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Causal networks in EIA

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Abstract

Causal networks have been used in Environmental Impact Assessment (EIA) since its early days, but they appear to have a minimal use in modern practice. This article reviews the typology of causal networks in EIA as well as in other academic and professional fields, verifies their contribution to EIA against the principles and requirements of the process, and discusses alternative scenarios for their future in EIA.
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1. Introduction

Causal networks are used in many academic and professional fields with various names, graphical implementations, and applications. For disciplines dedicated to the study of effects, such as Environmental Impact Assessment (EIA), causal networks seem like a useful instrument to easily relate and transparently demonstrate causes and effects. In fact, causal networks have been used in EIA since its early days, but they have never been particularly popular.

This article aims to (a) review the typology of causal networks in EIA, both from the literature and current practice, (b) briefly examine causal networks in other academic and professional fields, and (c) draft scenarios for the future of causal networks in EIA.

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2. Review

2.1. Characteristics of causal networks

Succinctly defined, causal networks are diagrams that demonstrate causal relations between their elements. The special identifiers of causal networks are a diagrammatic representation of relationships among elements and the attribution of causality to these relationships.

Networks are abstract diagrams with nodes and links. Nodes can be points, text, or shapes, and they represent the network elements such as activities, wildlife, stakeholders, etc. Links can be lines of various properties, such as pattern, thickness, direction, and colour, and they can represent relations between the network elements. With these combinations of nodes and links, it is possible to create many different types of networks, and some of them are illustrated in this article–especially in Sections 2.4 and 2.5. Causality deals with the functional relations between entities, thus enabling people to explain effects by diagnosing possible causes or to predict effects from the observation of relevant factors. To date there are two main alternative methods to identify and use causality, deductively or inductively (Williamson, 2005), which are illustrated in Fig. 1.

In the deductive method, a hypothesis about a causal relation is formed (near the central circle of Fig. 1), tested, and then proven or rejected—much like in the classic scientific method (Williamson, 2005). In a deductive approach, the conclusion about particulars follows necessarily from general or universal premises—i.e., the tested and approved causal relation, labelled "general rule" in Fig. 1. This type of thinking about causality is also known as variance theory, which sets out to determine experimentally or semi-experimentally (with statistical analysis)–but always in a "black box" approach–that certain effects are present when certain presumed causes are also present (Morris, 2005)—i.e., replicate the "individual observations" of Fig. 1.

In the inductive method, data are collected after observations, and a causal relationship is induced—i.e., a generalised conclusion is inferred from particular instances (Williamson, 2005). This type of thinking about causality is also known as the process theory, which draws

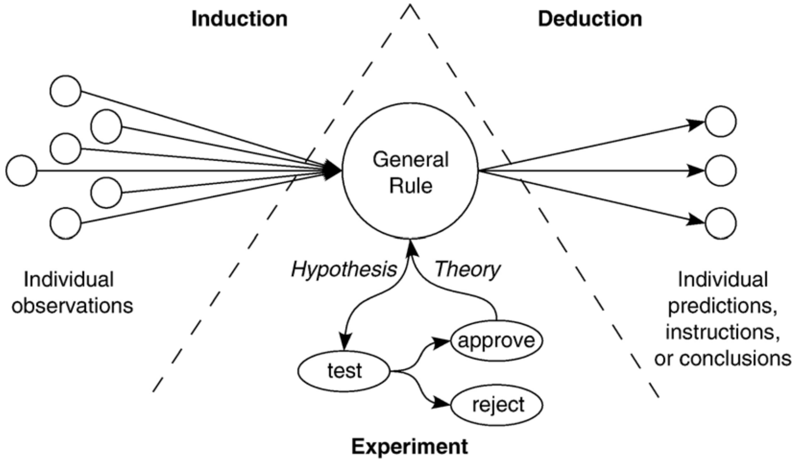

Fig. 1. Schematic layout of induction, deduction, and experiment.

on theory and/or experience to describe the mechanism by which the effect is thought to be caused (Morris, 2005).

2.2. Overview of causal networks in EIA

Both the network logic and the causality logic of causal networks seem to tie in well with the EIA process. Causal networks presuppose (a) that there are links (or interaction pathways) between individual elements of the environment and activities (network logic), and (b) when one element is specifically affected this will have an effect on those elements that interact with it (causality logic) (European Commission, 1999). Thus, causal networks have been used in EIA since its early years (Wathern, 1988), and mostly as an analytic technique (Barrow, 1997).

The role of causal networks in EIA has been assigned predominantly to impact identification, prediction, and assessment (Canter, 1996), and particularly regarding cumulative impacts, indirect impacts, and impact interactions (European Commission, 1999), but not to evaluation or further phases of the EIA process (European Commission, 1999). In their given role, causal networks are considered to be best applied to ecological impacts, and difficult to apply to socio-economic impacts, mostly due to lack of data and relative difficulty (e.g., time delays) to conduct research in the latter environments (Barrow, 1997). Causal networks are known to be particularly good for making explicit mechanisms of cause and effect and understanding impacts (European Commission, 1999), and for seeking where and how impacts arise (Glasson, 2001). The highlight of causal networks seems to be their capability to follow impacts to several levels through sequences of interactions (Wathern, 1988)—a fact that also gives them the alternative name "sequence diagrams" (Canter, 1996). Thus, they are particularly appreciated for discovering indirect impacts—e.g., secondary, tertiary, and subsequent levels (Htun, 1988).

One of the two drawbacks of causal networks appears to be their certain difficulty to deal with time and space (Canter, 1999; European Commission, 1999). Their second drawback appears to be their potential risk for increased complexity (European Commission, 1999; UNEP, 2002) beyond the optimum level of simplification (Holling, 2001). It is suggested that when causal relationships appear too complex, people tend to either simplify in their own way or ignore the causal model altogether (Goldvarg and Johnson-Laird, 2001).

2.3. Non-graphical expressions of causality in EIA

2.3.1. Text

Causality, a fundamental notion for EIA, can be expressed by non-graphical means such as text. Text gives much freedom of expression when describing project and environment elements, as well as their interactions. Eventually, though, the complexity of the systems involved in EIA normally oblige so many cross-references that text may lead to confusion or omissions. Text, in its appropriate formulation, is capable of providing all the necessary explanations about the causal relations among elements, as the following example illustrates.[1]

> The damage caused during construction from the compaction of soil, change in groundwater level and changes in the micro-climate caused by the removal of vegetation would also impact

[1] This quote is from a case study presented and commented in Section 2.6; the text is transformed, together with similar statements, into two alternative diagrams: Figs. 16 and 17.

Environmental Parameters

Activities	Noise	Air Quality	Vegetation	Aquifers
Excavation	X		X	
Irrigation				X
Traffic	X	X		
Construction	X	X		

X = significant effect

Fig. 2. Sample impact matrix extract with significant effects marked.

on the habitat networks, causing shifts in the composition of the animal and plant communities. (Source: European Commission, 1999, p.A2–32)

2.3.2. Matrices

Impact matrices have been another alternative to express causality in EIA. They have been an efficient instrument to relate the system components with the project actions one by one. Matrices express causality by crossing information in pairs between two sets of data, the columns and the rows, which represent the development actions and the environment, respectively. This relation permits the study of the effects of individual actions to individual environmental parameters. The main body of the matrices allows space to mark detailed information in each interaction, such as the duration of the relationship, reversibility, probability to occur, etc., or simply mark the significant impacts (Fig. 2).

2.4. Types of causal networks in EIA

2.4.1. Digraphs

Digraphs–or directed graphs–are perhaps the simplest form of causal networks. Their elements are nodes and directional links (uni-directional arrows), with optional additional information marked directly on these elements (Fig. 3, see also Canter, 1996). Many causality networks share this feature of directionality to represent causality between elements.

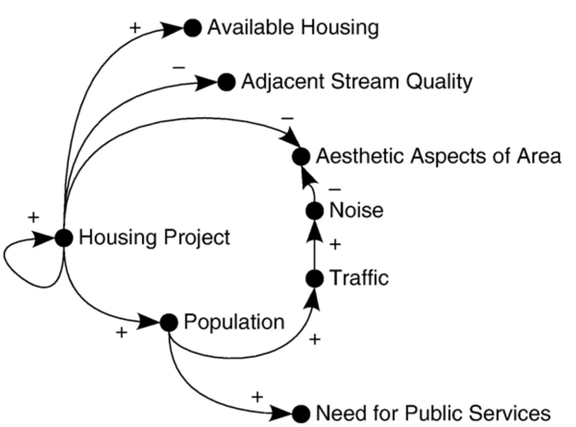

Fig. 3. Sample of a Directed Graph, or Digraph; adapted from Canter (1996); the + and − symbols are used in the sense of accompanying change (+) or reacting to change (−); in addition to the +/− symbols, more information can be indicated by the arrows, such as the probability or magnitude of change.

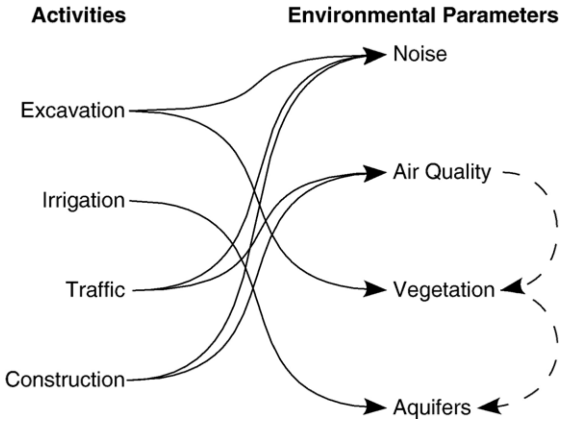

Fig. 4. Transformation of the matrix of Fig. 2 into a simplified digraph-type causal diagram, with additional information (impact interactions).

While impact matrices allow the representation and study of interactions, they are limited to doing that between only two sets of data. They register these interactions (effects or impacts) in their main body as a resulting third data set. Further exploration of the third set of data (e.g., interaction among impacts, indirect impacts, or cumulative effects) is not easy to carry out or mark in the same matrix. This limitation becomes evident and can be subsequently overcome, by an alternative representation of the information contained in the matrix as a simplified digraph-type causal network (Fig. 4).

In the digraph causal network (Fig. 4), the arrows represent the significant effects identified in the matrix (Fig. 2). Had the matrix included more information, such as a characterisation of the effects as positive/negative, the arrows could also include this information. The causal network raises further

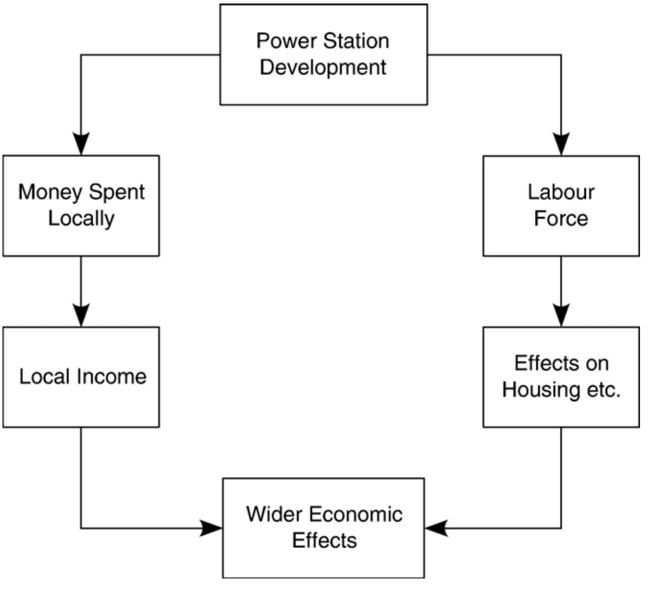

Fig. 5. Sample of a cause-and-effect diagram; Based on Glasson et al. (2005) and Glasson (2001).

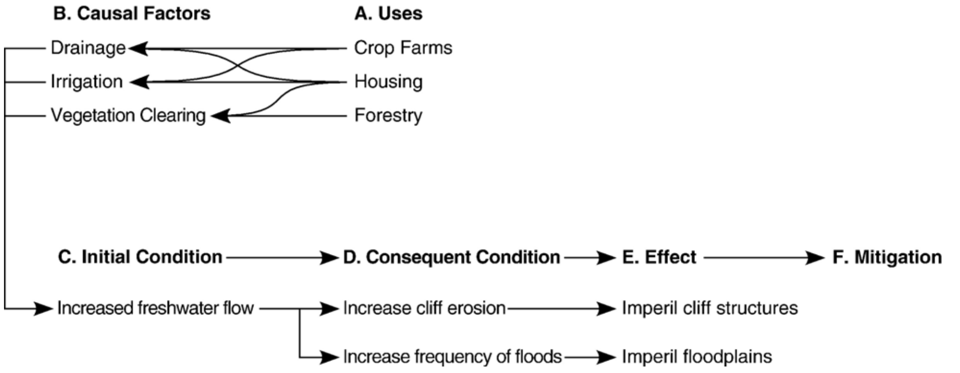

Fig. 6. Sample of a Sorensen network; Adapted from Canter (1996); the modified-matrix part of the network is shown at the top of the figure, in steps A and B; the sequence part of the network is the lower part, steps C to F.

questions regarding effect interactions (examples represented with dashed arrows). The activities and environmental parameters in Fig. 4 are stacked in order to illustrate the data sets equivalent to the corresponding matrix, but in digraphs (as in most causal networks) all the elements act usually both as causes and effects, so the ordering in the graphical space is done by logical grouping (e.g., geology, agriculture) rather than by their cause/effect role.

2.4.2. Cause-and-effect diagrams

Cause-and-effect diagrams are directed graphs, but their elements are stated textually in various shapes—mostly rectangles. Causal relationships are marked by uni-directional arrows, usually carrying no quantitative information (Fig. 5). In general, therefore, cause-and-effect diagrams are more elaborated graphically but less rich in information than the simpler digraphs. Cause-and-effect

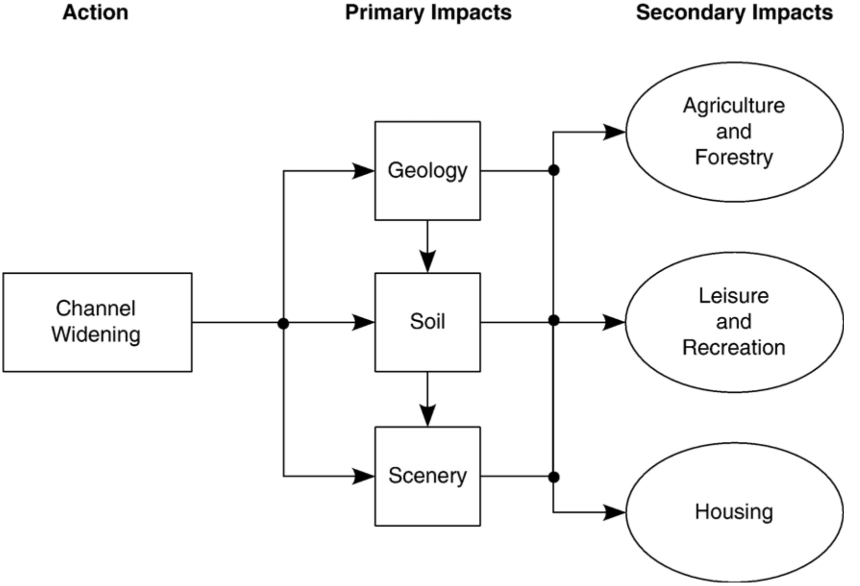

Fig. 7. Sample of the diagram used in the European Commission (1999).

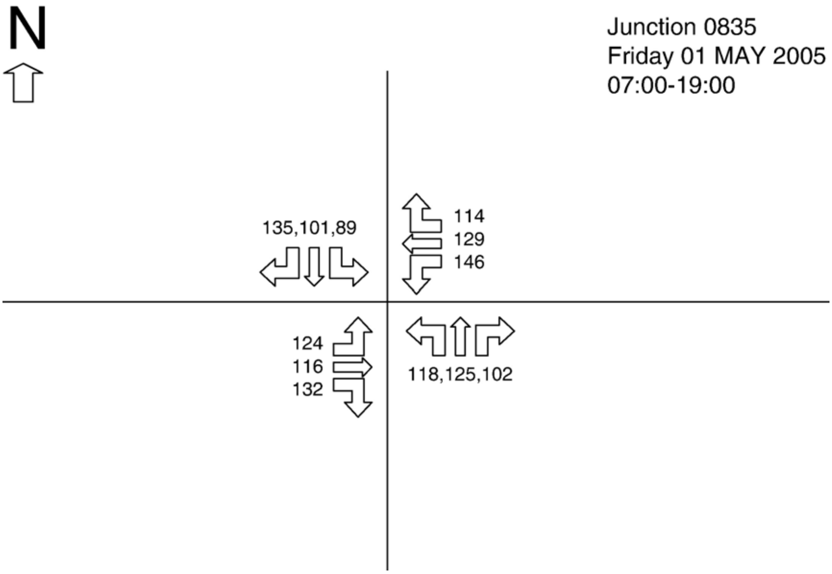

Fig. 8. Sample of a traffic flow diagram; based on Barton Willmore (2005).

diagrams are indicated for EIA use, mainly for the identification and prediction of impacts related to development projects (Glasson et al., 2005; Glasson, 2001; Canter, 1996; European Commission, 1999).

One of the earliest systems approaches to EIA are Sorensen networks (Barrow, 1997), which incorporate a cause-and-effect diagram with a built-in impact matrix (Fig. 6, see also Glasson et al., 2005; Canter, 1996; Barrow, 1997).

One of the recent highlighted studies involving causal networks comes from an EU guidance document (European Commission, 1999). The EIS regarding the project of stabilising the banks

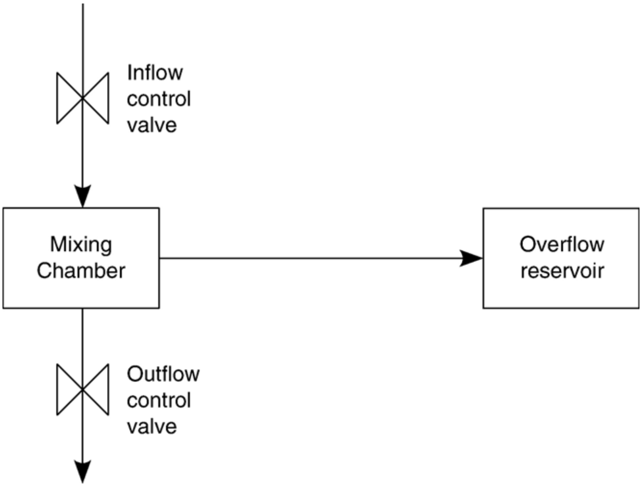

Fig. 9. Sample of a water flow diagram; based on Scott Wilson (2004).

of a 5-km section of the Kiel Canal (Rendsburg East) included a causal network analysis (Fig. 7), while the same information was also presented in the form of text. The network showed a very complex system of interactions–in particular illustrating the central functions of fauna and flora within the environment–demonstrating a sensitive system where an impact in one element implies likely changes in many other elements, and thus cause a system-wide perturbation. The network required no extra data and was reportedly useful in identifying indirect impacts and impact interactions.

2.4.3. Flow diagrams

Unlike the cause-and-effect diagrams, instead of tracing actions and their consequences, flow diagrams trace flows of materials and/or energy (Fig. 10). There are many types of flow diagrams or networks, but not all are causal. Typical traffic flow diagrams, for instance, merely represent vehicle flows (Fig. 8) without a hypothesis or indication of a cause for these flows.

Water flow diagrams (Fig. 9) represent the flow of water or other fluids in a hydraulic system. The causes for these flows may be indicated (e.g., a motor) or implied (e.g., gravity).

Specialised input–output maps (Glasson et al., 2005) and materials flowcharts (Glasson et al., 2005) are used to trace the flow of materials beyond (i.e., in and out of) or within, respectively, operations—e.g., industrial plants. Matter and/or energy flow diagrams (Wathern, 1988) are used for the quantification of interactions (i.e., matter or energy flows) among (eco-) system components (Fig. 10). A special case of energy-based diagrams are known as *Odum diagrams* (Bisset, 1988), after H.T. and E.C. Odum (Odum and Odum, 2000). Special variations of flow diagrams are used for tracing the pathways of pollutants and their effects (Canter, 1996).

Process diagrams (a.k.a. action diagrams, logic diagrams, or decision diagrams) contain some elezments of causality, whether explicit or implicit. For instance, Fig. 11 presents a sequence of logical action steps, involving several decision-making points. Certain elements

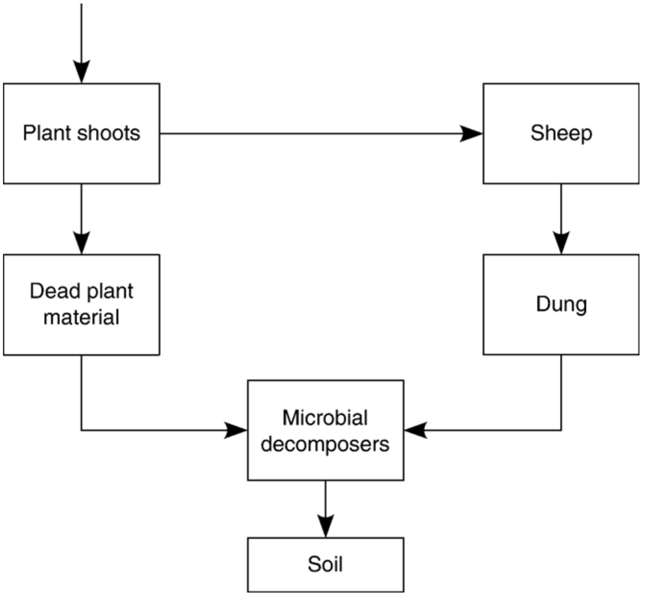

Fig. 10. Sample of a materials/energy flow diagram; based on Wathern (1988).

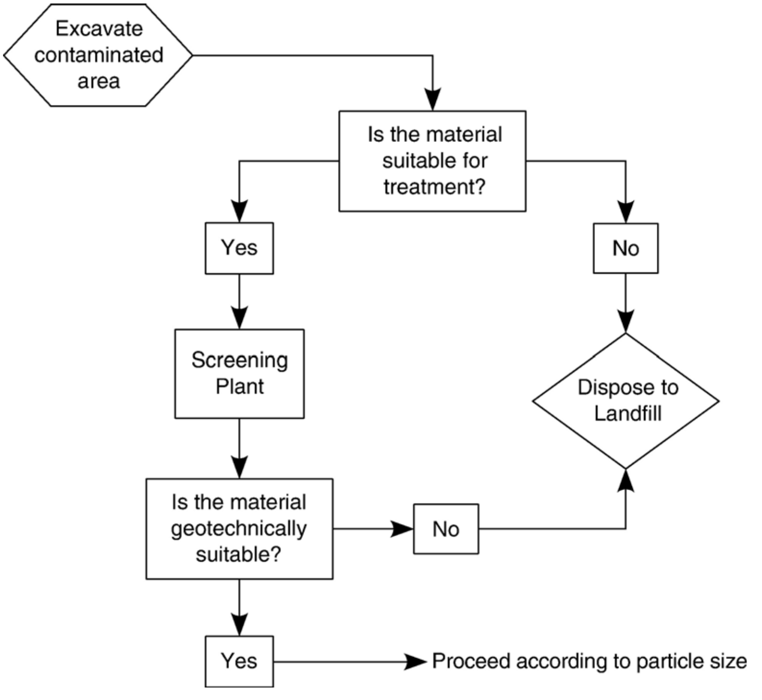

Fig. 11. Sample of a process flow diagram; based on David Lock Associates (2001).

of this network are effects of other elements, keeping in mind that the whole process is human controlled.

2.4.4. Tree diagrams

Tree diagrams branch out in a way that they resemble trees. They can be static or dynamic: static tree diagrams, such as road networks or the directory structure of a computer file system, are not causal

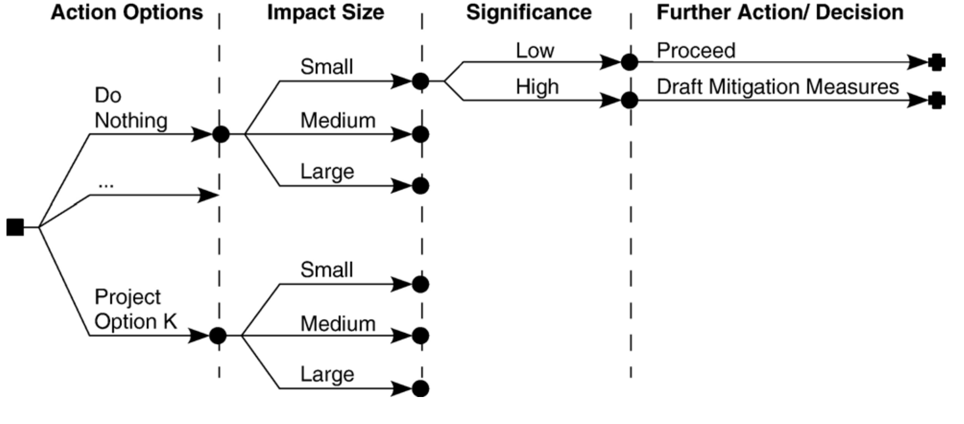

Fig. 12. Sample of a tree diagram, geared for decision-making; adapted from De Jongh (1988).

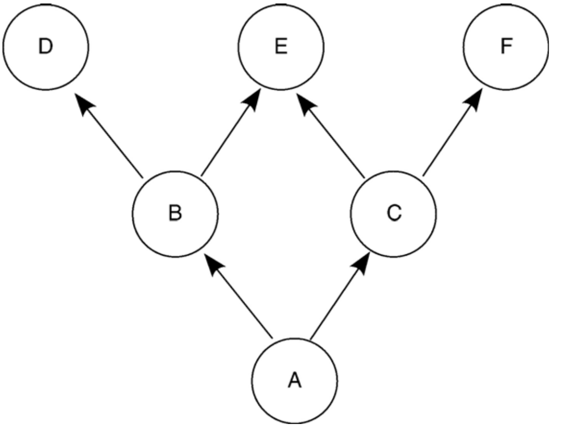

Fig. 13. Sample of a Bayesian network; based on Falzon (2006).

and thus are beyond the scope of this article. Dynamic tree diagrams present several development pathway options simultaneously.

A specific type of tree diagrams, decision trees (De Jongh, 1988; Glasson et al., 2005), are used for tracing action, consequences, and outlining the corresponding decision options (Fig. 12). Another type of tree diagrams, event trees (Barrow, 1997; UNEP, 2002), are used for exploring the development options simultaneously as alternatives (scenarios).

2.5. Causal networks beyond EIA

Besides the experience of causal networks in EIA, which may be labelled "the EIA school," this article considers two other notable schools of causal networks: Data Mining and System Dynamics.[2]

2.5.1. Data mining school

Data mining is a group of techniques used to extract information out of databases (Chen and Shen, 2005). Some of these techniques feature networks, and some of these networks are causal. Bayesian networks (Falzon, 2006; Lee and Lee, 2006; Nadkarni and Shenoy, 2001, 2004; Wong and Lin, 2003) are directed acyclic graphs, representing probabilistically the causal relations in a particular knowledge domain (Falzon, 2006). By being directed they are capable of registering cause and effect relationships, similar to digraphs (Fig. 3) and several cause-and-effect diagrams. By being acyclical (Fig. 13), Bayesian networks cannot represent feedback loops, which are a common occurrence in natural (or environmental) systems.

Evidential causal networks are–like Bayesian networks–directed acyclic graphs. They are considerable data mining tools for discovering and updating causal networks hidden in database systems (McErlean et al., 1999). Being acyclical, though, they have the same limitations as Bayesian networks regarding feedback loop structures.

Neuronal networks can predict the behaviour of a process at specified values of inputs and parameters, but they are not capable of discovering the causal relationships among the

[2] Operational Research uses a mix of causal networks, so it is not featured as a particular school in this article.

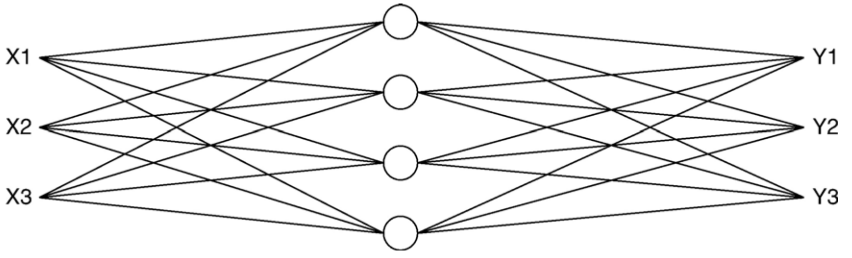

Fig. 14. Sample of a neuronal (non-causal) network; based on Huang and Wang (1999).

process parameters (Huang and Wang, 1999). Therefore, neuronal networks could work as "black box" simulation experiments, without the discovery of the underlying causal networks (Fig. 14).

Expert systems define causal relationships clearly, but their rules or logic seem to be more complex than reality—i.e., the systems under study (Huang and Wang, 1999). Fuzzy causal networks are capable of discovering and describing causal relationships (Huang and Wang, 1999), although only in acyclic chains—i.e., without feedback mechanisms (Fig. 15).

2.5.2. System dynamics school

System Dynamics is a methodology for the study and control of dynamic systems, such as the natural environment, social systems, economy, etc. (Sterman, 2000). System Dynamics involves two main types of diagrams, Causal Loop Diagrams (CLD) and Stock-and-Flow Diagrams (SFD), and corresponding sets of equations.

Causal loop diagrams (CLD) are special digraphs (Stave, 2002; Sterman, 2000; Ford, 1999; Deaton and Winebrake, 2000) that easily identify and represent key features of dynamic systems, such as causal relationships, feedback loops, delays, and link polarity (Fig. 16). CLDs manage to be richer in information than the typical digraphs by taking into consideration certain important control aspects, such as delays and the types of the feedback loops.

Stock-and-flow diagrams (SFD) (Sterman, 2000; Ford, 1999; Deaton and Winebrake, 2000) are flow diagrams, but they also contain cause-and-effect elements (Fig. 17). SFDs contain more information than the corresponding CLDs, which makes the former capable of numerical simulations—a feature that could be very useful in forecasting or decision-making. In their numerical form, SFDs permit simulations of outcomes based on given scenarios (e.g., project action, mitigation measures, resilience of the terrestrial plant community, etc.).

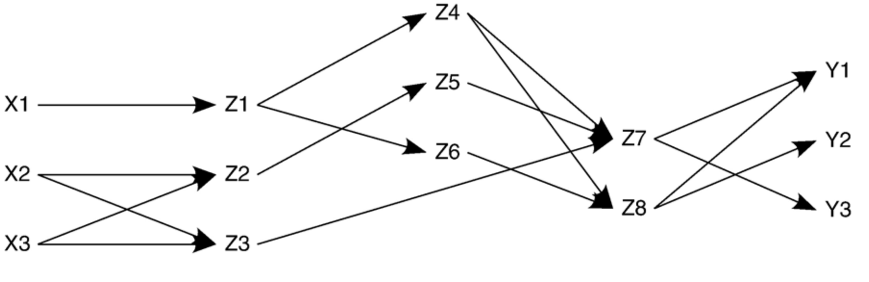

Fig. 15. Sample of a fuzzy causal network; based on Huang and Wang (1999).

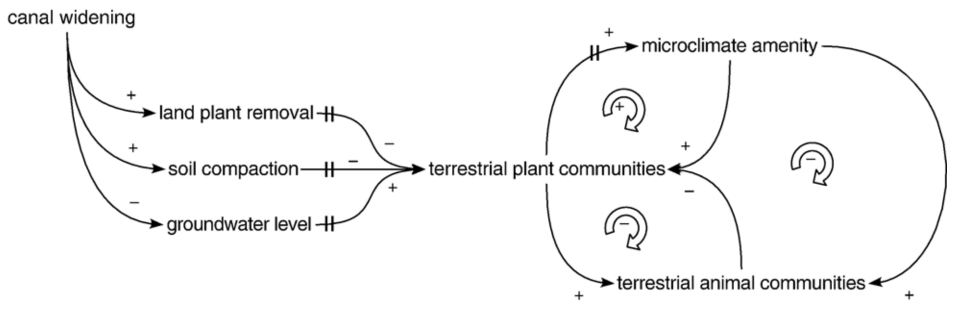

Fig. 16. Sample of a Causal Loop Diagram (CLD), demonstrating link polarity (+/−), delays (||), and feedback loops (↻); adapted from Perdicoúlis (in press).

Both CLDs and SFDs can be translated into equations. Among the possibilities to express causal relations as equations, there is the mathematics style (e.g., Eq. (1)) and the chemistry style (e.g., Eq. (2)).

$$\text{fauna alterations} = f(\text{vegetation clearing}) \tag{1}$$

$$\text{project infrastructure} \rightarrow \text{vegetation clearing} \rightarrow \text{fauna alterations} \tag{2}$$

2.6. EIS case study

The case study to accompany the literature review was carried out in the Resource Centre of the Impact Assessment Unit, at Oxford Brookes University. Twelve (12) Environmental Impact Statements (EIS) were collected at random, filtering only for the date to be post-1999 (i.e., after the implementation of the EU Council Directive 97/11/EC in the UK law). These EISs were from various categories of projects, and they totalled 36 volumes (see endnote after the list of references).

The search in the EISs was for the existence of causal networks of any type that placed the proposed project into the environmental setting of one or more locations. Traffic flow diagrams were excluded from the count, as non-causal. One process diagram was found (David Lock Associates, 2001), which might be considered to contain causality, but its scope was limited in relation to the project and involved no components of the natural environment. Therefore, it can

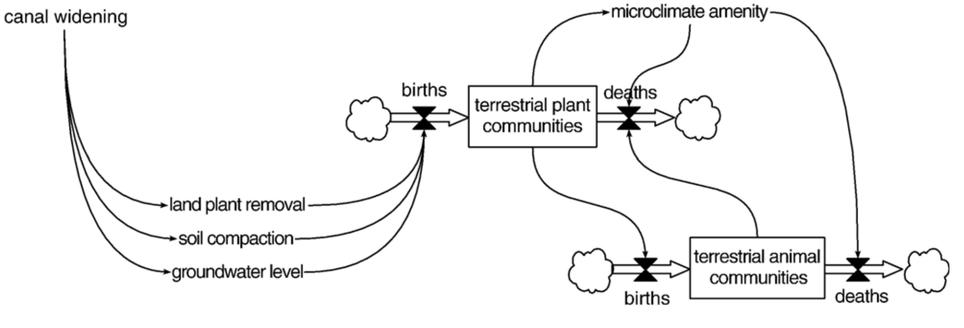

Fig. 17. Sample of a Stock-and-Flow diagram (SFD), corresponding to Fig. 16; adapted from Perdicoúlis (in press).

be concluded that the random sample of the EIS case study resulted in zero counts of causal networks.

The findings of this EIS case study are in line with the recent results of a relevant research (Wood et al., in print), indicating the use of similar methods (e.g., flow charts, decision trees) by practitioners in England and Wales in the determination significant impacts as extremely low, at the order of 3% or less. It is notable that the literature that does mention causal networks usually refer to relatively old applications, of the 1970s and 1980s (see Section 2.4), and these instances are sometimes shared among the textbooks. Some EIA textbooks mention nothing about causal networks (Gilpin, 1995; Porter and Fittipaldi, 1998), which may be an additional evidence to their scarcity in EIA practice.

3. Discussion

3.1. Back to basics

With a relatively strong support for causal network use from EIA textbooks (Section 2), and a relatively scarce application record (Section 2.6), it seems necessary to look back into the foundations: the principles of EIA. Particularly three principles of EIA, namely, "transparency," "integration," and "systematic" (IAIA, 1999), demand tasks that seem tailor-made for causal networks—even though it may be argued that they can always be carried out by text.

- By being "transparent," EIA should inter alia "identify the factors that are to be taken into account in decision making." These factors correspond to the nodes of the causal networks, leaving additional space for identifying and marking the relations among them.
- By being "integrated," EIA should "address the interrelationships of social, economic and biophysical aspects. Causal networks combine well with inquisitive spirits to seek for causes and effects to a reasonably good mix and scope."
- By being "systematic," EIA should "result in full consideration of all relevant information on the affected environment, of proposed alternatives and their impacts, and of the measures necessary to monitor and investigate residual effects." Causal networks are quite efficient in identifying missing elements, alternatives, impacts, etc.

The outlook of causal networks against the EIA principles seems favourable and encouraging. Taking this as a starting point, the rest of this section takes a look forward, examining the main options of investing in causal networks or abandoning them altogether.

3.2. Investment plan

3.2.1. Directions for more involvement

So far, causal networks are receiving credit in textbooks and guidance documents about their contributions in the early phases of the EIA process, mainly around impact identification and prediction (Section 2). Since causal networks stimulate a non-conventional type of thinking (systemic, causal, dynamic, etc.), they have the potential to contribute to EIA in two ways.

3.2.2. Reinforcement

Causal networks can become the "base map" in impact identification and prediction, by which all the other impact description and assessment techniques will be oriented. This is very important because the clarification and transparency of cause-and-effect relationships between the variables involved (in the locality of intervention and the proposed project) is fundamental for all prediction methods in EIA (Glasson, 2001).

3.2.3. Extension

Later phases of the EIA process can also benefit from causal networks (once created for the earlier steps, this later-phase contribution comes as a bonus), such as mitigation (e.g., to identify where to interfere in order to stimulate or inhibit certain effects) and monitoring (e.g., to verify that the most important factors are being monitored, or to produce a quantitative and functional dynamic model with all the provided data).

3.2.4. Causality thinking

It is apparent that the approaches to causality perception diverge into deductive/experimental and inductive. At the cost of some thinking and time investment, it is possible to merge the two approaches into a unique and more efficient one. This new method may derive from any side: it may extend the deductive/experimental method by starting somewhat more on the left–i.e., forming the hypothesis not ad hoc, but based on careful observations and experience, or it may extend the deductive method by adding an experiment mechanism to the formulated causal hypothesis–something like an experiment-like simulation.

Two of the criteria used in testing a causality hypothesis are (a) co-variation of cause and effect variables and (b) whether the relationship “makes sense,” or is logical (e.g., respects precedence in time, mutability of the receiving variable) (De Vaus, 2001). Although the “sense” criterion is apparently more fragile to scientific proof, the co-variation criterion has a major weakness: causal relationships cannot be observed or confirmed statistically, mainly due to time delays—i.e., the cause and effect may not be both observed at the time, as the effect may manifest later.

3.3. On the ground

3.3.1. Complementarity and contribution

With causality being a fundamental notion in EIA, causal networks are a prime candidate for use in EIA. Several attributes of causal networks make them suitable for being key instruments in the development of an EIS, such as simplicity, clarity, abstraction, and aggregation. Rather than replacing other methods, causal networks seem to complement text and matrices and still make their original contributions (European Commission, 1999). For the most popular methods used to study impacts in EIA, such as professional judgement and experience, consultation, and check-lists (Wood et al., in print), causal networks would introduce a higher degree of rationality into the process, including the highly valued transparency (IAIA, 1999).

Causal networks are likely to provide original suggestions for impact identification and mitigation (European Commission, 1999), satisfy several EIA principles, and honour the observation that the clarification of cause–effect relationships is fundamental for all prediction methods in EIA (Glasson, 2001).

3.3.2. Costs and drawbacks

Causal networks may require no additional data than conventional methods (European Commission, 1999). However, more familiarity or experimentation with causal networks in EIA seems necessary, to make them faster and better applied (appropriate types, less errors in symbology, etc.), and less mysterious or “fearsome” to the end users.

The time and space handling, as well as the potential explosion of the physical dimensions, which usually appear as drawbacks to causal networks, can be easily improved with special techniques that EIA practitioners can acquire from modelling professionals (Ford, 1999; Sterman, 2000; Deaton and Winebrake, 2000).

3.3.3. Chances for progress

Causal networks appear to exist as good ideas, recommended by literature, but with little practical existence in modern EIA applications (Section 2). The reasons for this shall be investigated in a forthcoming project, but the mere fact of "unpopularity" of causal networks may reinforce some fears about their perceived drawbacks regarding complexity and space–time handling. As a precaution, some authors advocate the use of simple and data-light techniques for impact forecasting (Wood, 1995; Therivel, 2004).

A certain unfamiliarity of EIA practitioners with causal networks, together with the apparent technical difficulties, may have led to a poor experience with causal networks in EIA in the later years. This non-encouraging/non-inviting situation, in turn, may feed back into the view of practitioners and thus bring causal networks more distant to practice. As time passes and the technique falls into low use (or disfavour), the less chances it has to come into practice. This constitutes a reinforcing feedback loop, commonly known as a vicious cycle.

One way to break that vicious cycle would be to give credit to and re-launch causal networks into EIA practice, with certain conditions such as modern professional practice examples, simple and accessible methodology, and available consultancy by competent bodies (e.g., university research centres).

3.4. Recommendations

After the previous discussion, the recommendations of the article are summarised into a couple of alternative strategy scenarios.

3.4.1. Business as usual

Following the apparent trends, the use of causal networks is likely to dwindle and disappear from the EIA practice. This scenario does not require any particular effort or investment other than following the professional trends, and no particular returns are expected.

3.4.2. Active investment

The investment scenario may turn into one of many directions for developing and experimenting with causal networks in EIA, such as the "reinforcement" or the "extension" options (Section 3.2). As part of the investment scenario, causal networks must become more accessible to EIA practitioners, which may involve training, technological developments (e.g., software), and leadership. The expected results are higher transparency and more efficiency in EIA.

4. Conclusion

There are several types of causal networks recommended in the literature, but with an apparent reduced application in modern EIA (UK) practice. Their recognised contribution so far is mainly in impact identification and forecasting (early EIA phases), especially regarding indirect impacts, cumulative impacts, and impact interactions. Causal networks are well suited to satisfy particular principles of EIA practice, such as transparency, integration, and being systematic. This encourages for their future development and more involvement in EIA practice, either by fortifying their present contribution to EIA (early phases) or extending their contribution by applications in impact mitigation and impact monitoring (later phases). The default scenario for their future in EIA may be a continuation of the present trend, to dwindle and disappear, while an investment scenario is capable of re-introducing causal networks in EIA practice, with expected benefits such as transparency and clarity of reason. This investment can be supported by training, technological developments, and leadership.

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