also reactive, as it perceives and responds to its environment. Finally, it has social ability and interacts with other agents (Wooldridge and Jennings 1995, Wooldridge 2002, p. 23).

According to the degree in which agents possess their defining characteristics, a distinction can be made between cognitive and reactive agents. Cognitive agents were developed in the tradition of artificial intelligence, emphasising knowledge and goal-directed behaviour (Ferber 1999, p. 16).

Reactive agents, typically used in the artificial life tradition, are based on the idea that agents can be very simple and do not need intelligence themselves for the system as a whole to have intelligent behaviour. They have a stimulus–response behaviour, communicate through simple signal propagation and have no internal representations of their environment (Ferber 1999, pp. 27-28).

Examples of multi-agent simulation are:

- multi-agent population models that represent individuals as agents and the number of individuals in a given species as a result of the behaviours of all agents (Ferber 1999, p. 36);
- multi-agent simulation models of a human society that represent individual people (or organisations and similar entities) as agents and phenomena, such as growth of social complexity as a result of their behaviour (Wooldridge 2002, pp. 259-263);
- multi-agent simulations of humans who interact with a technical system (Davidsson 2001).

Multi-agent simulation is particularly suitable to simulate complex systems, as it offers a natural way to describe system components and their interactions and can be used effectively to simulate such systems to study their behaviour.

A FIM system can also be described in a very natural way as a system of interacting agents. Therefore, multi-agent simulation could be used to gain insight into such a system. In Chapter 3 a proposal is made as to how this could be done.

2.2.14 Emergent models

We have seen how complex systems can be modelled using multi-agent simulation. We have also seen how evolutionary algorithms, and in particular genetic programming, are general-purpose algorithms to solve a variety of optimisation problems.

In Stolk (2005) ideas from multi-agent simulation and from evolutionary algorithms are combined in a novel methodology to discover emergent macro-level regularities or patterns in simulations of complex systems. These macro-level regularities are models of the behaviour of macro-level agents, in other words emergent models. Therefore, the new methodology is called the emergent models methodology.

It defines ways to derive macro-level behaviour from micro-level properties and behaviour, and discovers models at the macro-level implied by those that describe the micro-level.

This methodology can also be applied to the inverse problem of discovering micro-level behaviour of the composing entities of a complex system from data on its macro-level properties and behaviour. Emergent models offer a powerful methodology to study complex systems in general and FIM systems in particular.

2.3 A practical complex systems approach to flood incident management

To be realistically applicable to the FIM system of the Agency, a complex systems approach should:

- be practical enough to enable modelling of real systems – much complex systems research is devoted primarily to demonstrating general and abstract principles of complex systems, which thus rules out approaches such as graph theory and complex networks, computational complexity theory and artificial life;
- be suitable to be applied to complex systems with the particular characteristics of a FIM system, which rules out approaches such as genetic regulatory networks;
- be applicable without complete information about the state of a system and a precise definition of all elements of the system, which rules out approaches such as non-linear dynamics and iterative maps, stochastic iterative maps and Markov chains, neural networks, cellular automata and game theory;
- take into account probabilistic aspects of the system, which rules out deterministic non-linear dynamics and iterative maps;
- be suited to incremental improvements to the existing system, as long as a fundamental restructuring of the existing system is not considered a realistic option in the short term, which rules out approaches that focus on general structural characteristics of complex systems, such as graph theory and complex networks.

Based on the discussion in Section 2.2, it can be concluded that a practical approach to assess the 'weak links' in the FIM process can be developed as follows:

- Use a multi-agent simulation method to model in an intuitive way the systems involved. Multi-agent simulation is a practical method to model real systems and is flexible enough to define models of a FIM system and the agents that manage such a system. This is a flexible approach and aspects of incomplete information, uncertainty and probability can, in principle, be incorporated. In a multi-agent simulation one is free to alter any aspect of the system in a simulation, so the method can be used to simulate any system alteration, from small improvements to complete restructuring.

- Combine multi-agent simulation with Bayesian networks to take account of risk and uncertainty. While multi-agent simulation can be used to model the structure and operation of an organisational system in an intuitive way, Bayesian networks can model the probabilistic relationships between different components of the system. Probability estimates do not need to be objectively defined quantities. In the absence of objectively determined information, they can be incorporated based on expert judgements.
- It may be possible to use evolutionary computation to find optimal solutions to particular problems.
- It may be possible to use geographical information systems and/or cellular automata to incorporate spatial aspects, such as information provided by flood mapping.
- The above approaches are used in an extended emergent models methodology suited to emergency response and, in particular, to FIM.

3 Conceptual framework for risk assessment in flood incident management based on complex systems

The Environment Agency's FIM system is a complex system. Complex systems can be modelled by *multi-agent simulation*. Therefore, the proposed methodology includes modelling FIM using multi-agent simulation. Risk is an important aspect of FIM. In the context of artificial intelligence much research has been done on *Bayesian networks* as a method to analyse uncertainty and risk. *Influence diagrams* are an extension of Bayesian networks particularly suited to decision making in circumstances of uncertainty. While Bayesian networks contain nodes that represent causes and effects with associated conditional probabilities, influence diagrams in addition contain nodes that represent decision variables and nodes that represent objective variables. Several algorithms are available to analyse Bayesian networks and influence diagrams. Therefore, the proposed methodology includes the use of influence diagrams to model risk and uncertainty.

In the proposed methodology multi-agent simulation and influence diagrams will be integrated in a coherent conceptual framework for risk assessment in FIM.

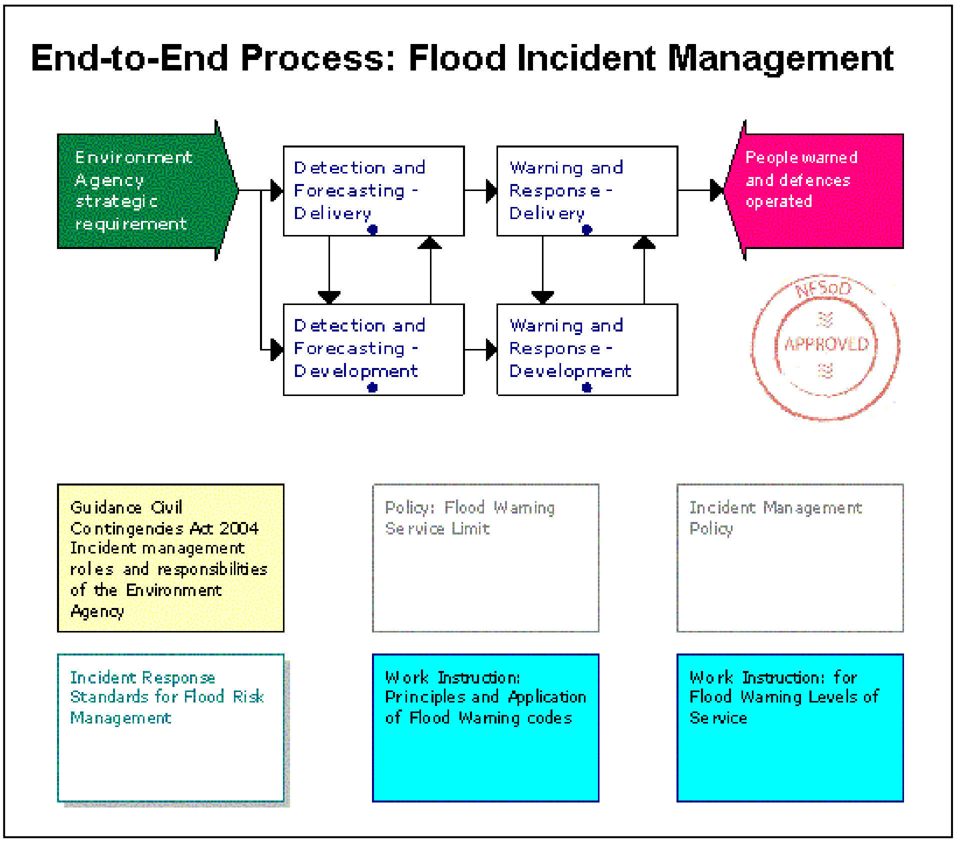
3.1 The Environment Agency's flood incident management model

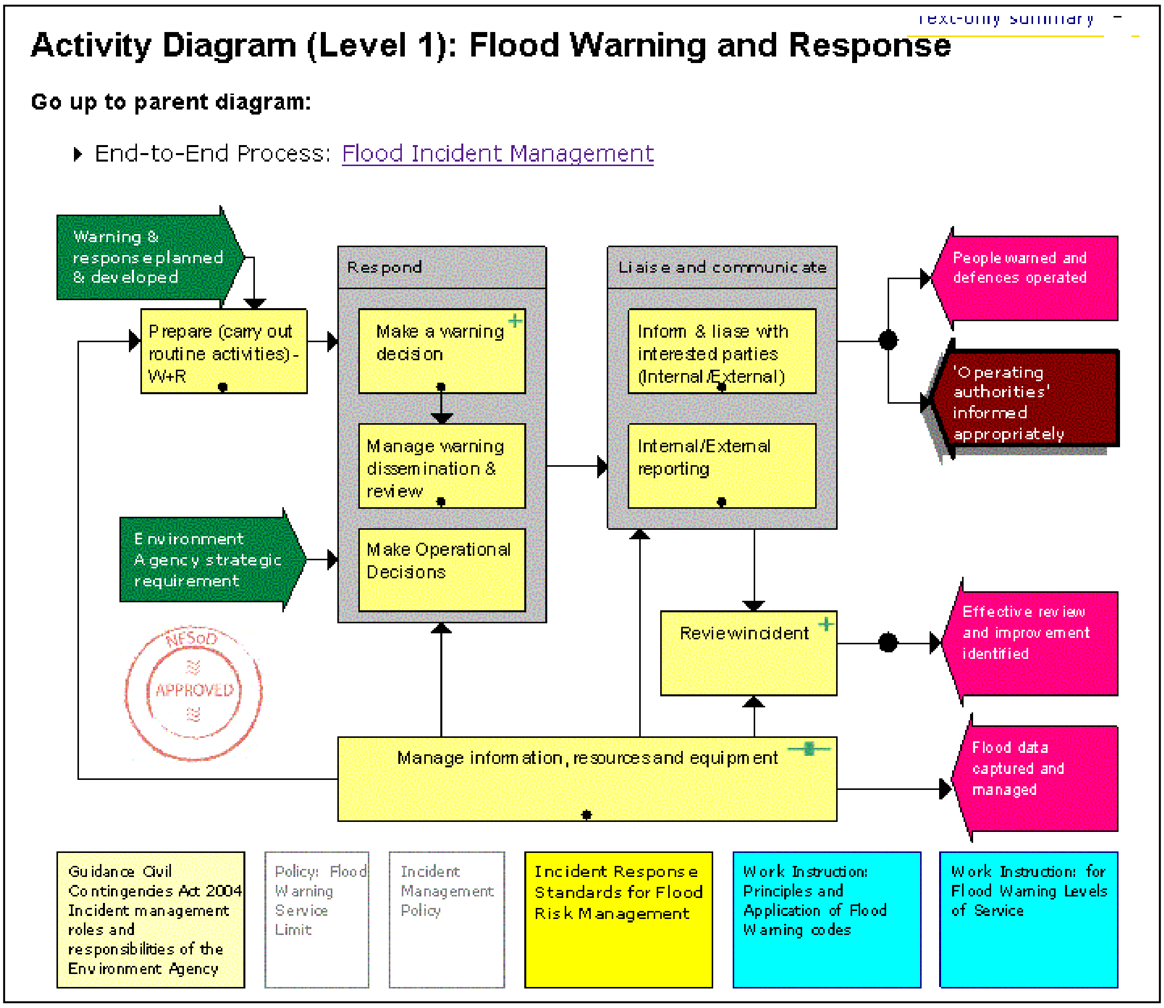
The Environment Agency's management system defines the FIM model. This model describes processes at several levels:

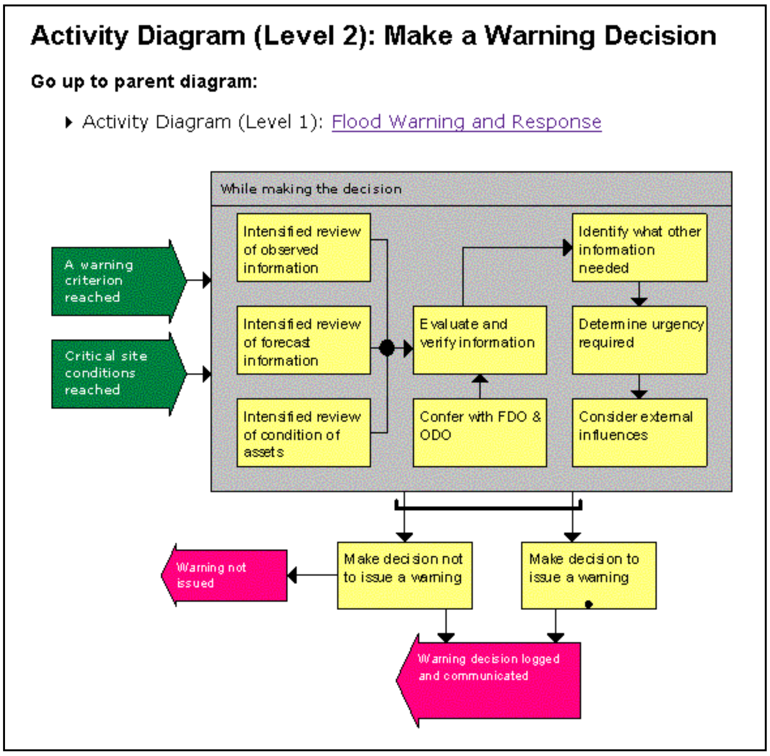
- end-to-end process – FIM;
- activity diagram (level 1);
- activity diagram (level 2);
- activity diagram (level 3).

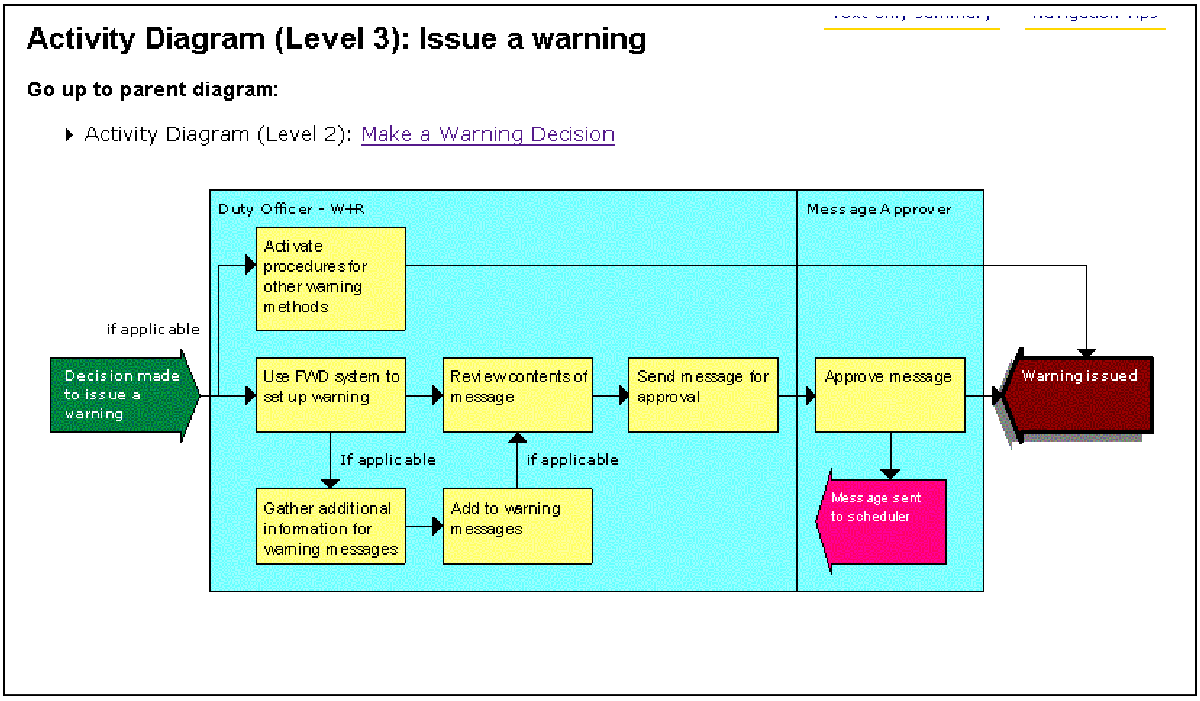
Part of the FIM model defines processes related to flood warning and response. As an example, these processes are detailed in *Figure 3.1*, to be used in Section 3.4 as an illustration of the proposed methodology. We see that FIM processes are described as interacting components at several levels of detail. The top-level end-to-end process is refined in successively more detailed sub-processes.

Figure 3.1 Flood incident management processes (FDO, Forecast Duty Officer; ODO, Operations Duty Officer).






Activity Diagram (Level 2): Make a Warning Decision
Go up to parent diagram:
Activity Diagram (Level 1): Flood Warning and Response
While making the decision
A warning criterion reached
Critical site conditions reached
Intensified review of observed information
Intensified review of forecast information
Intensified review of condition of assets
Evaluate and verify information
Confer with FDO & ODO
Identify what other information needed
Determine urgency required
Consider external influences
Warning not issued
Make decision not to issue a warning
Make decision to issue a warning
Warning decision logged and communicated


Activity Diagram (Level 3): Issue a warning
Go up to parent diagram:
Activity Diagram (Level 2): Make a Warning Decision
Duty Officer - W+R
Message Approver
if applicable
Decision made to issue a warning
Activate procedures for other warning methods
Use FWD system to set up warning
Review contents of message
Send message for approval
Approve message
Warning issued
If applicable
if applicable
Gather additional information for warning messages
Add to warning messages
Message sent to scheduler

3.2 Multi-agent simulation of complex systems

In *multi-agent simulation* active entities in the world and their behaviour are represented in a computer as software entities called agents. This makes it possible to represent a phenomenon as the result of the interactions of a set of autonomous agents (Ferber 1999, p. 36; see also, for example, Holland 1998, pp. 116-118, Wooldridge 2002). It can be applied to any system composed of individual entities.

Multi-agent simulation is a special case of multi-agent systems, which have been developed in the field of distributed artificial intelligence in computer science. A *multi-agent system* is a computing system of artificial entities in an environment or space. Agents and other objects are situated at positions in the environment. Relations link these agents and objects to each other. Agents can perceive, produce, consume, transform and manipulate objects. The reactions of the world to agents' actions, or the 'laws of the universe', are also represented (Ferber 1999, pp. 4, 11).

An *agent* is an entity with tendencies or objectives it tries to satisfy by acting in an environment and communicating with other agents. Doing this, it takes account of its resources and skills. Its actions depend on its perception and representation of the environment, and on communications it receives (Ferber 1999, p. 9). In other words, an agent is proactive, with goal-directed behaviour, and takes the initiative to satisfy its objectives. It is also reactive, as it perceives and responds to its environment. Finally, it has social ability and so interacts with other agents (Wooldridge and Jennings 1995, Wooldridge 2002, p. 23).

According to the degree in which agents possess their defining characteristics, a distinction can be made between cognitive and reactive agents. *Cognitive agents* were developed in the tradition of artificial intelligence, emphasising knowledge and goal-directed behaviour (Ferber 1999, p. 16). *Reactive agents*, typically used in the artificial life tradition, are based on the idea that agents can be very simple and do not need intelligence themselves for the system as a whole to have intelligent behaviour. They have a stimulus–response behaviour, communicate through simple signal propagation and have no internal representations of their environment (Ferber 1999, pp. 27-28).

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- multi-agent simulation model of a human society that represents individual people (or organisations and similar entities) as agents and phenomena, such as growth of social complexity, as a result of their behaviour (Wooldridge 2002, pp. 259-263);
- multi-agent simulation of humans who interact with a technical system (Davidsson 2001).

Agents have some clear advantages compared to traditional approaches to complex systems models. They provide a sufficiently general framework to model any entity – they observe the state of its environment and react by executing some action in the same environment.

In an application developed in Stolk (2005), insects are modelled as agents that observe the presence or absence of plants in their environment, and react by adjusting their movement behaviour. In another application genes are modelled as agents that observe the state of their environment (that is, other genes' expression levels) and react to that environmental state by updating their own expression levels.

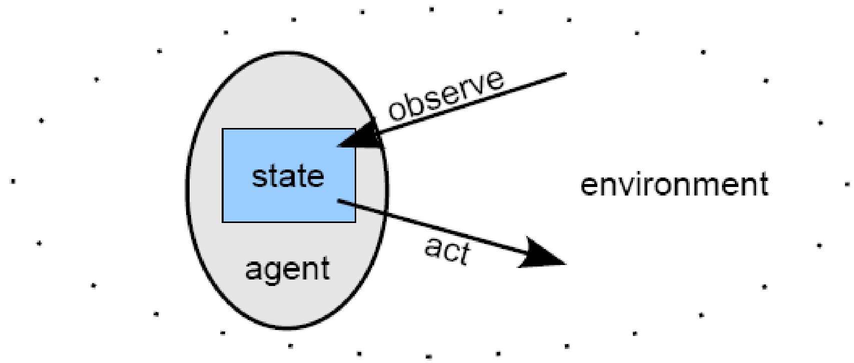


Figure 3.2 An agent with internal state.

More sophisticated agents are not only reactive, but have an intermediate internal state. Such agents observe their environment and, depending on the information gathered about the state of the environment, update their internal state. Their actions in the environment depend on their internal state, as illustrated in *Figure 3.2* (see, for example, Wooldridge 2002, pp. 31-36). This resembles the behaviour of living organisms. Therefore, organisms can usefully be modelled as agents with internal state. Agents have a conceptual advantage when modelling of systems of arbitrary complexity. Relatively simple agents interact to give rise to a complex system. Multi-agent simulations reveal the behaviour of the system as a whole, so, in principle, a system of agents can *discover emergent models* that describe the macro-level behaviour. In particular, group agents can work out an appropriate macro-level model that corresponds to given micro-level models of individual agents. At the next higher level, group agents can be individual member agents of the higher level group agent, and the process can be repeated.

Organisations are good examples of complex systems suitable for simulation using multi-agent approaches as described, for example, in Ferber (1999), Ciancarini and Wooldridge 2001, Wooldridge 2002, D'Inverno *et al*. 2002, Wooldridge *et al*. 2002). When the characteristics of organisations are examined, it becomes clear why this is so.

First, in an organisation relatively autonomous entities (organisational units, individuals) with their own behaviour respond to environmental stimuli, as well as satisfying goals. Likewise, agents have autonomy (that is, they exhibit internal properties only modifiable by some action of the agent itself), and they have their own behaviour without being under the control of other program constructs, such as a master program. Unlike an object, which only does something when a different object calls one of its methods, an agent, when created, starts to do something on its own. In principle, every entity in the world can be modelled as an agent.

Second, organisational units and individuals in an organisation interact with each other and with processes in their environment. Agents can simulate this by appropriate communication capabilities.

Third, organisations are structured hierarchically. Micro-level entities act together to constitute macro-level entities. Macro-level properties and behaviour are derived from micro-level properties and behaviour. Yet, the macro-level can be described by a macro-model that does not include the micro-level. Agents can form groups, which can model macro-level entities. Properties and behaviour of group agents are emergent properties and behaviour, derived from properties and behaviour of their members. Yet group agent properties and behaviour are different from individual agent properties and behaviour.

A fundamental problem is the *emergence problem*. How can we derive properties and behaviour at the group level, or macro-level, from those at the individual level, or micro-level? Multi-agent approaches with group agents have been used to simulate physical systems, for example in Servat *et al*. (1998a, 1998b), in which agents collectively form group agents with group membership determined from individual agents' properties and behaviour. In these simulations, whereas group membership can be said to emerge from individual behaviour, the multi-agent simulations do not automatically produce a description or model of the *emergent behaviour* of group agents. We just observe the results of the simulations and say they are produced by, or emerge from, all the individual actions. For example, the gathering of a pond of water is described as an emergent result of actions of water droplets.

To elucidate emergence through computer simulation, we would like to have a systematic method to derive macro-properties and -behaviour, to obtain models on the level of group agents in simulations, as illustrated by *Figure 3.3*.

A group agent has to have a way to derive its properties from the individual properties of its members. As seen in the introduction of this chapter, to define *group properties* is a non-trivial problem. However, if we assume that relevant properties have been defined, their values can usually be derived using some aggregation mechanism. For example, group mass is the sum of individual masses, group density the number of individuals divided by surface, etc.

The derivation of *group behaviour* is less straightforward. Since a group agent does not have pre-established rules of behaviour, these rules must be discovered. Group behaviour could be described in general with a computer program that implements agent behaviour. For simplicity, let us confine our attention to the case of one method in which the group agent implements a function that relates some group level properties to other group level properties, environmental influences, etc. A number of parameters of this function are unknown and the group agent should employ *knowledge discovery and learning* techniques to derive these parameters. In a more general approach, we can even assume that the shape of the function is unknown and also has to be discovered.

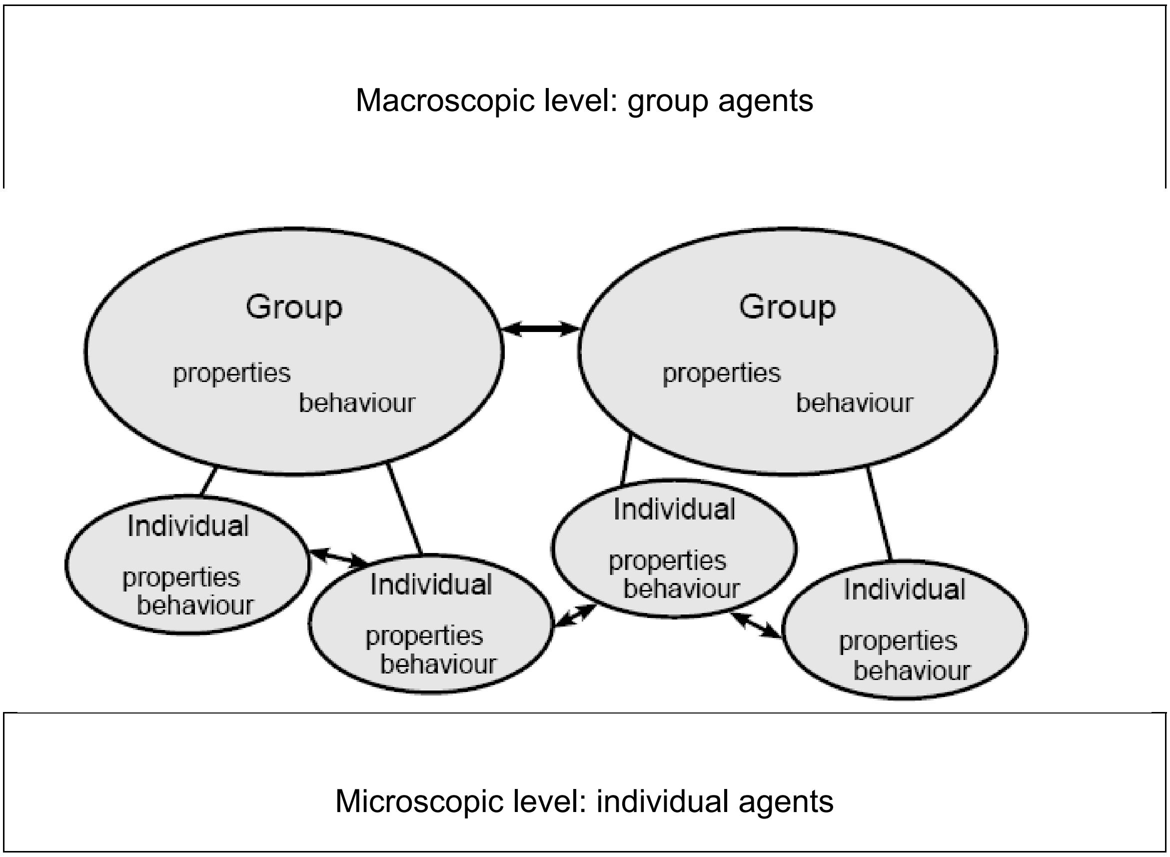


Figure 3.3 Levels in a multi-agent simulation.

3.3 Bayesian networks and influence diagrams

A simple example of a Bayesian network is reproduced in *Figure 3.4*. The arrows represent causal connections between different elements in a situation. They have probabilities associated with them. The situation described by this network is that of a family with a dog. The family can be at home or have gone out. The network can be used to solve problems such as to determine the probability that the family is at home, having observed that the lights are on, or that the dog has barked. For example, the dog is left outside when the family is out, but also when it has a bowel problem. If the dog is outside, one is likely to hear it bark (p = 0.7), but there is also a small probability of 0.01 of hearing it bark when it is inside.

In general, Bayesian networks describe situations in which elements in a situation can be causally connected, with conditional probabilities associated with the connections. They can be used to determine probabilities of particular states of events in the described situation, when some part of the situation has been observed.

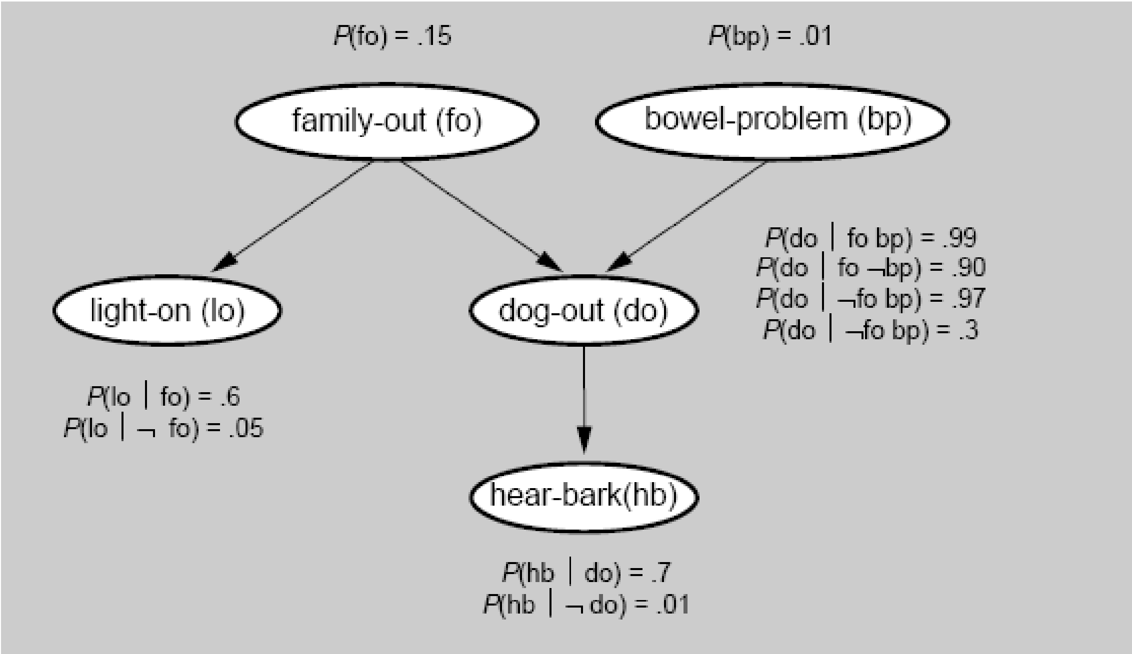
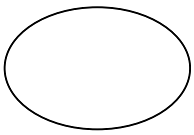


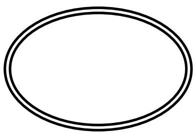
Figure 3.4 A simple Bayesian network (from Charniak 1991).

Influence diagrams are an extension of Bayesian networks suitable for decision support. An example is reproduced in *Figure 3.5*. Most nodes are the same as those in a Bayesian network, with added decision nodes (rectangles) and a value node (rounded rectangle).

The following nodes are used in a Bayesian network (see, for example, Shachter 2005).



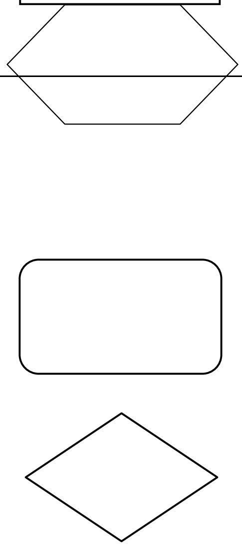
An *uncertainty node* represents a variable that is uncertain and that cannot be controlled directly.



A *deterministic node* represents a variable that is a deterministic function of the quantities that it depends on.

An influence diagram, in addition, contains the nodes (see, for example, Shachter 2005):

A *decision node* represents a variable that the decision maker has the power to control.



A *value node* represents an objective variable that is a quantitative criterion to be maximised or minimised (value nodes are drawn in many ways).

The network can be used to calculate the probable impact of a decision (for example, make a tactical warning) on the value, that is the final result of the network on something desirable, such as life or economic value.

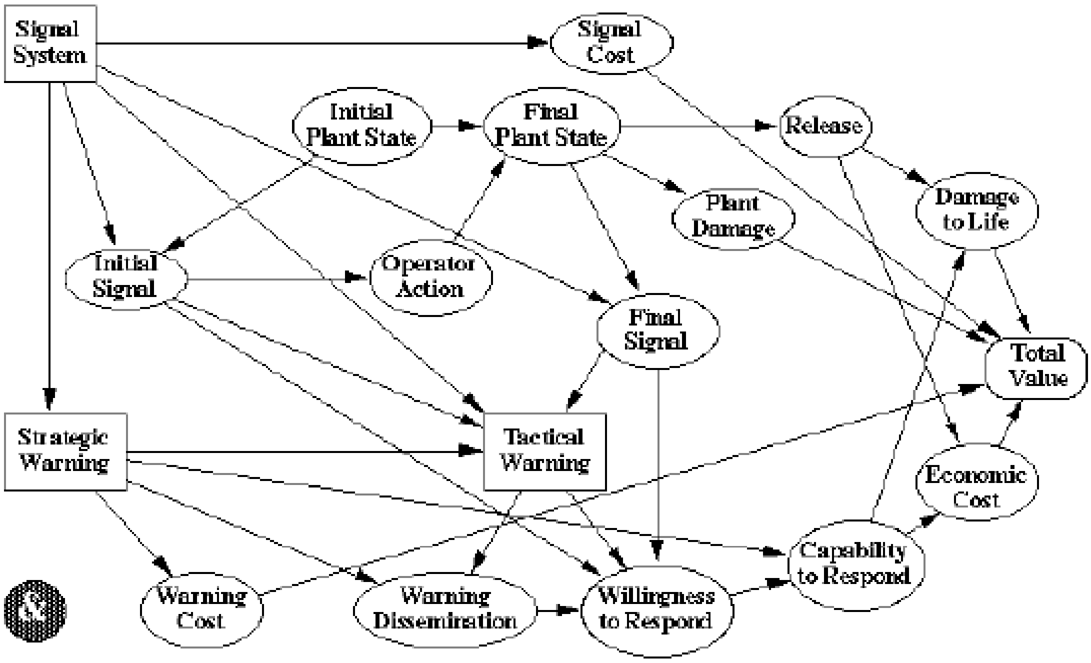


Figure 3.5 An influence diagram that describes an emergency response system for a nuclear plant (from Claudio 1985, cited in Shachter 1999).

3.4 Flood incident management, multi-agent simulation and influence diagrams

The FIM Model, as defined in the Environment Agency's Management System, can serve a basis for modelling the FIM process with multi-agent simulation. Loosely, every box in a diagram of the model would correspond to an agent.

The behaviour of an agent consists of:

- observing its environment;
- processing information obtained from observations;
- acting on its environment.

Part of the FIM model defines processes related to flood warning and response. Illustrative examples of agents identified in the process diagrams related to flood warning and response are shown in *Table 3.1*. Generic agent behaviour and specific agent behaviour are shown in the first and second columns, respectively.

Influence diagrams can be superimposed on this multi-agent system to model uncertainty and risk. Each action of an agent leads to different results with associated probabilities. So probabilistic nodes of the diagram represent aspects of agent behaviour, including uncertainties in observations (for example, reliability of observed or communicated information), information processing (for example, cognitive mechanisms, reasoning errors, faulty computing equipment) and actions (for example, faulty communication equipment, physical obstruction). Decision nodes can be incorporated to represent decisions made on various components of the system. The impact of such decisions on the final expected result of the system, represented as a value node, can be estimated by evaluating the network.

Of course, it is assumed we can quantify the output as one expected result. We have to assume this if we want to have a means to make a best decision. In fact, we always make implicit judgements about the value of the criterion to be maximised or minimised when we decide something. To quantify an objective criterion just means to make explicit the value we attach to things.

Probabilities associated with uncertainties in agent behaviour are shown in the third column of *Table 3.1*. Incorporating these probabilities in a multi-agent simulation of flood incident response would make it possible to model risk and uncertainty in the context of a complex system model and to take advantage of known algorithms to analyse Bayesian networks and influence diagrams.

It is, of course, essential to have a way to estimate the probabilities of outputs of each system component, depending on its inputs. The number should reflect the best information available. This can be done in several ways, for example, using:

- information on the behaviour of the components as assessed by scientific theory;
- empirical information on past behaviour;
- probability estimates of experts;
- probability estimates of FIM practitioners.

Risk can no longer be defined in the traditional way as probability of event occurring multiplied by consequences, as it is implicit in all the probabilities and the final outcome of the system. It is inherent in a whole-system approach that it becomes impossible to associate risk with a single event. However, it is possible to evaluate the expected effect on the outcome of the whole system of different decisions.

Table 3.1 Flood incident management agents.

Warning and response delivery agent

Behaviour	*Object of behaviour*	*Uncertainties*
Observe	Detection and forecasting information	Have correct information: p = ? Do not have correct information: p = ?
Process information		Information processed correctly: p = ? Information not processed correctly: p = ?
Act	Issue warning; operate defences	Warning issued: p = ? Warning not issued: p = ? Defences operated: p = ? Defences not operated: p = ?

Warning decision agent

Behaviour	*Object of behaviour*	*Uncertainties*
Observe	Intensified review of observed information Intensified review of forecast information Intensified review of condition of assets	Have correct information: p = ? Do not have correct information: p = ?
Process information	Confer with FDO and ODO Evaluate and verify information Identify what other information is needed Determine urgency required Consider external influences	Information processed correctly: p = ? Information not processed correctly: p = ?
Act	Make decision to issue a warning Make decision not to issue a warning	Warning issued: p = ? Warning not issued: p = ?

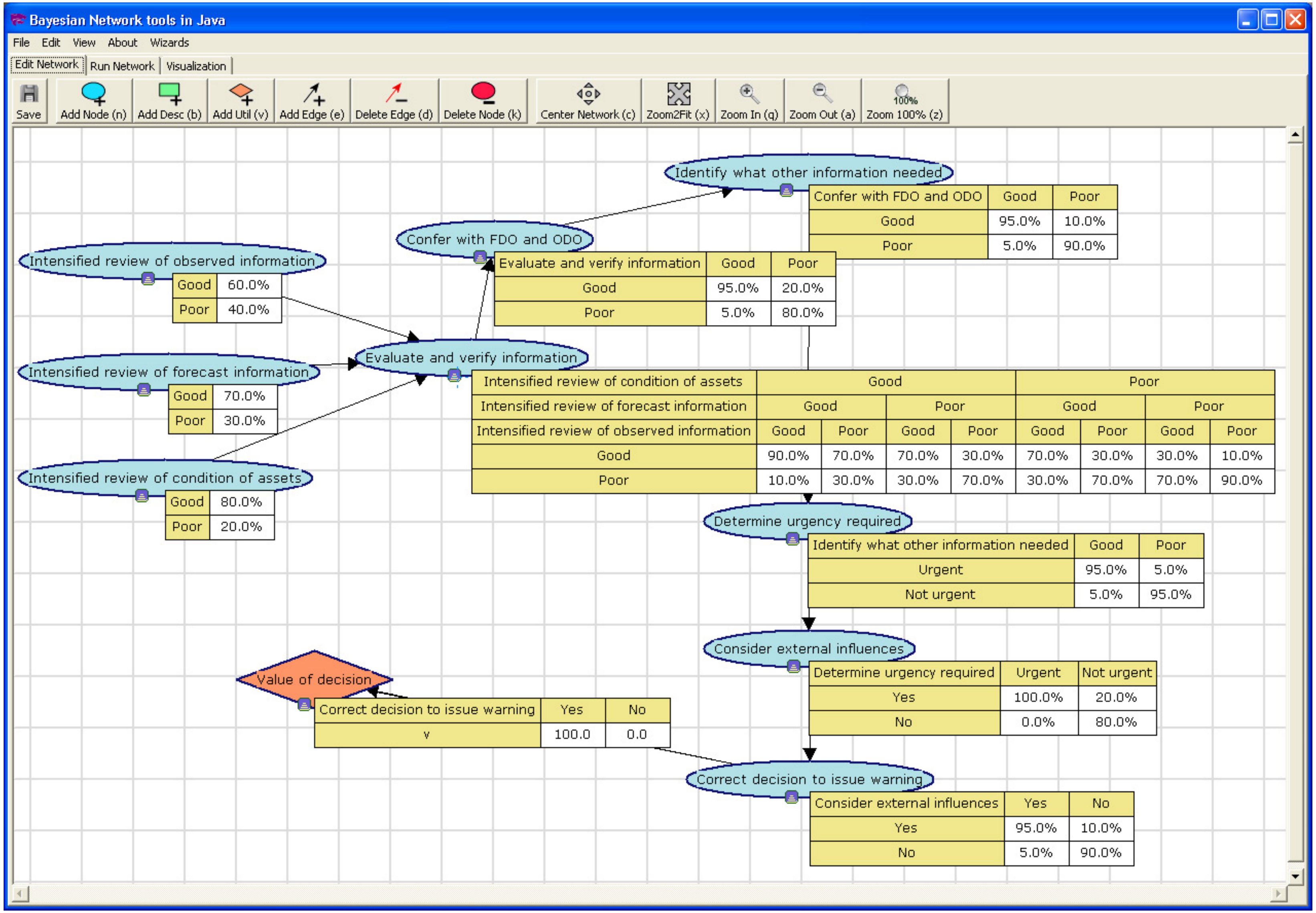


Figure 3.6 Example of Bayesian network representation of an Environment Agency process.

4 Requirements for complex systems simulation of flood incident management

It is proposed to develop a software environment that enables multi-agent simulation of the FIM process. As indicated in the other Work Packages, the concepts of agents, objects or functions are broadly consistent and multi-agent simulation can capture the common elements of the various approaches. The multi-agent simulation environment will incorporate Bayesian network analysis and, in particular, the influence diagram extension of Bayesian networks (which allows decision support as a method suitable for a whole system approach to risk).

In influence diagrams qualitative information is reflected in probabilities. Relationships between objects, agents or functions are reflected in a network of nodes and relevance arrows. It is assumed that management decisions can alter the probabilities of component performance descriptors and that cost information of decisions can be included. As in the case of quantifying the objective, cost estimates are always made at least implicitly.

This chapter summarily describes functional requirements of an environment that can serve as a support tool for decision making to optimise a FIM system. This description is intended as a basis for discussion to produce a full requirements specification document at the beginning of Project Phase 2. The full requirements specification should take account of guidelines such as those established by Institute of Electrical and Electronic Engineers (IEEE) standards for systems and software engineering (see IEEE 1998a, IEEE 1998b, Van Vliet 2000). System specification principles for engineering agent-based systems and software are formulated, for example, in Padgham and Winikoff (2004).

4.1 Functional requirements related to system components

- *Goal 1: understand, assess and model the uncertainty and reliability of different key flood incident management components (detection, forecasting, warning and response to emergencies):*
    - define all different system components:
        - detection (WP1),
        - forecasting (WP1),
        - warning (WP1),
        - response (WP1), which includes active and passive flood defence assets (WP2) and reactive mitigation measures in relation to the supporting infrastructure (WP3);
    - enter data on uncertainty and reliability of system components as estimated probabilities of different system component performance descriptors, using:
        - data on the response part of the FIM process (WP1);

- reliability data on operational failure of flood defence assets, such as failure rates (per year and/or on demand), failure modes and failure causes and consequences (WP2);
- data on probability and consequences of failure of reactive mitigation measures in relation to the supporting infrastructure (that is, assets other than flood defence assets) and personnel who manage the flood incidents, including transport, utilities (for example, gas, water and electricity), communication networks, emergency services and health services (WP3).

4.2 Functional requirements related to the whole system

- *Goal 2: understand and model the integration of operation (both human and assets) of key components within a complex system during an incident:*

    - define how all system components are interrelated (WP1, WP2, WP3, WP4);
    - simulate system behaviour using definitions of system components and their interrelationships, as well as data on uncertainty and reliability of components' performance (WP4).

4.3 Functional requirements related to management decisions about the system

- *Goal 3: understand, assess and model the improvement of reliability and management of uncertainty via flood incident management planning:*

    - define various options to improve reliability of performance of system components;
    - estimate costs and performance improvement (in terms of accepted performance criteria, such as reduction of loss of life, injury to people, flood damage to properties (WP1), for the different options);
    - simulate the system with the different options;
    - evaluate which option is the best in terms of overall system performance improvement in relation to cost.

- *Goal 4: support risk assessment and decision-making tool related to FCERM at different decision levels (National – NaFRA/RASP, Catchment – CFMPs/MDSF, Local – Development Control/FD2320 and Asset Management/PAMS):*

    - enable different user categories to use the decision-making tool with information available at their level.

5 Conclusion and recommendations

In this chapter conclusions and recommendations are formulated about the kind of complex systems-based approach to risk management that is considered suitable to improve FIM.

5.1 A practical approach to risk management from a complex systems point of view

For FIM a practical approach to risk management from a complex systems point of view is required to model real systems. To realise such a practical approach it is recommended to:

- Use multi-agent simulation to model, in an intuitive way, the systems involved. As detailed in Chapter 2, multi-agent simulation is particularly suitable to simulate complex systems, as it offers a natural way to describe system components and their interactions and can be used effectively to simulate such systems to study their behaviour. A FIM system can also be described in a very natural way as a system of interacting agents; therefore, multi-agent simulation can be used to gain insight into such a system. Chapter 3 details how this could be done.
- Combine multi-agent simulation with Bayesian networks to capture risk and uncertainty, and probability estimates can be incorporated via expert judgements. As seen in Chapter 2, Bayesian networks are a particularly relevant formalism to describe probability and risk aspects of a FIM system, because they offer an intuitive way to define probabilities of different outcomes on the level of individual system components. These probabilities need not be objectively defined, but can be based on the judgement of experts and Environment Agency staff with practical knowledge of the system. They offer a method to integrate component-level knowledge in an outcome at the whole-system level. In Chapter 3 more details are given on a possible implementation of such an approach for the FIM system of the Environment Agency.
- Possibly use evolutionary computation to find optimal solutions to particular problems.
- Possibly use geographical information systems and/or cellular automata to incorporate spatial aspects.
- Consolidate the above approaches in an extended emergent models methodology suited to emergency response and, in particular, to FIM.

5.2 Applying the approach to flood incident management by the Environment Agency

The FIM model, as defined in the Environment Agency management system, can serve as a basis on which to model the FIM process with multi-agent simulation, at least the part of this process directly under the responsibility of the Environment Agency. Agents should also be defined to simulate entities outside the Environment Agency involved in FIM, such as local authorities, communities, enterprises, voluntary organisations and affected individuals.

Loosely, every box in the FIM model diagram would correspond to an agent.

The behaviour of an agent consists of:

- observing its environment;
- processing information obtained from observations;
- acting on its environment.

Illustrative examples of agents identified in the process diagrams are given in Chapter 3 of this report.

Influence diagrams can be superimposed on this multi-agent system to model uncertainty and risk. Each action of an agent leads to different results with associated probabilities. Thus, probabilistic nodes of the diagram represent aspects of agent behaviour, including uncertainties in observations (for example, reliability of observed or communicated information), information processing (for example, cognitive mechanisms, reasoning errors, faulty computing equipment) and actions (for example, faulty communication equipment, physical obstruction). Decision nodes can be incorporated to represent decisions made on various components of the system. The impact of such decisions on the final expected result of the system, represented as a value node, can be estimated by evaluating the network.

Probabilities can be associated with uncertainties in the agent. Incorporating these probabilities in a multi-agent simulation of flood incident response would make it possible to model risk and uncertainty in the context of a complex system model and to take advantage of known algorithms to analyse Bayesian networks and influence diagrams.

5.3 Developing tools to support decision making on flood incident management

It is proposed to develop a software environment that enables multi-agent simulation of the FIM process. The multi-agent simulation environment will incorporate Bayesian network analysis and, in particular, the influence diagram extension of Bayesian networks (which allows decision support) as a method suitable for a whole-system approach to risk.

Influence diagrams can support management decisions to alter the probabilities of component performance descriptors to achieve better performance of the FIM system, while controlling the cost of change.

Chapter 4 of this report summarily describes functional requirements of an environment that can serve as a support tool for decision making to optimise a FIM system. This description is intended as a basis for discussion to produce a full requirements specification document at the beginning of Project Phase 2, which takes account of established guidelines and principles for systems and software engineering and, in particular, for engineering agent-based systems and software.

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