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Abstract: This paper presents an approach for constructing and testing a decision analysis process for adaptive water management under uncertainty. Water resources management as a complex dynamic system contains nonlinearities, feedback loops, and delays. Qualitative system dynamics modelling (e.g. causal loop diagram) is employed within a participatory integrated framework (integrating social, environmental and economic elements) to identify major drivers and their trends, potential evolutionary paths and their interdependencies, and also possible actions that can be taken to reduce impact of these drivers. An evolutionary Bayesian belief network-based methodology is developed to guide stepwise decision making during the transition process taking into account key uncertainties. Causal loop diagrams, as directed graphs, have no restrictions with feedback loops. Loops in causal maps are usually the result of dynamic relationships between variables across multiple time periods. However, Bayesian belief networks are hierarchical acyclic graphs, therefore have no means of handling feedback loops. The proposed methodology addresses this major shortcoming of Bayesian belief networks.

Keywords: System Dynamics, Feedback loop, Evolutionary algorithm, Bayesian belief network, Adaptive management, Uncertainty, Learning.

1. INTRODUCTION

Sustainable management of water resources in light of global and climate changes is one of the most pressing challenges of the 21st century. This requires approaches that take into account full complexity of the systems to be managed and the need to develop adaptive and integrated management approaches (Pahl-Wostl, 2006). This requires planning and managing water resources in a holistic manner. In order to succeed, it is important to take into account a wide range of (e.g. physical, environmental, economic, social and political) factors that impact on the water resources. It is equally important to identify the best way of linking these factors together and to simulate the interactions between them. Uncertainty is another important problem, which is an inherent feature of environmental systems. These systems are rarely well structured (Simonovic, 1996) as there is no definitive formulation, no true or false solution, and no test of a solution for these problems. This has earned them the title of wicked problems (Rittel and Webber, 1973). Causal Loop Diagrams (CLD) as system dynamics tool can provide a framework within which the environmental structure can be developed and the interactions and relationships among different variables can be investigated. System dynamics is important in understanding the cyclical behaviour of a system. In general, a feedback control system exists whenever the environment causes a decision that in turn affects the original environment (Forrester, 1958). System dynamics introduces the possibility that a system may display non-equilibrium behaviour as it flips between positive and negative feedbacks. The result is much more complex patterns of movement over time (Stacey, 2002). Nowadays CLDs are mainly used for articulation of dynamic hypothesis of the system as endogenous consequences of the feedback structure (Sterman, 2000).

CLDs can be a good start for system modelling, however, in dealing with complex systems with high uncertainties other tools are required. Bayesian belief networks (BBNs) are used to simulate domains or systems containing some degree of uncertainty caused by imperfect understanding or incomplete knowledge of the state of the system (Jensen, 1996). BBNs have the advantage of dealing with uncertainties while avoiding overly complicated mathematical methodologies. BBNs are directed acyclic graphs; therefore transformation of CLDs with feedback loops to BBNs is not a straightforward process. In what follows, an evolutionary Bayesian belief network-based methodology is presented. The suitability of the developed integrated methodology is discussed in facilitating generation of robust management options as well as the way delayed feedback loops are handled.

2. ADAPTIVE WATER MANAGEMENT

Adaptive management is a systematic process for improving management policies and practices by learning from the outcomes of implemented management strategy (Pahl-Wostl, 2007). This requires incorporation of iterative learning cycles in the overall management approach. Considering and analyzing different hypotheses and scenarios about system behaviour under uncertain future development can be used as a guiding process in adaptive management. Figure 1 shows an adaptive management cycle including consideration of scenarios and hypotheses as learning process in an iterative policy cycle.

Figure 1. Adaptive management cycle

Adaptive management increases adaptive capacity by shifting linear decision making process to a cyclic learning process that iteratively integrates problem bounding and definition, policy formulation, implementation and monitoring in order to track and manage changes (Sendzimir et al., 2007). This requires a number of decisions along any path of change, the consequences of which are uncertain and evolutionary. Such consequences can be modelled in system dynamics using feedback loops that show ways in which a system can unexpectedly shift its behaviour. Feedback loop simply means that the outcome of a previous action is fed back as information that guides the next action in such a way that the discrepancy between the actual outcome and the desired one is reduced until it disappears to reach equilibrium state of behaviour for a system. A number of different forecast scenarios should be prepared to take into account unforeseeable events (Stacey, 2002). A loop can dominate the system's behaviour until accumulating influences suddenly allow another feedback loop to take over control. Even though feedback loops add to dynamic complexity of systems, all learning depends on them. As discrepancies between

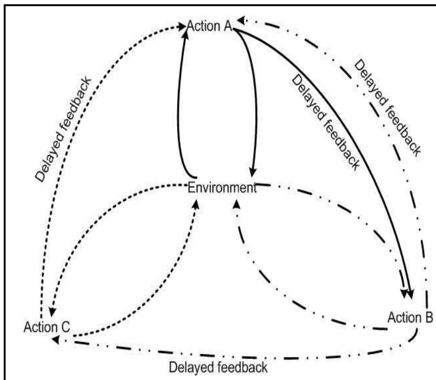


Figure 2. Delayed feedbacks as drivers of policy resistance and learning.

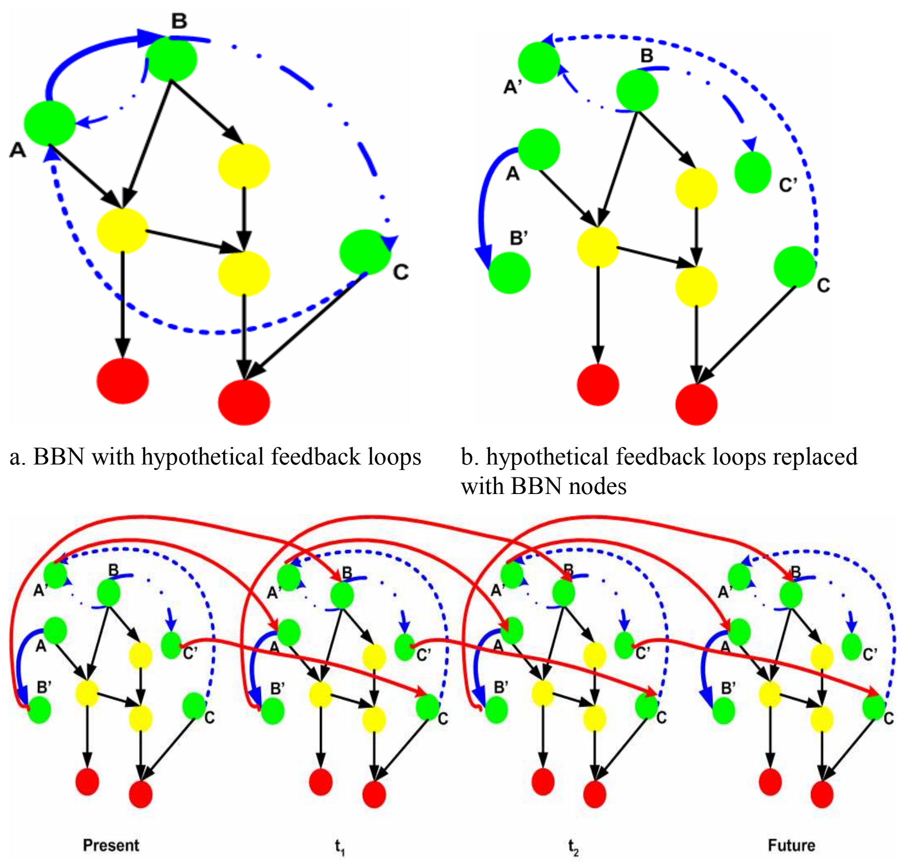
desired and actual states is perceived, actions are taken that hopefully will cause movement towards the desired state (single-loop learning). On the other hand double-loop learning results in more deep changes i.e. changes in mental models, goals and values (Sterman, 2006).

Figure 2 shows that each intervention has a consequence. Actions not only alter the environment and the future decisions, they also can have delayed effects that need to be addressed by other actions in order to restore equilibrium in the system.

3. EVOLUTIONARY BAYESIAN BELIEF NETWORK METHODOLOGY FOR ADAPTIVE MANAGEMENT

Increasing uncertainties require a more adaptive and flexible management approach to realise a faster coping cycle that allows the rapid assessment and implementation of the consequences of new insights. Adaptive management can be defined as a systematic process for improving management policies and practices by learning from the outcome of implemented management strategies. Being adaptive thus means being able to constantly change internal structures in order to respond to external changes. This requires innovative approaches to facilitate improved learning and adaptation in addition to control (Pahl-Wostl, 2007). Robustness is a key criterion for good decisions under uncertainty (Rosenhead, 1993). The most effective form of adaptive management employs management programmes that are designed to experimentally compare selected policies or practices by evaluating alternative hypotheses (Gunderson, 1999). In general, there is no single solution for complex and uncertain problems. There are often trade-offs that require choices. Scenario planning is a strategic method that can be used to make flexible long-term plans. Scenarios represent the outcome of the feedback loops with complex interactions and long delays based on a set of assumptions about key driving forces. They assist in the assessment of impacts, adaptation and mitigation processes.

To learn effectively in a world of dynamic complexity when evidence cannot be generated through experiments, virtual worlds and simulation become the only reliable way to test hypotheses and evaluate the likely effects of policies. The virtual worlds are models or simulations in which decision makers can conduct experiment, rehearse decision-making and play. They can be physical models, role-plays, or computer simulations (Sterman, 2006). The proposed methodology, which is based on the integration of evolutionary multiobjective optimisation algorithm and Bayesian belief, facilitates design of robust and flexible management strategies through an iterative decision making process. The two software are linked via Microsoft Excel where all the data exchange takes place. In this methodology, first different management strategies are identified (Fig.3.a). This is followed by identification of future states of the system based on scenarios, which has been done by introduction of new nodes (nodes A', B' and C', Fig.3.b). Scenarios represent possible consequences and effects of each action solution on other aspects of the system through feedback loops (Fig.3.b). A Bayesian belief network is set up for each time step. In the simplest from, on one hand, this is similar to the temporal extension of BBN which means that the network structure or parameters do not change dynamically, but that a dynamic system is modeled. On the other hand, as it consists of time-slices (or time-steps), with each time-slice containing its own variables that are generated using EMO, it resembles single loop learning where only actions and strategies can be changed. However in complex systems with a large number of feedbacks, not only it models temporal nature of the problem, but also introduces changes to the next time step as they are identified in each time step. Changes here refer to those that will affect structure or parameters of the existing Bayesian belief network. From decision making point of view, the former deals with sequential decision making task while the latter, so called dynamic decision making task, is more concerned with controlling dynamic systems over time.



a. BBN with hypothetical feedback loops

b. hypothetical feedback loops replaced with BBN nodes

c. output from each time step is fed as input of next time step.

Figure 3. Handling feedback loops in BBN

The developed Bayesian belief networks are considered simultaneously in identification of robust decision paths (Fig.4). The outcomes of each time step are the inputs of the following time step (Fig.3.c). The trade-offs between different objectives are evaluated. The stopping criterion for the algorithm is defined as identification of a management strategy that is reinforced by other strategies enabling its growth and stabilization. The evolutionary based model facilitates this and identifies, based on the concept of survival of the fittest, the robust pathways in a co-evolving environment. Figure 5 demonstrates the main steps of the proposed methodology. The algorithm starts by initialising action or strategy nodes using randomly generated values from EMO software. This change will then have a knock on effect throughout all those nodes linked to it. In this way the impact on the whole system can be evaluated. The criteria for stopping this part of algorithm are that either several consecutive decisions support similar actions or a predefined large finite time

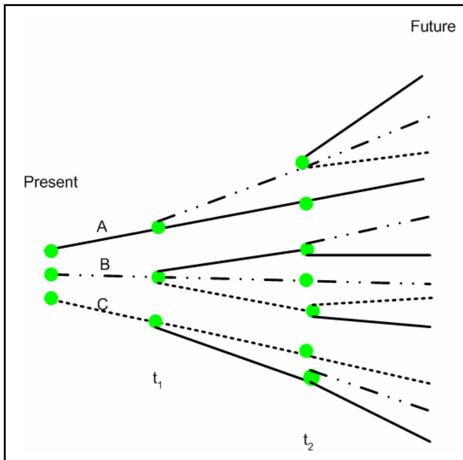


Figure 4. Decision tree.

horizon has reached. If the former criterion is not satisfied and depending on the information provided by additional nodes representing the impacts of the feedbacks, two possibilities exist. If additional nodes indicate no need for change in structure or parameters of the system, the next step action plans generated by EMO will be implemented otherwise the changes will be fed back to latest Bayesian network and the process will be continued. This process will be repeated for all the solutions generated by EMO. The evaluated results will be ranked based on their objective function values. The procedure will be repeated until no improvement is made on Pareto optimal front or maximum number of generations is reached.

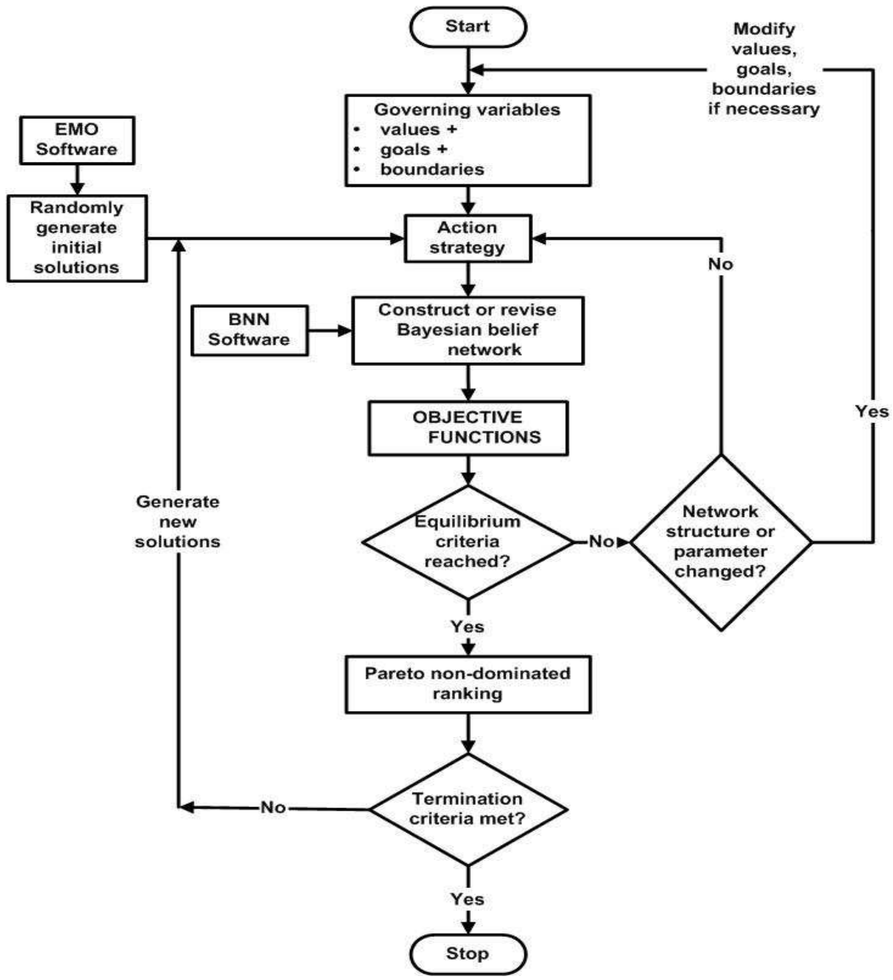


Figure 5. The proposed methodology

The methodology proposed in this work is not only anticipatory but also exploratory. Anticipatory in a sense that it starts with prescribed vision of the future and then works backwards in time to visualize how this future could emerge (focusing on long term). On the other hand it is exploratory as it starts in the present and explores possible trends into the future. This methodology is similar in a way to transition management (Rotmans et al., 2001) which involves long-term planning process in small and incremental steps. These planning and management methodologies take uncertainty and complexity as starting point rather than as closing entry; they take learning as guide rather than fixed goals and are co-evolutionary. Evolutionary planning and decision making process is aimed at different interventions at different levels in time and space (Rotmans, 2006).

Despite our efforts to present the methodology by application to a flood plain management problem, we were not able to quantify our developed conceptual models due to lack of data.

We are hoping presentation of it at the conference would results in some interest from participants and possibly a suitable case study to better illustrate the methodology.

4. CONCLUSIONS

High complexities due to nonlinearities, feedbacks and delays in environmental decision making problems require more advanced techniques. In this paper an evolutionary Bayesian belief network methodology is proposed to guide stepwise decision-making during the transition process taking into account key uncertainties. In the proposed methodology, complexities are considered as uncertain information and treated as elements of Bayesian belief networks. The effects of delayed feedbacks are modelled using scenarios and hypotheses. The outcome of each time step is fed back as input for next time step. Simultaneous consideration of the all time steps under different feasible interventions using evolutionary algorithm will result in a set of adaptive decision options that trade-off between different objectives.

The proposed decision analysis approach allows decision makers to use computer models to plan a wide range of feasible paths into the long term. Decisions made in this way are robust because they are adaptive as they are explicitly designed to evolve in response to new information.

ACKNOWLEDGEMENTS

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