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Clean energy investment scenarios using the Bayesian network

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Clean energy investment decisions are getting more difficult to make due to public reactions. In order to support the policies in the field, analysis of the positive conditions is needed. This research aims to construct the positive scenarios for nuclear energy and renewable energy investments in the state of Oregon, USA. The Bayesian network technique will be used to create the scenarios. Oregon has a wide range of renewable energies; hence, investment is becoming more complex. Criteria affecting the decisions are taken from the literature, but were reviewed with energy authorities in Oregon in order to define the interactions.

Keywords: Bayes network; clean energy; scenario analysis

1. Introduction

Investment in sustainable energy is rapidly increasing as people become more concerned about global warming. Clean energy investment is a strategic approach for local and global governors, and policies are designed to invest in clean energy without harming the natural environment. Although conflicts about reducing CO2 emissions and destroying the rivers cause public reactions, several researchers have shown that ecological sustainability is only possible by avoiding investments in fossil energies.

The idea behind the need for a vigorous clean energy investment is rooted in the lack of concern about climate change. Climate change is a real and tangible dilemma and today more people believe that a more robust use of clean energy is one of the solutions for preventing climate change (Keane 2007).

Policies are designed based on the analysis of the attributes that affect the regional evaluation of generally accepted criteria. An alternative combination of conditions can alter the policies. These attributes involve multiple criteria to be input into the decision-making process equation. Some attributes to consider, although not all, are initial costs, operating costs, job intensity, perceived acceptability, ecological impact, environmental factors and efficiency (Daim and Suharto 2012).

This study supports the local authorities in designing policies by constructing alternative scenarios for investing in nuclear energy or renewable energies. The Bayesian network (BN) technique
was used to select the best conditions among a wide variety of values. The application of the technique executed in collaboration with energy authorities in the state created the necessary conditions.

A brief background on clean energy follows in the next section. Causal maps (CMs) and the BN technique are explained in Section 3 and details of the application follow that. The final section presents conclusions and recommendations for further studies.

2. Background

Concern over the global energy system is driven by three major factors: the combustion of fossil fuels as a driver of global warming, national security related to energy trade and global scarcity due to anticipated supply shortages (Cullen, Allwood, and Borgstein 2011). This concern has been discussed widely and in many different fields but with a focus towards energy efficiency and alternative energy sources. Discussion on the alternative energy resources becomes more complex not only due to the different alternatives that the scientists are working on, but also due to many other factors that can drive which portfolio can be chosen among the alternatives (Spivey 2005).

In most scenarios, the problem of supply shortages or demand growth is generally approached using a scenario of low-cost conservation and energy-efficiency resources. However, looking at the global tendency to shift the focus to renewable energy resources that are friendlier to the environment, i.e. clean energy, most countries have been working to stimulate more production of that kind of clean energy.

Supply substitution from fossil energy to alternative energy resources is gaining more attention globally. This is reflected in the International Energy Agency (IEA) data on worldwide research and development expenditures on energy, where less than 10% of spending has been on energy efficiency in comparison with 40% for nuclear fusion alone (IEA 2008). In the USA, for example, the government established Renewable Portfolio Standard laws, which require the states’ power producers to generate a significant percentage of their electricity from specifically designated, low-impact renewable energy sources by a stipulated date (Northwest Power and Conservation Council 2010).

Clean energy investments deliver improvements in both economic and environmental conditions, which cannot be disregarded by the regional governments. Hanson and Laitner (2004) summarised some of the ecological advantages of the investment in clean energies as less waste production; reduction in CO₂ emission, which results in less air pollution; and more efficient use of energy resources. These also result in reductions in the cost of energy production and energy consumption.

Efficient utilisation of energy takes an increasingly important role in future sustainability. Dovi et al. (2009) observed that if the electricity consumed in industry and homes was met by using clean energy, the atmosphere would be cleaner than today for a hundred years. However, this will only be possible by educating individuals and by publicly supported programmes for the business world.

The fact that fossil energy limits are well known is also obliging wider usage of clean resources in energy production. Clean energy resources include nuclear energy as well as renewable energies. Because of the security issues in nuclear energy production, the focus is mainly on renewable energies. However, the cost and efficiency advantages do not allow us to neglect nuclear energy (Buskirk 2006). Clean energy, therefore, is the general term for nuclear, hydro, solar, wind, geothermal and bio energies.

As the alternative sources and the variety of energy technologies increase, the complexity of investment decisions increases. Predictions of events have an important role in decision-making. In forecasting, the main assumption is that the future will be much like the past. Therefore, the
Table 1. Oregon’s electric generation supply mix.

<table>
<thead>
<tr>
<th>Source</th>
<th>Annual energy (aMW)</th>
<th>Percent of total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hydro-electric</td>
<td>2414</td>
<td>44.1</td>
</tr>
<tr>
<td>Coal</td>
<td>2285</td>
<td>41.8</td>
</tr>
<tr>
<td>Natural gas</td>
<td>386</td>
<td>7.1</td>
</tr>
<tr>
<td>Nuclear</td>
<td>187</td>
<td>3.4</td>
</tr>
<tr>
<td>Biomass and MSW</td>
<td>136</td>
<td>2.5</td>
</tr>
<tr>
<td>Wind and geothermal</td>
<td>53</td>
<td>1.0</td>
</tr>
<tr>
<td>Oil and other</td>
<td>9</td>
<td>0.2</td>
</tr>
<tr>
<td>Total</td>
<td>5470</td>
<td>100</td>
</tr>
</tbody>
</table>

Note: MSW, municipal solid waste.

forecaster must analyse and understand the structure of past events to make accurate predictions. However, uncertainty in the real world has created problems for capturing the dynamic structure of events. Recently, CMs and as a special case Bayesian maps have been used in decision support (Trucco 2008). The Bayesian mapping gives a chance for networking and detailed probability analysis to create scenarios for energy investments (Cinar and Kayakutlu 2010).

Oregon is a unique case with regard to its commitment to clean, renewable and sustainable energy production as evidenced by Senate Bill 838, the Oregon Renewable Energy Act, which states that 25% of Oregon’s electric load must come from new renewable energy sources by 2025 (Daim et al. 2009). In addition, the Governor’s 2006 Energy Action Plan called for keeping energy prices competitive over the long haul, reducing dependence on overseas energy sources, protecting Oregonians from expected spikes in the price of fossil fuels, and reducing emissions that lead to global warming. The governor also sought to promote investment in clean energy and the associated creation of ‘green jobs’. One estimate is that for every $100 million invested in clean energy, Oregon will see the creation of more than a thousand new jobs (Economic Revitalization Team 2009). For this reason, Oregon has a vital position with regards to renewable energy sources.

Other methods have been used in evaluating renewable energy in Oregon. Daim et al. (2009) used a technology assessment method for the wind energy technology. Daim, Kayakutlu, and Cowan (2010) used a fuzzy goal programming method for developing a renewable energy portfolio in Oregon while Cowan, Daim, and Anderson (2010) focused on technology development and adoption of sustainable hydro-electric power in the Pacific Northwest. Daim and Cowan (2010) used multiple perspectives for assessing a renewable energy portfolio; Daim and Suharto (2012) utilised optimisation methods for assessing storage technology for wind energy. This paper enriches the findings from the earlier research.

3. CMs and BN

3.1. CMs

In a real-world situation, decision maker(s) utilise the available information for the analysis and reaching decisions. The process of data analysis and decision-making can be considered a prediction process. Liu (2001) mentioned that, in general, there are two types of tasks in this process, which require different approaches: (1) classification, which is concerned with deciding the nature of a particular system given the features, which usually produces labelled data; (2)
and causal prediction, which is concerned with the effect of the changes in some features to other features in the system.

The later process – causal prediction – is more related to causal inference, which is concerned with the degree of change of feature(s) in the prediction process. This change will directly or indirectly alter some of the features in the data. In order to understand the effect of the change(s), decision maker(s) must have mechanisms that can discover the cause-and-effect relations from the data set. CMs are widely known to provide an approach to such a problem. Eden (2004) defined CMs as a ‘directed graph characterized by a hierarchical structure which is most often in the form of a means/end graph’. In the last decades, CMs have been widely used to construct a framework and represent major factors, knowledge and conditions that influence decision-making processes (Nadkarni 2004; Sahin, Ulengin, and Ulengin 2006).

Causal relationships can be either positive or negative, as specified by a + or a – sign, respectively, on the arrow connecting two variables. The variables that cause the change are called cause variables and the ones that undergo the effect of the change are called effect variables (Lazzerini and Mkrtchyan 2010).

CMs provide a rich representation of ideas, through the modelling of complex structures, representing the chain of arguments, as networks (Nadkarni 2001; Eden 2004). Often the last stage of intervention process is to identify and agree to a set of potential strategic options. In some cases, the preferred direction may naturally emerge from a process of negotiation; in others, further, more or-less formal, analysis to evaluate the options and to understand their impacts on the goals can be helpful (Montibeller and Belton 2006). CMs can help us to look at the problem more extensively than other decision tools, which consider causal relations, such as regression. CM has been widely used in international relations, administrative science, political science, sociology, policy analysis, organisational behaviour and management (Eden, Ackermann, and Cropper 1992; Liu 2001; Eden 2004; Nadkarni 2001, 2004; Siau and Tan 2005; Montibeller and Belton 2006).

One major concern that needs to be addressed is that CMs are not easy to define and the magnitude of the effect is difficult to express in numbers. In general, CMs are constructed by gathering information from experts, who are more likely to subjectively express themselves in qualitative rather than quantitative terms (Lazzerini and Mkrtchyan 2010). Kosko (1986) introduced the concept of fuzzy CMs (FCMs) to overcome the problem. FCM represents the concepts linguistically with an associated fuzzy set. FCM is a signed directed graph that allows feedback and employs concepts (nodes) and weighted edges between concepts (Huang, Ni, and Miao 2009). The degree of relationship between concepts in an FCM is either a number in [0; 1] or [−1; 1], or a linguistic term, such as often, extremely and some. (Lazzerini and Mkrtchyan 2010).

3.2. BN

Bayes’ theorem was developed by Thomas Bayes (1702–1761); since then the theory has had a major effect on statistical inferences. The probability of a cause is inferred by the Bayes theorem when the effect of the cause is observed. The theorem has expanded over time, and it has been used as a cause-and-effect diagram since the end of the twentieth century (Neapolitan 2009). Some of the advantages of using BNs are that (1) BNs can handle incomplete data sets and (2) BNs focus on causal relationships and then facilitate the combination of background knowledge and experimental data (Spiegelhalter et al. 1993; Nadkarni 2001).

BNs are models in which events are connected to each other with probabilities. This model can be anything; for example, economic reasons, vehicle parts and ecosystems can be modelled with BNs. If the probabilities of events that affect each other are known exactly, the results are closer to the true results (Norsys Software Corp. 2011).
BNs are directed acyclic graphs (DAG), which means there are no cycles. In other word, BNs are probabilistic graphical models that restrict the graph so that it is directed and acyclic. Other models such as Markov random fields have no such restrictions (Mortensen 2006; Ho 2011). If there is a link between A and B (\( A \rightarrow B \)), we say that B is a child of A and A is a parent of B (Jingjing, Yan, and Ting 2008; Zeng, Xiang, and Pacekajus 2008). In BNs, a link from node A to node B does not always imply causality. It implies a direct influence of A over B and the probability of B is conditioned on the value of A (Alpaydin 2004; Thibault, Bonnevay, and Aussem 2007).

The direction of the arrows in BNs can be explained with causality as long as the arrows do not cause an endless loop. The advantage in comparison with other statistical models such as regression is that causality can supply missing information and details as well as bring the priorities and key factors into focus (Siau and Tan 2005). Besides, the network is constructed in such a way that in the beginning all factors have the same certainties.

If A and B are the occurrences of two factors, the Bayes rule is defined as follows:

\[
P(B/A) = \frac{P(A/B) \times P(B)}{P(A)},
\]

where \( P(A) \) gives the probability of the occurrence of factor A and \( P(A/B) \) is the probability of the occurrence of A when the B event has occurred. Hence, the link from node A to node B means that factor A has a direct effect on factor B. Furthermore, the probability of B depends on the probability of A (Changliang and Zhanfeng 2009). Each node of the network is annotated with a conditional probability distribution (CPD) that represents \( P(X_i|Pa(X_i)) \), where \( Pa(X_i) \) denotes the parents of \( X_i \). The pair \( (G, \text{CPD}) \) encodes the joint distribution \( P(X_1, \ldots, X_n) \). A unique joint probability distribution over X from G is factored as follows:

\[
p(X_1, \ldots, X_n) = \prod_i (p(X_i|Pa(X_i))).
\]

BNs help us to observe the whole structure of factor interactions from a graph. This way, marginal and conditional probabilities of the factors can be computed by marginalising over the joint (Trucco 2008).

4. Application

The BN technique was used to construct scenarios of energy investment for Oregon, where energy generation, stability and efficiency are vital problems. A literature review showed a variety of factors affecting the decision of energy investment. These factors were a collection of attributes analysed by using multi-criteria decision-making (Chatzimouratidis and Pilavachi 2008), variables studied in fuzzy optimisation (Martinsen and Krey 2008) or qualitative methods (Mulugetta, Mantajit, and Jackson 2007). We observed 29 decision-driving forces covering ecological, economical, technological and social variables. These factors were reduced to 11 factors through the execution of a cognitive map study.

4.1. CMs development

See Cinar and Kayakutlu (2007) for more detail on how the CM process on clean energy was formulated and executed. The 11 factors for Oregon, which correlated with each other, are explained in the following:
Table 2. Interrelation of energy investment criteria.

<table>
<thead>
<tr>
<th></th>
<th>Renewable energy investments</th>
<th>Nuclear energy investments</th>
<th>Primary energy consumption</th>
<th>Primary energy import</th>
<th>Renewable energy production</th>
<th>Fossil fuel production</th>
<th>GDP per capita</th>
<th>Population</th>
<th>Urbanisation</th>
<th>Industrialisation</th>
<th>Greenhouse emission</th>
</tr>
</thead>
<tbody>
<tr>
<td>Renewable energy investments</td>
<td>0</td>
<td>-1</td>
<td>0</td>
<td>-1</td>
<td>1</td>
<td>-1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>-1</td>
</tr>
<tr>
<td>Nuclear energy investments</td>
<td>-1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>-1</td>
<td>-1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>-1</td>
</tr>
<tr>
<td>Primary energy consumption</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Primary energy import</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Renewable energy production</td>
<td>1</td>
<td>-1</td>
<td>0</td>
<td>-1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>-1</td>
</tr>
<tr>
<td>Fossil fuel production</td>
<td>-1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>-1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>-1</td>
</tr>
<tr>
<td>GDP per capita</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>-1</td>
</tr>
<tr>
<td>Population</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>-1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Urbanisation</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Industrialisation</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Greenhouse emission</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>-1</td>
<td>1</td>
<td>-1</td>
<td>-1</td>
<td>0</td>
<td>-1</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
1. **Renewable energy investment**: The probability of investment in hydro-energy, solar and wind energy, geothermal energy and biomass in all the regional energies.

2. **Nuclear energy investment**: The probability of investment in nuclear energy in all the regional energies.

3. **Primary energy consumption**: Total amount of energy consumption in Oregon.

4. **Primary energy import**: Amount of energy bought from other states or imported from abroad (e.g. Saudi Arabia).


6. **Fossil fuel production**: Heating energy produced by using fossil resources.

7. **Gross domestic product (GDP) per capita**: Economic strength of the consumers in Oregon.

8. **Population**: Growth rate of population in the state.

9. **Urbanisation**: Rate of migration from rural areas to the big cities.

10. **Industrialisation**: Increase in rate in manufacturing sites in the state.

11. **Greenhouse emission**: Average amount of greenhouse emission effect in the state.

### 4.2. Cognitive matrix development

A cognitive survey was run among the electricity authorities of Oregon. Seven experts answered the interactions by indicating if the relation was positive (+1), negative (−1) or none (0).

The experts’ seven responses were combined by taking the mode of responses. The resulting comparison matrix is given in Table 2. The matrix can be read from row to column. For example, renewable energy investment affects primary energy imports negatively, which means that if renewable energy investment increases, energy imports will decrease.

Equipped by the cognitive matrix given in Table 2, we developed our original CM as shown in Figure 1.

---

**Figure 1.** Original CMs.
Figure 2. Bayes map of energy investment.

Figure 3. Scenario 1: Optimistic conditions with nuclear energy investment.
It seems that each variable or node in the original CMs as shown in Figure 1 has reciprocal influences on others, something that is not allowed in developing a Bayesian causal map (Nadkarni 2001).

4.3. Converting CMs to a Bayesian causal map

Several rules need to be addressed in converting CMs to a Bayesian causal map (Nadkarni 2004):

*Direct causality between variables:* As mentioned above, a BN is a DAG that only allows variables to have direct causality. For example, if we look at the connection between urbanisation-energy consumption and greenhouse emission in our original CM in Figure 1, it seems that urbanisation affects both energy consumption and greenhouse emission. In fact, urbanisation causes greenhouse emission through the increase in energy consumption. Therefore, the direct effect from urbanisation to greenhouse emission should be eliminated because it is redundant.

*Deductive reasoning:* The experts were instructed that an arrow should be directed from cause to effect only.
Figure 5. Scenario 3: Stable conditions with nuclear energy investment.

**Similar timeframes to avoid loops and reciprocal influence:** The following rules were applied in forming the network:

BN is an independent map. \( A \rightarrow B \) means \( A \) is related to \( B \). In addition, \( A \rightarrow B \rightarrow C \) means, \( C \) is conditionally independent of \( A \) given \( B \). This allows removal of arrows that are conditionally independent.

Direct and indirect effects are described between factors. Indirect effects are eliminated in the BN.

As mentioned earlier, no cycles are allowed in the BN.

### 4.4. Probabilistic stage

The last stage is the probabilistic stage. For this purpose, the historical data for Oregon for all variables were examined and then tabulated. One of the benefits in using Netica® software is it allows us to incorporate tabulated data into our model and then Netica computes the marginal and conditional probabilities of all variables based on that incorporated data (Norsys Software Corp. 2011). All data were continuous except for urbanisation, industrialisation and the decision nodes (clean energy investment). The interval for all states (low, medium and high) on all variables was set up and verified by the experts.
5. Results and discussion

The necessary data to be applied in the BN given in Figure 2 were collected from secondary sources (Federal Ministry for the Environment Nature Conservation and Nuclear Safety 2004; Energy Department of Oregon 2010; Northwest Power and Conservation Council 2010; Oregon Department of Energy on APPR 2010). After the initial conditions were designed and the major probabilities were stated, data were entered into Netica. Design of the model in Netica was completed by defining the conditions.

In our attempt to construct the Bayesian causal map, we used two different approaches: a data-based approach and a knowledge-based approach. The data-based approach was used when the variables in our model had significant data to be introduced to our model, while the knowledge-based approach used the causal knowledge of the domain experts in constructing BNs (Lauritzen et al. 1990; Heckerman 1999). The knowledge-based approach is especially useful in situations where domain knowledge is crucial and data are scarce (Nadkarni 2004).

When the software was run, six scenarios were developed in the analysis of full nuclear investment or full renewable investment. The scenarios were alternated by defining three different possibilities: optimistic, stable and pessimistic based on greenhouse emission and import factors.
The stable case occurs when the current percentages and rates continue without any increase or decrease. The optimistic case occurs when greenhouse emission is improved and imports are reduced (more in-state production). On the contrary, pessimistic scenarios consider that greenhouse emissions are getting worse and imports are increasing (less in-state production).

The optimistic scenarios shown in Figure 3 show full investment in nuclear energy when greenhouse emissions are improved and in-state production is increased. Just the opposite of these conditions is shown in Figure 4, where improvements in greenhouse emissions and in-state production are used for full investment in renewable energies.

The stable scenarios shown in Figures 5 and 6 demonstrate when the GDP rate of increase is medium, population increase is low, and urbanisation and industrialisation are medium, the energy consumption increase rate becomes low. In that case, greenhouse emissions and energy imports are also low. Scenario 3 investigates nuclear energy investment under these conditions, whereas scenario 4 investigates renewable energy investments under the same conditions.

In the pessimistic scenarios shown in Figures 7 and 8, all the conditions in stable scenarios are kept except a low GDP increase rate and a low industrialisation rate. In all three cases, the greenhouse emission changes and energy imports are investigated; the results achieved are summarised in Table 3.

As observed in Table 3, in optimistic scenarios investments in nuclear energy cause more increase in both greenhouse emissions and energy imports in comparison with the renewable energies.
Figure 8. Scenario 6: Pessimistic conditions with renewable energy investment.

Table 3. Scenario results.

<table>
<thead>
<tr>
<th></th>
<th>Greenhouse emission</th>
<th>Energy import</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Optimistic</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nuclear</td>
<td>53.1</td>
<td>57.5</td>
</tr>
<tr>
<td>Renewable</td>
<td>42.4</td>
<td>48.9</td>
</tr>
<tr>
<td><strong>Stable</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nuclear</td>
<td>58.4</td>
<td>54.2</td>
</tr>
<tr>
<td>Renewable</td>
<td>42.7</td>
<td>41.6</td>
</tr>
<tr>
<td><strong>Pessimistic</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nuclear</td>
<td>57</td>
<td>50.6</td>
</tr>
<tr>
<td>Renewable</td>
<td>46.2</td>
<td>41.9</td>
</tr>
</tbody>
</table>

6. Conclusion, limitations and future research

According to Nadkarni (2001), most of the focus in CMs has been in their use for knowledge representation. This study enables decision-makers in clean energy to use CMs for decision-making
by converting the map into BNs. Once a BN is constructed, it can be used to make probability inferences about the variables in the model. The modified map can be validated qualitatively through experts’ consensus, and quantitatively through examining the posterior probabilities of decision variables under different scenarios.

BNs are quite an effective method to conclude plans that have a complex structure. Energy also has a complicated structure because of the numerous factors that affect the energy investment. In this study, with the help of the BN method, the framework was generated for the planning investment in energy.

The results obtained in the optimistic, stable and pessimistic scenarios shown in Table 3 indicate that both greenhouse emissions and energy imports will be improved if investments are realised fully in renewable energy resources, thus allowing Oregon to continue all its plans of increasing investments in renewable energy resources. Nuclear energy investment is not suggested in Oregon if greenhouse emissions are targeted to be reduced and with the objective to decrease dependence on other states or countries for energy.

This study was limited to major ecological and industrialisation objectives. Further studies involving more detailed objectives such as job intensity, perceived acceptability, ecological impact, environmental factors technology efficiency among alternatives would give more confidence to decision-maker(s) in Oregon, especially when the need to create more jobs and save the environment at the same time become the main focus for Oregon’s objective as stated in the Governor’s 2006 Energy Action Plan (Economic Revitalization Team 2009).

Another enhancement on the subject would be comparing scenarios among several renewable technologies. The driving variables then would be redefined.

This study brings a new dimension for energy policy-makers. This study was done by utilising the probabilistic inference procedure of BNs to make inferences about variables in CMs. Comparing the result of BNs with other methodologies for analysing the CMs in more dynamic scenarios such as using system dynamics would surely enrich the knowledge of decision-makers since system dynamics allows causal loops within the CMs, something that is not permitted in BNs since BNs require direct acyclic CMs.

References


