Application of multi-agent systems and ambient intelligence approaches in water management

P. Mikulecký, A. Bodnárová, K. Olševičová, D. Ponce, J. Haviger

University of Hradec Králové, Rokitanského 62, 500 03 Hradec Králové, Czech Republic Correspondence to: P. Mikulecký (peter.mikulecky@uhk.cz)

Abstract

Various recently intensively investigated approaches, based on certain type of embedded intelligence exploitation, can be used also in the area of water management. A big class of them, based mainly on various types of multi-agent systems, are useful for incorporating complexity in ecosystem modelling in general. By incorporating a high degree of social and spatial heterogeneity multi-agent systems could also represent "nested hierarchies" and phenomena emerging across different scales. This is also an appropriate approach for capturing spatial phenomena in biophysical modelling. It enables the investigation of lower-level mechanisms that might lead to the development of higher-level structural and dynamical features in landscapes.

The paper is oriented on summarization of recent results of existing as well as possible multiagent systems application in various sub-areas of water management. As multi-agent systems are very suitable also as a framework for ambient intelligence environment, some first ideas about exploitation of these approaches in water management and especially for river basin management will be presented as well. All the results are based on a series of ongoing mutually interconnected research projects.

1 Introduction

Our research is focused on application of information and knowledge technologies in the area of water reservoir management. The recent project AQUIN was dedicated to the development of knowledge-based system that would capture the expertise of dispatchers who control the outflow from single reservoir (which is a source of drinking water for inhabitants along the river). For details, see (Toman et al., 2004) or (Olševičová and Ponce, 2004). In the current project AQUINPro, we explore the suitability of applying computational intelligence methods and knowledge engineering approaches in solving more general task: in managing systems of several reservoirs. Results of both projects will be used by professionals of the water management company from Western Bohemia.

1.1 ICT support of decision making in water management

The dispatchers who manage the water reservoir tend to keep the water level in reservoirs as high as possible, except situation when the danger of flood appears after intensive rainfalls (then the levels have to be decreased preventively to allow reservoirs to accumulate extra volume of inflowing water). The manipulations on the reservoir outflow have to satisfy sets of objectives, defined by customers of the water management company, who ask for

• delivering required amount of water to consumption points, changing the flow in the river (to water down the contamination, to oxygenate water for fish),

• achieving certain flow in given time slot (increasing flow for canoeing competitions) etc. These objectives are often contradicted (Ponce, 2003), (Ponce, 2006). The process of decision making about manipulations on reservoir outflows is highly complex, requiring data, information, and domain expertise. The dispatchers take into account current and historical data from measuring stations on reservoirs and rivers, general characteristics of river basins, weather forecasts etc. Each dispatcher applies his specific knowledge and domain expertise. Newcomers need at least 3-5 years to learn about manipulations on particular system of reservoirs.

Except operational decisions about manipulations, dispatchers participate on solving long-term tasks, such as

- changing the hydrodynamic models describing the river basin,
- planning reconstructions of river banks,
- strategic reasoning about the need of new reservoirs construction etc.

Operational, as well as strategic decision making can be supported by information and communication technologies. We can think of two kinds of applications:

- centralized knowledge based system or decision support system can simulate dispatcher's activities and can provide solution his/her task, such as manipulation recommendations,
- several task-specific subsystems can be used to support dispatcher's final decision making e.g. by summarizing data, searching for similarities in data, visualizing data etc.

Both kinds of solutions can rise from the multi-agent paradigm.

Typical tasks in water management are usually described in literature as socio-economic ecological modelling. Generally, a system of interactions between ecological (biological, hydrological, physical, geological) dynamics, social dynamics and economic dynamics is investigated. Typical questions in this area involve:

- How to manage collectively the common/shared property (water and land management policies, costs, effects; tradeoffs between competing water and land uses; optimal allocation of water and land resources)?
- What impact would have alternative use of natural resource (alternative resource management policy, alternative land and water use, alternative crop growth and technology usage), e.g. impact of alternative land use on cover changes (trends in deforestation and reforestation, sustainability of agricultural practices, evolution of settlements)?

The socio-economic ecological model is usually composed of two models:

- Ecological model
- Socio-economic model

Ecological model can have components such as land units (described in terms of size, soil texture, soil depth, land slope), land use, river, irrigation canal, village. Dynamics of the ecological model is also be defined, e.g. water balance model (using parameters such as rainfall, irrigation, runoff, deep drainage, water stored in the soil reservoir, evapotranspiration). Several modelling techniques can be used.

The belief in the omniscient model which, thanks to the differential equations, calculation power and remote sensing, would lead to the construction of a model capable of calculating water and material flows at each point of a river basin, is not realistic (Wasson et al., 2003). It seems that this approach failed (Beven, 1989) due to two reasons:

- Difficulties of a conceptual nature related either to grid discretisation, or to the physical laws used (e.g. Darcy's law was developed for homogenous and isotropic environments and its extension to a kilometric grid is far from obvious);
- Technical difficulties: a great many data, especially those concerning subsoil, are inaccessible. Generally, acquisition of all data is economically incompatible with an

operational context. This means that certain parameters require calibration, quickly making the associated numerical problems (parameter sensitivity) insolvable.

Socio-economic model have components called stakeholders, e.g. farmer, land owner, migrant representative. Dynamics of the socio-economic model is also defined, typically using theory of game-playing. Multi-agent system is used here as a modelling technique.

The complex socio-economic ecological model can be supported also by GIS (Berger, 2000).

How the physical space and the social space will be interconnected? Emerging social norms, land allocation to immigrants, and common pool resources management, in general, are examples where micro-level phenomena influence macro-level outcomes that in turn affect units at the micro scale (Berger, 2000).

In models of complex systems, interdependencies and heterogeneity of biophysical environment often lead to what are called nonconvexities – an irregular and rugged abstract surface describing the relationship between the parameters of the system and possible outcome states (Parker et al., 2001).

Interrelated socioeconomic and biophysical processes can be represented at multiple scales which mean that we incorporate complexity in natural resource use modelling (Berger, 2000).

Integrating land and water is essential for capturing the dynamics of interrelated biophysical systems (Lambin et al., 1999) and it is itself a complex task.

Artificial life techniques are useful for incorporating complexity in ecosystem modelling in general. By incorporating a high degree of social and spatial heterogeneity multi-agent systems could also represent "nested hierarchies" and phenomena emerging across different scales (Parrot, 2000). It is also an appropriate approach for capturing spatial phenomena in biophysical modelling.

In a sense related cellular modelling techniques, such as cellular automata and Markov models have been applied to landscape modelling ((Bockstael, 1999); (Parker et al., 2001)) as well. The basic units for modelling locally interacting "objects" are cells forming a grid, whose transition rules include their previous state and the state of the neighbouring cells. Advanced models use Geographical Information Systems to store information about the state of cells in a landscape and feed this information back into the cellular automaton. The cellular automata approach can also be used to represent the interactions of humanlike agents in physical or social space. Typically, the agents occupy positions on a two-dimensional grid of cells and the distances between them influence their interactions. (Balmann, 1997) and (Berger, 2000) employ a cellular automaton and hydrology modelling.

In a couple of our recent projects we tried to apply some knowledge-based approaches into the water management area first. These results are described, e.g., in (Mikulecky, Olševičová, Ponce, 2008). Our recent effort is oriented on employing various approaches of watershed modelling using multi-agent systems and first ideas on ambient intelligence principles exploitation appeared as well. We shall describe these in more detail in the following parts of the paper.

2 Multi-agent paradigm

According (Russell and Norvig, 2003), an agent is anything what perceives surrounding environment through sensors and acts in the environment through actuators. This initial definition was refined by numerous authors, namely by enumerating the essential properties of agents. (Lee, 2006) defines intelligent agent (IA) as the exemplification of human intelligence in a device. The agent's intelligence consists of possessing knowledge (with three levels: derived knowledge,

stimulated knowledge, and intuitive knowledge) and the manipulation of knowledge (the "thoughts or thinking" which consists of three levels: logical thinking, lateral thinking, and intuition). This device (the IA) can exist in the form of a system, a software program, a program object, or even a robot. The agent should possess ten following properties: autonomy, mobility, reactivity, pro-activity, adaptability, communicativeness, robustness, learning ability, task-based orientation, goal-based orientation (Lee, 2006).

Three main categories of agents are differentiated in the literature. Except intelligent agents, there are reactive agents, and social agents.

- The *intelligent (rational, deliberative, reasoning) agent* operates with an internal representation of the world and plans activities with respect to the given goal. Architectures such as belief-desire-intention model allow us to define mental states of agents and apply modal and temporal logic to them; see e.g. (Rao and Georgeff, 1991). Then the intelligent agent's behaviour approximates human ways' of problem solving. In the design of the agent, the research results of artificial intelligence, game theory, statistics and other disciplines are reused.
- *Reactive agent* has no memory, does not plan activities and only reacts to stimuli from the environment. Hardware reactive agents (robots) are much cheaper in comparison with intelligent agents what makes them quite attractive (Brooks, 1999).
- *Social agent* acts in group. The behaviour of the agent populations is often significantly different from the behaviour of single agent. The emergence of new qualities in agent populations is intensively researched.

The design of agent is derived from its mission and depends on characteristics of the environment. The features of the environment are discussed in (Russell and Norvig, 2003). Fully observable, deterministic, episodic, static, discrete environment with one agent is much easier to be analyzed, than partially observable, stochastic, sequential, dynamic, continuous environment with several heterogeneous agents. Real-life (social, natural) processes tend to have the least desirable characteristics.

The agent-based approach is worth mentioning in case we face open, highly dynamic, variable, bad structured, uncertain situations, where

- environment can be seen as a system of autonomous, cooperating or competing entities,
- data, control or expertise are distributed,
- the system can be divided into independent components

(Wooldridge and Jennings, 1995), (Wooldridge, 2002). In the domain of water management, the multi-agent metaphor is applicable in different directions, as we explain bellow.

3 Proposed solutions

In the scope of our first project AQUIN, the architecture of the centralized system, based on CommonKADS methodology (Schreiber et al., 2000) was specified. In CommonKADS, the term *agent* corresponds to any entity that provides or processes data, information or knowledge (e.g. dispatchers, water management company customers, measurement stations along the river, hydropower plant). The software design according CommonKADS is focused on agents that solve tasks reusing domain knowledge models. Typical tasks in water management domain follow.

- In *classification*, the input data about the current state are interpreted and evaluated. Dispatcher classifies situations in the river basin, e.g. using weather data he discriminates between dry and wet periods.
- In *diagnosis*, the data are processed to identify problem. Dispatcher explains the changes

of inflow to reservoir according his knowledge about accumulation of water in woods around the reservoir.

- In *forecasting/prediction*, it is examined how the world change in dependence on certain variables. Dispatchers forecast the impacts of manipulations.
- In *generating possibilities*, the objective is to create alternative ways of problem solving. Dispatcher generates alternative sequences of manipulations to decrease the level in the reservoir in requested period.
- In *action recommendation*, the alternative plans are compared. Dispatcher chooses the plan of manipulations to optimize the usage of hydro-power plant installed on the reservoir.

In terms of multi-agent systems, our final application was seen to be either knowledge-based system simulating activities of human dispatchers (i.e., generating and explaining scenarios of manipulations on reservoirs), or decision support system (solving partial tasks, or evaluating variants defined by human dispatcher), Then we elaborated other scenarios of usage multi-agent metaphor in the context of the project.

3.1 Dispatcher as a single agent

An intelligent agent refers to computer software that has access to one or multiple, heterogeneous and distributed information sources, pro-actively searches for and maintains relevant information on behalf of users or other agents preferably just-in-time. An intelligent system should be adaptive, flexible and robust (Florian, 2003). It must be able to react to situations which are similar to previous and adapt to new situations and to the changes in its environment. The intelligence of such system is conditioned by:

- Ability to learn from data and gain knowledge
- Ability to save knowledge
- Ability to use these knowledge in real concrete situations

Developing intelligent agent needs expertise from different disciplines: artificial intelligence, advanced databases and knowledge systems, distributed information systems, adaptive information retrieval, and human computer interaction (Friedewald and Da Costa, 2003).

The knowledge-based system, able to suggest manipulations on reservoirs, can be modelled as an intelligent agent (*digital dispatcher*). Its knowledge base contains the expertise of human expert (dispatcher of the water management company). As there work several dispatchers in the company, the knowledge acquisition has to be organized using methods of knowledge engineering and knowledge management (see e.g. (Awad and Ghaziri, 2003)). Except consultation with domain experts, data-mining methods can be applied to discover knowledge from archives and repositories. Unhappily, in the company a significant part of historical records is not stored in an electronic form. In water management domain this means a bottleneck. The prediction of inflows into reservoirs can be based on comparing current situation with historical cases. In context of Czech climatic conditions, similar hydrological situations appear only in the same period of the hydrological year. Then, the daily records from previous 20 years mean 20 classes of month records, each containing 30 daily values. This amount of data does not enable usage of machine learning and data mining methods.

The critical component of *digital dispatcher* would be its interface. Part of input data is collected, delivered and stored automatically, but part of it is obtained from plain text (e.g. weather forecasts, historical records about manipulations), images (satellite scans) or even from phone calls records (e.g. with operators on reservoirs). The introducing of knowledge-based system in

the company can not generate new stereotype duties for employees, i.e. we can not expect dispatchers to spend time on loading data to the application.

The advantage of *digital dispatcher* is that it could serve as a tutoring agent for newcomers. Less experienced dispatchers learn about reservoirs behaviour and need training cases and feedback from experienced dispatchers. The newcomer can learn by observing the reasoning and outputs of *digital dispatcher*. Moreover, the application equipped with tutoring module can generate assignments for learner and evaluate his/her performance. Here it is important to separate the dispatcher's knowledge model and logic from the tutoring knowledge model and logic. The tutoring functions are independent on the problem domain and the independence on knowledge model of partial river basin enables the application to be used in other water management companies. For details about electronic tutoring agents, see e.g. (Shaw et al., 1999).

3.2 Dispatching as a multi-agent system

There are several dispatchers in the company and during one day, only one of them makes decisions. The rotation of dispatchers in relays influences the total quality of decision making, because of impacts of individual decisions on situation in the river basin in several next days.

The functioning of dispatching centre can be simulated by the multi-agent system (*digital dispatching*), where each dispatcher is modelled by one reasoning agent. For coordination of agents the blackboard architecture is suitable (Jackson, 1999). The blackboard serves as the media for communicating manipulation scenarios (and relevant constraints) suggested by different dispatchers.

Each agent operates with its individual knowledge base, corresponding to unique experience of the human dispatcher. In each (relay), only one agent is active and can change the content on the blackboard.

For the purpose of exchanging information among agents in *digital dispatching*, ontologies establish common understanding of concepts and relations in the domain (Gómez-Pérez et al., 2004). Internal design of each agent can be different. Although we do not expect experts from the same domain to use totally different reasoning procedures, this is the way how to capture the contradictory expertises of individual specialists.

The architecture of *digital dispatching* allows introducing different types of agents, such as agents modelling customers of the water management company. These agents can access the shared blackboard to present their requirements. (In practice, at the dispatching centre in the company a real blackboard is used for communicating operational requirements).

In crisis (during floods) human dispatchers make decisions in the group. In this case the negotiation and coordination techniques can be applied (Wooldridge, 2002).

3.3 Fully decentralized application

The network of rivers and technical devices along them (reservoirs, dams, hydro-power plants, sewerage plants, consumption points) can be seen as the network of autonomous agents. Part of agents can act (and by action also influence its surroundings), e.g. setting of the reservoir outlet influences the flow in the river down stream. These agents can be modelled as locally reasoning agents, with certain range of actions. Other agents, such as measurement points, only provide data. The neighbouring agents (in sense of real physical distance of modelled objects) can communicate; typically they exchange values of variables.

In this conception, the reasoning process is fully distributed and decentralized. There is no central

authority (no single digital dispatcher). Each agent is equipped with relevant part of knowledge model of the domain and its individual objectives. The deputing the decision making to the lower level simplifies the reasoning process of each agent.

As well as in communication of dispatchers, the exchange of information among neighbouring agent requires establishing the shared vocabulary, based on ontologies. More than in *digital dispatching*, the negotiation and coordination techniques are relevant. The agents of upper objects in the river basin have to be proactive and benevolent to needs of agents of lower objects. Typically the setting of the upper reservoir outflow must be acceptable for the lower reservoir.

3.4 Agent-based simulations

When they reason about manipulations on reservoirs, human dispatchers face the uncertain values of most parameters that have to be estimated (typically the saturation of soil, the progress of rainfalls, snow melting speed). Instead of traditional numeric hydrological, geological and meteorological models, the simulation on principle of reactive agents can be used for description of processes in the area close to reservoirs and rivers. For better demonstration of this idea, we developed the extension of model in NetLogo.

3.5 Demonstrator in NetLogo

NetLogo (NetLogo, 2007) is an environment for development of complex, multi-agent models, evolving in time. It is possible to create populations of movable agents in the grid of stable agents.

Our sample models were created by extending the model Grand Canyon (Wilensky, 2006), using data from (Seamless Data Distribution System, 2007). The original model operates with GIS data. The area of 9,6 x 9,6 km is divided into squares 32x32 m (patches). In our model, the experimental data were obtained from the GIS model of Eastern Bohemia. It was area of 15x15 km divided into squares 50x50m. For each square, the value of elevation is defined. The movable agents (raindrops) appear (fall) in random locations and flow downhill. If no nearby patch has a lower elevation, the raindrop stays where it is. Raindrops pool until they flow over the land nearby (Wilensky, 2006).

In our extension of the model, we added new parameters and modified the rules of agents moving:

- There are different types of bedrock defined for each patch. According the bedrock, the raindrops flow slower or more quickly.
- There are several classes of vegetation. The raindrops behave differently in patches with values indicating forest, meadows or inhabited areas.

The course of simulated rain can be predefined. In the interface of the model, it is possible to choose subareas with or without rainfalls, and define the periods of raining.

The natural consequence of flowing water downhill is that the watersheds and reservoirs form in the lowest parts of the modelled landscape. Through additional interface elements, user can manage the course of simulation by operating on such reservoirs.

If the GIS data are detailed enough (i.e. the granularity of the grid of patches is fine enough), the watersheds correspond to real rivers. In case of less detailed division (with larger patches), the watersheds are wider and correspond to parts of landscape under water during floods. The highest possible precision of the model is determined by the GIS data and computing capacity for parallel processing.

The results of simulation can be visualised in graphs and data can be stored for further processing in statistical software.

Our simulation model helps knowledge engineers to communicate with domain experts, because dispatchers can perform their reasoning by solving modelled situations. The model is based on simple physical principles, but its large-scaled modifications are possible.



Screenshot 1 - empty map



Screenshot 2 - simulation model of rainfalls after 100 iterations



Screenshot 3 - simulation model of rainfalls after 300 iterations



Screenshot 4 - simulation model of rainfalls after 1000 iterations

3.6 Neural network approach

In the past decades there were developed numerous methodologies used for forecasting in water management (Jowett, 1997). All of these methodologies need a large amount of long-term high-quality data (Alcázar at al., 2008). Likewise data sets are rarely disposable so we need methodology for processing of incomplete or small-amount data sets. Models of artificial neural networks are suitable solution, they can be applied in fields where statistical models are not effective (Atzberger, 2004) (Alcázar at al., 2008).

In (Valverde Ramírez et al. 2005) a feedforward neural network and resilient propagation learning algorithm is used to generate site-specific quantitative forecasts of daily rainfall. Meteorological variables from the ETA model are used as input data to the trained networks, which generate rainfall forecast for the next time step.

(Schleiter et al., 1999) tested the suitability of various types of artificial neural networks for system analysis and impact assessment in temporal dynamics of water quality based on weather, urban storm-water run-off and waste-water effluents; in bioindication of chemical and hydromorphological properties using benthic macroinvertebrates; and in long-term population dynamics of aquatic insects.

(Moradkhani et al., 2004) explored the applicability of a Self Organizing Radial Basis function, which uses Gaussian Radial Basis Function architecture in conjunction with the Self-Organizing Feature Map to one-step ahead forecasting of daily streamflow.

A study of the hydrological behaviour based on modelling the performance of the runoff produced by the river at different temporal scales of the Xallas river basin presents (Castellano-Méndez et al., 2004). They used and compared classic statistical Box-Jenkins models and

artificial neural networks.

(Hsu et al., 1995) presents the structure and parameters of three-layer feed forward ANN model and demonstrates the potential of such model for simulating the nonlinear hydrologic behaviour of watersheds. Booth in (Tokar and Johnson, 1999) and (Minns and Hall, 1996) is a rainfall-runoff model based on an artificial neural network presented. In (Alcázar at al., 2008) ANNs has been applied to environmental flow estimation.

As we can see, ANNs become a very useful tool in the field of water management too. The most important feature of neural networks is that they are a universal approximator of function. That allows us process data where the classical methods are unsuitable.

4 Ambient Intelligence

Insofar Ambient Intelligence is "a set of properties of an environment that are in the process of creating", therefore it is impossible to define this concept explicitly. According to the (ISTAG, 2005), fulfilling the AmI vision depends on numerous domains and components, including:

- sensor technology, bridging the physical world and the cyberspace,
- embedded systems development technology,
- ubiquitous communication including networks for active and passive tagging or internet access,
- adaptive software that is self-managing and self-adjusting,
- media management and handling supporting "produce one, present anywhere".

Ubiquitous computing is characterized by interactions that are not channelled through a single workstation. Technical features of UbiComp systems include (Alcaniz, 2005):

- 'invisible' file systems, so user can access data without knowing specific file names, locations or formats,
- automatic installation and optional migration of programs from a computer to another without requiring fundamental changes in configurations,
- personalized information that is tailored to the user's requirements.

AmI environment is characterized by merging of physical and digital space: tangible objects and physical environments are acquiring a digital representation. AmI artifact (also smart object, smart device) is an element of AmI environment which process information, interacts with environment, is autonomous, collaborative, composeable and changeable (Kameas, 2005).

Independently from the wide range of the possible approaches, any AmI Environment is characterized by the following five key technologies (Aarts, 2003):

- Embedded systems: devices are (wired or not) networked in the environment.
- Context awareness: the system is able to recognize people and situational context.
- Personalized applications: the system customized itself to meet people needs.
- Adaptivity: the system is reactive to new habits, behaviours, needs of the user.
- Anticipatority: the system anticipates human desires without conscious mediation.

One of the most important problems in an intelligent environment is interaction of the user with the environment surrounding her/him. There is a number of very interesting approaches developed by various authors. We shall briefly analyze the most interesting ones.

Ambient intelligence environments may be considered as strongly related with multi-agent systems in that they can be adequately modelled using multi-agent systems of various types. One of the most interesting approaches is based on the idea of so-called ad hoc agent environments.

An ad hoc agent environment (Misker et al., 2004) is a way for users to interact with an ambient intelligent environment. Agents are associated with every device, service or content. The user

interacts with his environment as a whole, instead of interacting with individual applications on individual devices. Devices and services in the environment have to be more or less independent, which fits well with the notion that agents are autonomous. The research was oriented on how the user is able to interact with the environment in such a way that he/she would have the control over collaborating agents. Some experiments showed certain tension between the user being in control and the autonomy of agents. Therefore the notion of cooperating groups was introduced as a way for users to gain control over which agents collaborate. Users can then establish connections between devices and content that are meaningful to them, in the context of their task.

5 Aml application possibilities for watersheds

The organizational model Aalaadin (Ferber and Gutknecht, 1998) has been quite often used when speaking about participative water management support. The core concepts of the Aalaadin are agent, group and role (Abrami et al., 2002):

- An agent is defined as an active communicating entity, no constraints other than those triggered by the ability to play a role or not.
- A group is defined as a set of agents.
- A role is defined as an abstract representation of an agent function, service or identification within a group. The role encapsulates the way an agent should act within a group. Roles are local to groups.

According to (Abrami et al., 2002) an agent can simultaneously play different roles in different groups, i.e. groups can freely overlap. An agent can enter or leave groups by acquiring or resigning a role, that is, groups are dynamic structures. Groups represent organizational levels and roles represent functions within these levels; through the roles it is handling, an entity gathers information from the different processes it is involved in without concern about eventual scale or time heterogeneity of these processes.

If we adopt this approach further on, we can combine it with the ad hoc agent environment concept by (Misker et al., 2004) described above. This idea gives us a potential of using ambient intelligence concepts based on multi-agent models, usable for enhancing the watershed by various AmI artifacts capable of ubiquitous communication and helping intelligently to manage the watershed. The further research in this direction is on the way.

6 Conclusion

The multi-agent metaphor is reasonably applicable in water management domain. We identified several scenarios of multi-agent system usage in the scope of decision support of dispatchers from the water management company. Except traditional centralized architecture of single reasoning agent (computing counterpart of human dispatcher), it is possible to use systems of reasoning agents, or to apply multi-agent simulations for verifying hypotheses about the next course of processes in the river basin. Partial implementations of multi-agent applications are expected to simplify communication with domain experts during the process of modelling their knowledge, identifying their needs and summarizing requirements on final application functioning. Our next research will be focused on development of demonstrators of all presented scenarios of multi-agent applications.

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References

Aarts, E., Marzano, S. eds. (2003) The New Everyday: Visions of Ambient Intelligence, 010 Publishing, Rotterdam, The Netherlands.

Abrami, G., Barreteau, O., Cernesson, F. (2002) An Agent-Group-Role based modelling framework for participative water management support. In: Proc. of the iEMSs 2002, Vol. 3, Lugano, pp. 497-502.

Alcaniz, M., Rey, B. (2005) New technologies for ambient intelligence. In: Riva, G.; Vatalaro, F.; Davide, F. Alcaniz, M. (eds.): Ambient Intelligence. IOS Press. Available on http://www.ambientIntelligence.com.

Alcázar, J., Palau, A., Vega-García, C. (2008): A neural net model for environmental flow estimation at the Ebro River Basin, Spain, Journal of Hydrology, Elsevier Science, Volume: 349, Issue: 1, Page: 44 – 55, ISSN: 0022-1694.

Atzberger, C., (2004) Object-based retrieval of biophysical canopy variables using artificial neural networks and radiative transfer models. Remote Sensing of Environment 93, 53–67.

Awad, E.M., Ghaziri H. M. (2003) Knowledge Management. Prentice Hall.

Balmann, A. (1997): Farm-based modelling of regional structural change: A cellular automata approach. In: European Review of Agricultural Economics 24, 85-108.

Beven, K. (1989). Changing ideas in hydrology – The case of physically-based models, J. Hydrology, 105, 157–172.

Berger, T. (2000) Agentenbasierte räumliche Simulationsmodelle in der Landwirtschaft. Anwendungsmöglichkeiten zur Bewertung von Diffusionsprozessen, Ressourcennutzung und Politikoptionen. Agrarwirtschaft Special Issue 186, Agrimedia.

Bockstael, N., Irwin, E. (1999): Economics and the Land Use-Environment Link. Working Paper 99-04. Department of Agricultural and Resource Economics. University of Maryland.

Brooks, R. (1999) Cambrian Intelligence – The Early History of the New AI. MIT Press

Castellano-Méndez, M., González-Manteiga, W., Febrero-Bande, M., Prada-Sánchez, J.M., Lozano-Calderón, R. (2004) Modelling of the monthly and daily behaviour of the runoff of the Xallas river using Box-Jenkins and neural networks methods. Journal of Hydrology 296, 38–58.

Ferber, J. and O. Gutknecht. A meta-model for the analysis and design of organizations in multiagents systems. In Demazeau, Y., editor, ICMAS'98, pp. 128–135, Paris, 1998.

Florian, R. V. (2003), Autonomous artificial intelligent agents. Technical Report Coneural-03-01.

Friedewald, M., Da Costa, O. (Eds.) (2003), 'Science and Technology Roadmapping: Ambient Intelligence in Everyday Life (AmI@Life)', final report of the JRC-IPTS/ESTO project "Ambient Intelligence in Everyday Life Roadmap,", Seville. Available at: http://fiste.jrc.es/download/AmIReportFinal.pdf Gómez-Pérez, A., Fernández-López, M., Corcho,O. (2004) Ontological Engineering with examples from the areas of Knowledge Management, e-Commerce and the Semantic Web. Springer-Verlag.

Hsu, K.L., Gupta, H.V., Sorooshian, S. (1995) Artificial neural network modeling of the rainfall– runoff process. Water Resources Research 31 (10), 2517–2530.

ISTAG (2005) Ambient Intelligence: from vision to reality. In: Riva, G.; Vatalaro, F.; Davide, F. Alcaniz, M. (eds.): Ambient Intelligence. IOS Press. Available on http: //www. ambientIntelligence. com.

Jackson, P. (1999) Introduction to Expert Systems. Addison Wesley Longman

Jowett, I.G. (1997) Instream flow methods: a comparison of approaches. Regulated Rivers: Research & Management 13, 115–127.

Kameas A., Mavrommati I., Markopoulos, P. (2005) Computing in tangible: Using artifacts as components of ambient intelligence environments. In: Riva, G.; Vatalaro, F.; Davide, F. Alcaniz, M. (eds.): Ambient Intelligence. IOS Press. Available on http://www.ambientIntelligence.com.

Lambin, E., et al. (1999) Land-Use and Land-Cover Change. Implementation Strategy. IGBP Report 48 – IHDP Report 10.

Lee, R.S.T., (2006) Fuzzy-Neuro Approach to Agent Applications: From the AI Perspective to Modern Ontology. Springer-Verlag.

Mikulecký, P. (2004) On the way to knowledge-based water management. In: In: Hydrology: Science and Practice for the 21st Century (Webb, B., Acreman, M., Maksimovic, C., Smithers, H., Kirby, C., eds.), Vol. II, pp. 434-438. London, British Hydrological Society, 2004, ISBN 1-903741-11-4

Mikulecký, P., Olševičová, K., Ponce, D. (2008) Knowledge technologies in water resources management. Poster, 13th World Water Congress, Montpellier, September 2008.

Mikulecký, P. – Ponce, D. – Toman, M. (2003) A knowledge-based solution for river water resources management. In: Water Resources Management II. Southampton, WIT PRESS 2003, pp. 451-458, ISBN 1-85312-967-4

Minns, A.W., Hall, M.J. (1996) Artificial neural networks as rainfall–runoff models. Hydrological Sciences Journal 41 (3), 399–417.

Misker, J.M.V., Veenman, C.J., Rothkrantz, L.J.M. (2004) Groups of collaborating users and agents in ambient intelligent environments. In: Proc. ACM AAMAS 2004, ACM, New York, 2004, 1318-1319

Moradkhani, H., Hsu, K.-L., Gupta, H.V., Sorooshian, S. (2004) Improved streamflow forecasting using self-organizing radial basis function artificial neural networks. Journal of Hydrology 295, 246–262.

NetLogo homepage (2007) [online] http://ccl.northwestern.edu/netlogo/

Olševičová K, Ponce D (2004) Knowledge analysis of the system for water reservoir control. In: Proc. of International Conference on Hydrology: Science & Practice for the 21st century, London, pp. 453-458, ISBN 1-903741-12-2

Parrott, L., Kok, R. (2000) Incorporating Complexity in Ecosystem Modelling. Complexity

International Vol. 7. Accessed at: http://www.csu.edu.au/ci/vol07/lparro01/.

Parker, D., Manson, S., Janssen, M., Hoffman, M. and Deadman, P. (2001) Multi-Agent Systems for the Simulation of Land-Use and Land-Cover Change: A Review. CIPEC Working Paper CW 01-05. Bloomington: Center for the Study of Institutions, Population, and Environmental Change, Indiana University.

Ponce, D. (2003) Reports from AQUIN project meetings (internal materials).

Ponce, D. (2006) Reports from AQUINPro project meetings (internal materials).

Rao, A.S., Georgeff, M.P. (1991) Modelling rational agents within a BDI-architecture. In Proc. of the Second International Conference on Principles of Knowledge Representation and Reasoning (KR'91), Morgan Kaufmann, pp473-484

Russell, S., Norvig, P. (2003) Artificial Intelligence: A Modern Approach. 2nd edition, Prentice Hall

Schleiter, I.M., Borchardt, D., Wagner, R., Dapper, T., Schmidt, K.D., Schmidt, H.H., Werner, H. (1999) Modelling water quality, bioindication and population dynamics in lotic ecosystems using neural networks. Ecological Modelling 120 (2-3), 271–286.

Schreiber, G. et. al. (2000) Knowledge Engineering and Management – The CommonKADS Methodology. MIT Press

Seamless Data Distribution System [online] http://seamless.usgs.gov/

Shaw, E., Johnson, W.L., and Ganeshan, R. (1999) Pedagogical Agents on the Web. In Proc. of the Third Int'l Conf. on Autonomous Agents, pp. 283-290

Tokar, A.S., Johnson, P.A. (1999) Rainfall–runoff modelling using artificial neural networks. Journal of Hydrologic Engineering 4 (3), 232–239.

Toman, M., Mikulecký, P., Olševičová, K., Ponce, D. (2004) Znalostní technologie ve vodním hospodářství. Vydavatelství ČVUT, Praha. (in Czech)

Valverde Ramírez, M.C., de Campos Velho, H.F., Ferreira, N.J., (2005) Artificial neural network technique for rainfall forecasting applied to the Sao Paulo region. Journal of Hydrology 301, 146–162.

Wasson, J.-G., Tusseau-Vuillemin, M.-H., Andréassian, V., Perrin, Ch., Faure, J.-B., Barreteau, O., Bousquet, M., Chastan, B. (2003) What kind of water models are needed for the implementation of the European Water Framework Directive? Examples from France. Intl. J. River Basin Management Vol. 1, No. 2, pp. 125–135

Wilensky, U. (2006). NetLogo Grand Canyon model.. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL. [online] http://ccl.northwestern.edu/netlogo/models/GrandCanyon

Wooldridge, M. (2002) Introduction to MultiAgent Systems. Jihn Wiley & Sons, Chichester, UK.

Wooldridge, M., Jennings, N., (1995) Intelligent agents: theory and practice. In: The Knowledge Engineering Review 10(2), pp115-152.