Masters Proposal:
The extension of the BPDA framework for real-time monitoring and validation.

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1 Introduction

Ecological sustainability and the sustainability of human development is rapidly becoming a greater concern for the global and local populations and the policy makers tasked with governance. Humanity's increasing population and economic activities are placing unprecedented strain on the environment. Likewise the global population is becoming increasingly vulnerable to both environmental catastrophes and to the varying rates of degradation of the environment on which it is dependent (Lubchenco, 1998).

This increased vulnerability causes both massive loss of life and negative impacts on quality of life in both developed and developing economies, as well as wreaking massive economic damage on many sectors (Lubchenco, 1998).

Humanity's impact on the earth is substantial and is rapidly increasing (Vitousek et al., 1997). It has become clear that human activities impact on a global ecological scale (Lubchenco, 1998). In this regard it has become vital to be able to carefully plan and adapt our actions with respect to their impact on the earth, as well as enlarge our understanding of pure ecological systems to incorporate social, economic and political effects. We must extend our understanding to deal with social and ecological systems as a "whole" system. This need has led to the introduction of the term *Social-Ecological systems* (Peter, 2010). The proposed masters intends to extend a modeling framework that assists policy development regarding social-ecological systems. The framework is to be extended by incorporating real-time data feeds to constantly calibrate and check the social-ecological models used in decision making.

1.1 Social-Ecological Systems

The study of social-ecological systems transcends the boundaries of traditional research disciplines. Since they incorporate aspects from many fields of ecological research and social studies it is unlikely that a single researcher or group will have an expert understanding of all the aspects of the system. However the participants and affected parties within social-ecological systems go far beyond researchers, scientists and politicians. They include the inhabitants of the system as well as those members of society that make a living off the ecology. As such when dealing with social ecological systems the decision making requires trans-disciplinary and broad participation (Baran and Jantunen, 2004). The great problem facing trans-disciplinary work is the fragmentation of understanding. Each participant in the research process has their view of the whole, maintaining their own *partial truth*. A collection of often contradictory partial truths can be damaging to the group understanding (Islam et al., 2006). This fragmentation is partially due to a lack of a common language and knowledge representation between disciplines and individuals.

Social-Ecological systems are *Complex Adaptive Systems*. In that they consist of many interacting subsystems giving rise to non-linear emergent behaviour and self-organisation(Cowan et al., 1994, Levin, 2006).

Complex adaptive systems are inherently difficult to model, especially those in the social-ecological domain (Wu and Marceau, 2002). This is due in part to the modeler being caught between two approaches. The first being the reductionist approach of trying to model all the individual agents in the system, however the inherent non-linearity of the system means that even the smallest deviations between model and system can cause huge emergent differences (Richardson, 2003). The second approach is to try take a qualitative holistic approach, however this lacks quantifiable rigor. The challenge is then to integrate these two seemingly contradictory approaches (Wu and Marceau, 2002).

Further global social, economic and ecological systems are becoming increasingly interconnected. This makes decisions made in one area and sector affect the sustainability of a host of other systems, areas and sectors (Folke et al., 2005). For example legislation passed by the US department of energy to promote the use of bio-fuels prompted fears of decreased food security, because land previously used for food production has been re-purposed for energy production and corn prices increased (Runge and Senauer, 2007). This very simple example illustrates how decisions made in different organisations and countries can have broad ranging effects outside of their traditional domains.

1.2 The difficulty of decision making in Social-Ecological systems

Decision makers are faced with a multitude of problems when making Social-Ecological decisions. The domain is often not well understood, and there is no single expert opinion on which to base the decisions. The links between actions and effects are unpredictable. Small interventions in the systems can have disproportionately large effects, both in and outside of the system. The increasing rate of technological progress coupled with a globalized economy have created a period of unprecedented rates of social-ecological change. These faster rates of change make historical understanding less relevant than an understanding of current-context. Consequently decision makers cannot prudently rely on precedent when making policies (Malhotra, 1999). Never the less, decisions have to made, in fact it is increasingly important that active intervention does take place. Thus decision makers are forced to make often ill-informed decisions, often with severe consequences.

1.3 The importance of monitoring in decision making

Whenever decisions are made they are based upon some presumed relationship between the variables of the system in question. In simple systems these relationships are clear and can be relied upon. However in complex systems the the relationships between variables are multi-faceted and difficult to determine. Inherent in modeling a complex system is a process of simplification, where information is lost. Due to this, and the non-linearity of complex systems, all models of complex systems have a degree of uncertainty, as well as a likely hood that they are only partial representations of the system. (Richardson, 2003).

Monitoring complex systems is important to for 3 reasons: Firstly to continue checking that the assumptions underpinning the decision were correct; secondly to check that the system has not evolved in some way that requires an reconsideration and adaption of the previous decision; and lastly to check that the decision is having the desired effect. Governance can only be effective if its rules and interventions change as the system it governs does (Dietz et al., 2003).

The consequences of making decisions based on incorrect models can be catastrophic. For example the crash of Long Term Capital Management in 1998 almost devastated the global financial economy, the crash fundamentally was brought about because the

Nobel prize winning economists[1], Merton and Scholes, did not fully take into account the complexity market uncertainty and incorrectly predicted the volatility of the Russian financial markets (Taleb, 2008).

1.4 Increasing amounts of available data

Large amounts of high quality data are becoming more and more accessible. Organisations such as the Long Term Ecological Research network (LTER) and the South African Earth Observation Network (SAEON) extract large quantities of data that is accessible to decision makers and researchers. The awakening realization of the importance of understanding climate change has lead many governments to invest in new and extended monitoring capacity. Added to this is the increased pressure on governments and scientific institutions to make data more accessible to the public.

This increasing amount of raw data must be put to use and harnessed to improve our decision making ability (Lubchenco, 1998). However rather than aiding the decision making process, information overload is hindering our ability to make sense of the data. In order to extract value from this data we need to be able to aggregate and represent it in a way that is useful to decision makers.

2 Related and Supporting Work

2.1 Complexity theory

Complexity theory (sometimes called *Complexity science*) concerns itself with the *multi-agent system* or the *complex adaptive system* (Heylighen et al., 2006). It has it origins in non-linear dynamics and chaos theory, but has since been developed and incorporated into many domains. An agent is an entity with known rules that govern its local behaviour (Heylighen et al., 2006). Complexity science deals with studying the behavioural interactions between these agents and with the unexpected emergent phenomena that their interactions produce. It accepts the inherent uncertainties that are present when dealing with complex systems, as opposed to reductionist philosophy which believes that any system can be understood if its component parts are accurately understood (Heylighen et al., 2006).

Complexity science has developed in parallel with agent-based computer simulation systems, also known as Bottom Up Computer Simulations (BUCS). However, Richardson (2003) shows that even agent based simulations do not capture the full complexity of many systems, thus forcing decision makers to embrace more qualitative forms of dealing with complexity. This is especially the case with social-ecological systems, resulting in the development of more advanced social-ecological management philosophies.

[1]Robert C. Merton and Myron Scholes received the 1997 Nobel Prize in Economics (The Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel) for their work on the pricing of options and corporate liabilities.

2.2 Advanced social-ecological management

Social-ecological systems provide a variety of problems that are not present, or are not as severe, in other management situations. These include:

1. The massive scale of ecological systems, in both spacial and temporal dimensions.
2. The variety of interests and participants in the systems.
3. The high amount of uncertainty caused by the complexity of the system.
4. The catastrophic consequences of mismanagement.

In response to these problems various new management techniques have been proposed. Most notably among these are *Adaptive management and governance* and *resilience*.

Adaptive management, originally proposed by Holling (1978), aligns the management of an environment more closely with the scientific investigation of that environment. Among many aspects it prioritizes the use of management action to adapt to emergent and uncontrollable circumstances and events. This is done by performing large-scale experiments through management action to verify or invalidate assumptions. The new information is then used to improve the shared understanding of the environmental system. A special emphasis is put on the use of computer models as a method to create and embody the shared understanding of a diverse group of participants.

Resilience, also a term coined by Holling (1973), is the ability of a social-ecological system to resist disturbances which could cause it to degrade to an unsustainable state. The difference in perspective offered by thinking in terms of "resilience" is it is less concerned with specific predicted risks than with the the ability to absorb any unforeseen disturbance. Given the degree of uncertainty planners are faced with it is not feasible to expect that all major risks can be predicted and specifically mitigated. Thus the goal of resilience thinking is to nurture an inherent robustness within the social-ecological system. Resilience is closely linked with adaptive management, which fosters a greater understanding of the many possible responses of the environment to disturbance.

2.3 Bayesian Networks for modeling social-ecological systems

A Bayesian Network is a statistical model that takes the form of a Directed-Acyclic Graph (DAG) where the nodes represent variables in the social-ecological system and the links represent a causal relationship between two variables. Each variable (or node) is separated into several possible states, these can be quantitative (0-10mm, 10-20mm, 20-30mm) or qualitative, (healthy, unhealthy). The relationship between a node and its parents (the nodes that affect it through a causal link) is defined in a Conditional Probability Table (CPT). The CPT relates possible combinations of the parent nodes' states to the states of the child node (Pearl and Shafer, 1988). These tables can be populated automatically through an equation or historical data; or manually by an expert in the field (Peter, 2010). Once a Bayesian network has been setup it can queried by setting the distribution of probabilities of the states of a subset of the nodes, which will then propagate to show the likely states of the remaining nodes, this is know as a "what-if" query(Potgieter, 2004). An example of a Bayesian network, showing its graphical structure is shown in Figure 1.

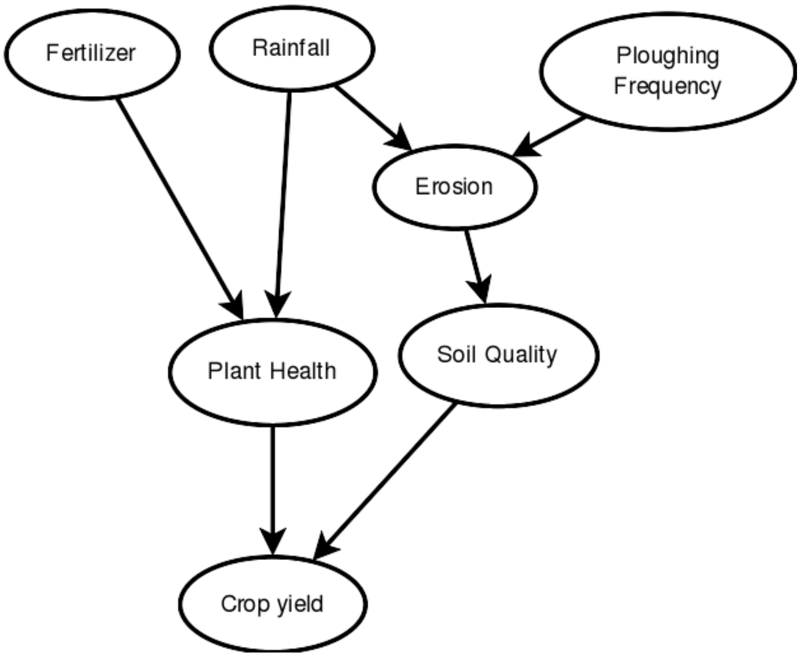

Figure 1: A toy example of a Bayesian network showing the relationships between the variables of an agricultural model.

Bayesian networks have been used extensively in many fields, especially medical diagnosis, financial modeling and machine learning.

Bayesian networks have been used as a tool to model social-ecological systems(Baran and Jantunen, 2004, Borsuk et al., 2004). They exhibit many desirable features for modeling complex systems. Most notably they are:

- The ability to create and change subsystems without changing the entire network (Borsuk et al., 2004).
- A simple graphical structure which makes participatory design more accessible (Baran and Jantunen, 2004).
- The ability to do scenario analysis through "what-if" queries, which allows for the interrogation of different courses of action for decision makers (Peter, 2010).
- They include uncertainty in the modeling predictions, giving decision makers an idea of the certainty of the represented knowledge.

These models were used to inform water regulations in the European union (Baran and Jantunen, 2004)and North Carolina in the US (Borsuk et al., 2004). They provide an excellent tool for facilitating shared understanding in adaptive management (Henriksen and Barlebo, 2008).

2.4 Bayesian Participatory-Based Decision Analysis

The Bayesian Participatory-Based Decision Analysis (BPDA) framework was developed by Camaren Peter (2010) during his PhD and over 5 years of work with the CSIR[2]. It

[2]CSIR - Council for Scientific and Industrial Research

formalizes an approach for trans-disciplinary case-study research using Bayesian networks. The BPDA process consists of 3 phases, which are initially sequential but iteratively become increasingly overlapping.

Phase 1 Interdisciplinary participatory processes are facilitated to create a graphical causal map showing the relationships between the core variables in the system.

Phase 2 Chains of evidence are formalized into probabilistic relationships. These are combined with the graphical causal maps to create a Bayesian network.

Phase 3 Critical gaps in the required knowledge are identified and focused quantitative research is done to close them. This new information is then used to constrain the graphical causal maps and the Bayesian networks from the previous phases. In this way the process continues iteratively.

The BPDA approach was developed out of and used in numerous case studies. It allows for truly trans-disciplinary participation through its ability to capture both quantitative and qualitative knowledge in a single representation . The resulting Bayesian network can be used to test hypotheses and uncover gaps in knowledge and errors in assumption.

The iterative nature of the development of the models creates a "multi-loop learning framework", a concept proposed by De Wit (2001), which he states is vital to developing a management policy for complex and dynamic systems. The core contribution of the proposed masters is to extend this "multi-loop learning" to the entire lifetime of the model through an iterative automated learning process.

3 Core Contribution

The crux of the proposed masters lies in turning the BPDA models into a monitoring framework by linking it up to real-time or near real-time data-sources. The purpose of this monitoring framework is to interrogate the correctness and ultimately the value of the models. Allowing for the best possible models to be developed and tested. This is done with a mindset based on the end use of such models, which is ultimately to assist decision makers in complex social-ecological problems.

Central to the reasoning behind the approach taken is the understanding that a model is inherently incorrect. As stated by Richardson (2003):

> ". . . the model is no more than a rough and ready caricature, or metaphor, of reality. As such the knowledge contained in the model should be regarded with a healthy skepticism, seeing it as a limited source of understanding. "

Given this understanding that models are inherently flawed, and that our interest in modeling social-ecological systems is primarily to aid decision makers, the proposed masters intends create a real-time monitoring system that:

- Helps researchers and decision makers interrogate the validity of the model
- Allows the model to adapt from live data feeds

- Reason between different explanations for observed behaviour, allowing the best hypothesis to be selected.
- Interrogates the validity of decisions made based on the model.

3.1 Interrogating the validity of the model

Fundamentally a model should represent reality to a satisfactory degree to allow reasoning about the system. A model that does not represent reality, or rather is consistently inaccurate in its prediction about reality, is of little use. Thus the first and most important monitoring task is to check that over time the model is generally correct. Obviously since Bayesian models are probabilistic in nature checking their accuracy requires a large amount of data. Further more the phrase “accurate” needs to be rigorously defined in a quantitative and qualitative sense.

Undoubtedly over time there will be discrepancies between the model and reality. Disc\r because the model is incorrect or because the system being modeled has undergone a change. Complex adaptive systems inherently exhibit emergent behaviour which can lead to rapid shifts between stable states. Fundamentally the discrepancies can be of a few very different types:

- Minor discrepancies in the model
- Major discrepancies in the initial model
- A result of an emergent phenomenon that was unaccounted for by the model.

3.1.1 Dealing with minor discrepancies

Minor tweaking of the Conditional Probability Tables with in the model is to be expected, when only minor discrepancies are detected the information gathered should be incorporated into the model, thus making it more accurate. This would seem to be especially useful in the cases where subjective expert opinion was used to generate the probability tables for a set of variables, as it would allow for the relationships to be accurately quantified.

3.1.2 Detecting a major discrepancy between the model and observed data

It is possible ,and often likely, that their are major inaccuracies in the initially designed model, in that it does not, and never did, reflect the reality of the system being modeled. In this case it is imperative to detect this as early as possible. Once detected It would be desirable to be able to localize the parts of the model that are the least correct. This approach is possible due to the separated nature of subsystems within a Bayesian network. Major errors in the model can also occur if an important variable has been left out of the model. In this case it would be interesting to try to see if some sort of statistical regularity can detect the presence of a hidden variable, in order to alert the system modelers to the possibility. Once a discrepancy is detected ideally the sub-systems would be re-modeled, and then incorporated back into the framework and used to review the decision making procedure.

3.1.3 Detecting and dealing with emergent changes and system evolutions

Complex systems have the capacity and propensity to evolve. They can often rapidly move between multiple stable states. When this occurs it is likely that the model will no longer reflect reality, however this is not because the model was incorrect, simply that it modeled the system in a previous state. Differentiating this from the case where there were initial errors in the model is vital. It would allow the monitoring framework to alert relevant parties that a phase shift has taken place. This would potentially lead to updating the model, but with the added information of why it is no longer reflective of reality.

Further if the stable states of an environment are known, or over time have been observed, the monitoring framework could switch models to use the model that best describes the new state of the system. Further the evolution of the system will now have been carefully monitored, showing how the relationships between variables changes, and which variables and relationships become more dominant.

Unfortunately given the time restrictions of the masters program this step may only be able to be achieved on simulated data. It is impractical to expect a monitored system to evolve in the time allocated to the research.

3.1.4 The model verification process

The above model verification procedures form part of a feedback cycle to iteratively improve the model. A diagram of the feedback cycle is shown in figure 2.

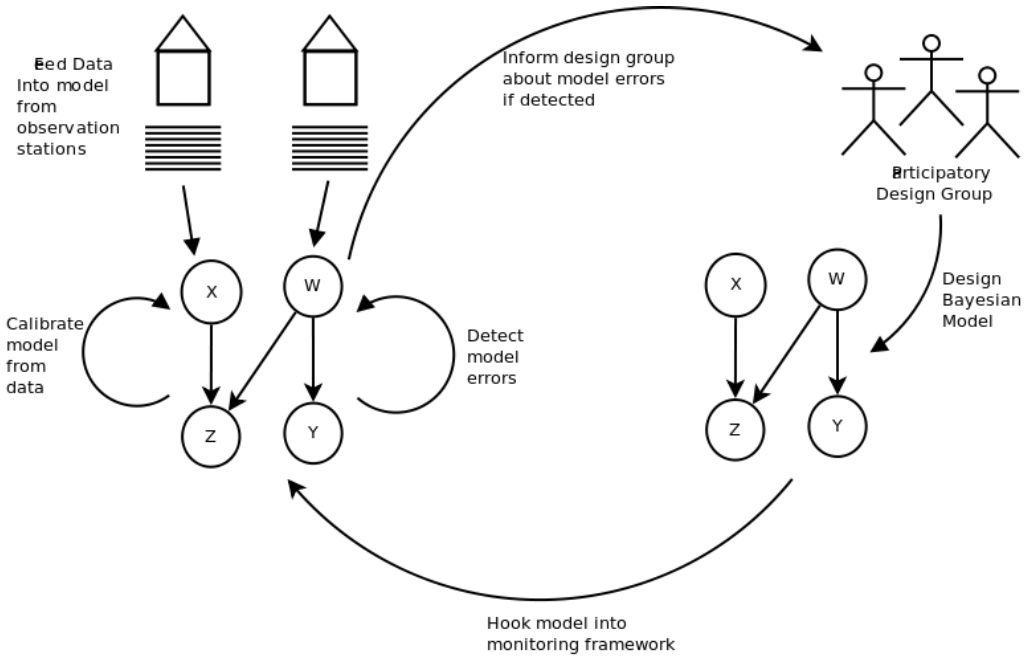

Figure 2: The model verification and updating process.

The feedback loop starts with the initial design of a BPDA model by a participatory design group. Once the model is designed it is hooked into the proposed monitoring framework.

The monitoring framework constantly feeds data into the model from observation stations in the environment. The data is used to calibrate the model if small discrepancies are found. at the same time the framework is checking the model for major defects, if one is found then the design group is informed with as much information about where in the model the error has been found as is available. The design group then makes the requisite changes to the model and the process iterates. At each stage of the process the model is improved, making it more robust to changes in the environment. More importantly an out-of-date model is never used to inform decision making.

3.1.5 Comparing possible hypotheses for observed phenomenon

Often there are multiple possible explanations for observed phenomenon, especially in a participatory design process. These explanations, or hypotheses, manifest them selves as different possible BDPA models. The proposed modeling framework could very easily be used to compare these hypotheses, in order to choose the best one or create a synthesis that best describes the observations. Competing models could simply be entered into the framework in parallel, with each model being given a score based on how little the observation deviates from it. This could then be interpreted by the design group in a similar feedback loop to the one shown in section 3.1.4.

3.2 Interrogating the validity of decisions

As previously stated decisions are made based on an assumption that some cause-and-effect relationship exists within the system. A decision is only useful so long as the relationship it is based on is correct and stays correct. To this end the most important role of the monitoring system is to monitor the correctness and continuing validity of the assumptions upon which a decision is based.

A necessary step in monitoring decision assumptions is to develop some way to codify these assumptions with relation to the model.

When a codified assumption is found to no longer be true, or is not found to be true with an acceptable probability, the monitoring framework should alert decision makers and modelers, allowing them to take further action. This will tie into the general interrogation of the validity of the model as well as the detection of system evolution.

3.2.1 The decision verification process

Decision verification is also a feedback cycle, illustrated in figure 3. Starting with a decision maker using a BPDA model and making a decision based on it. The decision is then codified and fed into the monitoring framework. Every time the model changes, whether due to calibration from data or remodeling in a participatory process, the assumptions are tested against the model to see if they still hold. If they do not hold, then the decision maker is informed about the consequences of the changes to the model. The decision maker then reconsiders the decision and decided on a new course of action. The new decision and policy then theoretically influence the system, which in turn may affect the model.

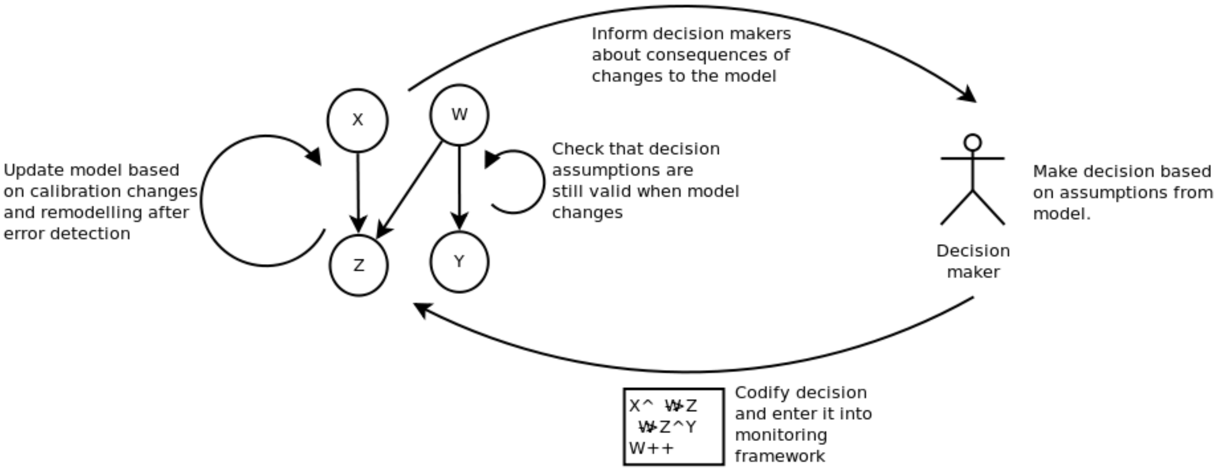

Figure 3: The decision verification process

4 Methodology and Outline of Activities

An iterative design and research philosophy is proposed for this masters. The process starts with a rapid prototype of the framework. The prototype will be built for a simplified version of the problems, a version where many restrictive assumptions have been made about the problem domain, such as assuming that the input data from the environment is of a standard spatio-temporal scale. Once a prototype of the full feedback system has been developed, then each restrictive assumption will be dropped, increasing the complexity of the problem. When the system works with the now more complex problem another assumption is dropped until the system works under the assumption of a realistic environment.

During the earlier stages of the research and development simulated data will be used. Simulated data is easier to produce than real data is to find. Further simulated data has the advantage of being easily manipulated, allowing many possible error scenarios to be generated and tested.

Once the framework is developed it is important to test it on a real case study. A case study, or part there of, from Camaren Peter's PhD can be used for this. The required artifacts from the case study are the BPDA models as well as access to new and historical data about the system. Access to this data will have to be organised early in the development cycle to ensure that it is available when testing needs to be done. The case study will have to be of the appropriate complexity to have a sufficiently interesting model, however too large a model will make it difficult to practically carry out much research since too much time will be spent on the data gathering process. The case study should also have large amounts of good quality data available. Success on a real case study should be seen as a definite sign that the framework works and the project is a success. However, it is impossible that all of the range of possible behaviour could be expected from any one case study, as such it is likely that only the core aspects of the system will be able to be tested in the case study.

5 Foreseeable Risks

5.1 Overly restrictive assumptions

If the assumptions that the framework is built around are not realistic then it will be of decreased usefulness. The proposed methodology is based around iteratively reducing the amount of unrealistic assumptions. The risk exists that the jump from an unrealistic assumption to a realistic one may have too many design implications, thus requiring significant reworking, which will waste time.

5.2 Reasoning about model inaccuracies

Much of the automated reasoning in the proposed system revolves around trying to quantify how much the model does not know. This raises the problem of not being able to bench mark in real systems, since we cannot know what we don't know. As stated by Taleb (2008):

> "We don't have the luxury of sitting down to read the equation that governs the universe; we just observe data and make assumption about what the real process might be and *calibrate* by adjusting our equation in accordance with additional information"

This raises obvious problems about judging the correctness of a prediction outside of simulated data.

5.3 Codification of decisions and assumptions

The codification of knowledge and intention is a subtle and complicated affair which can become and endless amount of possible work. The challenge here is to balance the need for a semantically meaningful representation with a simple, practical and achievable framework. This aspect should not dominate the other aspects.

5.4 Data collection

In any project where large amounts of data is required, gaining access to enough data sources becomes a problem. Further more, Bayesian machine learning requires data at standard spatio-temporal scale. In order to use all the available data sources some of the data will have to be preprocessed or interpolated, which in itself can bias the system.

The masters program will not cover a significant length of time in terms of social-ecological systems. This may make it difficult to get meaningful results for some of the more complicated matters surrounding system evolution. This will most likely require that simulations are used, which is a much less rigorous test of the system and theory.

5.5 Software complexity

The software underlying the BPDA framework is complex and multifaceted, as are most machine learning systems. There is a risk that too much research time is sacrificed to dealing with the extraneous complexities of the software.

6 Benefits of Research

The end goal of this line of research is to allow for complex model based management regimes to be more easily implemented and more reliable. The use of Bayesian networks as tools for social-ecological planning is becoming increasingly widespread, and as such their influence on decision making is increasing. However Bayesian networks are susceptible to many of the same problems of any other modeling technique, and as such must be validated. The BPDA reduces the likelihood of model errors through rigorous and iterative participatory process. This research would further decrease the likelihood of errors in the model through using real-time data.

This would help boost the *adaptive capacity* of social-ecological systems through:

- Increasing and improving the shared understanding of how social-ecological systems behave.
- Decreasing reaction times to unexpected emergent behaviour.
- Constantly updating and re-evaluating shared understanding with real-time data.

We only have one earth and we are increasingly stretching its ability to regulate and maintain itself. A deeper understanding, with hypotheses that are as tested as possible are necessary for humanity as a whole to better manage and govern our natural resources and our interactions with them.

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