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A Bayesian Network for Policy Evaluation

A CECAN Evaluation and Policy Practice Note for policy analysts and evaluators

A Bayesian network (BN), also known as a probability network or Bayesian belief network is one of the effective theoretical models for knowledge representation and reasoning under the influence of uncertainty.

What is a BN?

A BN is a model. It reflects the states of some part of a world that is being modelled and it describes how those states are related by probabilities. The model might be of your house, or your car, your body, your community, an ecosystem, a stock-market, etc. All the possible states of the model represent all the possible ways that the model's parts (variables) can be configured. The car engine can be running normally or giving trouble. Its tyres can be inflated or flat. Your body can be sick or healthy, and so on. Each variable is represented by a node in the BN and a conditional probability table is attached to each node (Figure 1). A link (or 'edge') between two nodes represents a probabilistic dependency between the linked nodes. The links are shown with an arrow pointing from the causal node to the effect node (the links are 'directed'). There must not be any directed cycles: one cannot return to a node simply by following a series of directed links. This means that BNs are Directed Acyclic Graphs (DAGs). Nodes without a child node are called leaf nodes (outputs), nodes without a parent node are called root nodes (inputs), and nodes with parent and child nodes are called intermediate nodes (states).

A BN represents dependence and conditional independence relationships among the nodes using joint probability distributions, with an ability to incorporate human oriented qualitative inputs. The method is well established for representing cause-effect relationships (Figure 1).

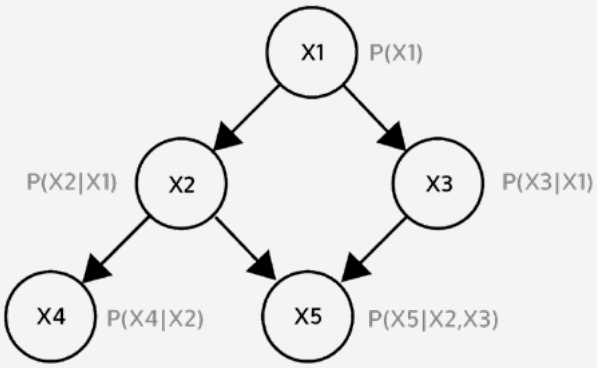
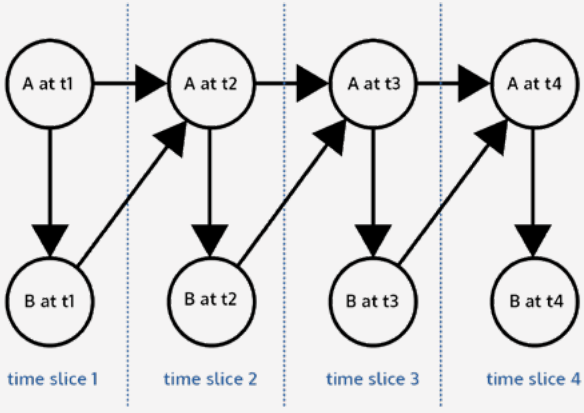


Figure 1 | Cause-effect relationships. An outgoing edge from node Xi to Xj indicates a causal relation between these two nodes, in which the value of Xj is dependent on the value of Xi. Xi is the parent node of Xj and Xj is a child node of Xi. A conditional probability attached to node Xi is conditioned on the set of all parents of node Xi, pa(Xi), and is represented by P(Xi|pa(Xi)).

What key terms are commonly used in a BN?

- Prior probability distribution: indicates the probability distribution of the values of each node that would express the modeller's beliefs about an uncertain quantity before any incorporation of data.
- Joint probability: indicates the probability of two events occurring together and at the same time.
- Posterior probability distribution: indicates the probability distribution of the prior belief about an uncertain quantity of a node (prior probability) after some evidence has been taken into account.
- Dynamic Bayesian Network (DBN): consist of a limited number of BNs, each of which corresponds to a particular time interval. The connections between adjacent BNs represent how the states of the system evolve over time. Figure 2 shows a simple two-node DBN with feedback over four time steps. In Figure 2, node A at t1 affects node B at current time slice t1, but is in turn affected by node B in the next time slice, t2. This amounts to a feedback loop, since A affects B and B affects A (at time t2).
- Hybrid Bayesian network (HBN): random variables can be discrete such as someone's gender or continuous such as someone's age. A BN which contains both discrete and continuous variables is called an HBN.
- Bayes' theorem: this theorem provides a way to update the prior probabilities in light of new or additional evidence.

Figure 2 | Dynamic Bayesian Network representing a feedback loop.



What preparation is needed in order to create and use a BN?

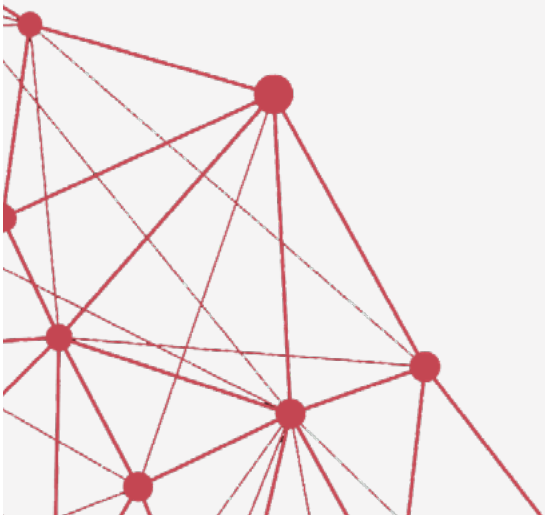
When planning the use of the BN method, it is important to bear in mind that:

- At least one member of the evaluation team needs to have (or gain) an understanding of, and ability to apply, Bayesian probability inference.
- The model and the prior probabilities can be constructed on the basis of computer-based simulation, expert input or a combination of both.
- For a computer-based simulation, first a database is selected as input. Then an algorithm such as MCMC (Friedman and Koller, 2003) takes the input and generates a BN as output. The database may have incomplete data, and may contain noise. BN can be used to solve the classification learning problem.
- The BN is computational: software is needed to run the model.

Why Use Bayesian networks for policy evaluation?

Applications of BN methods are found in a growing number of disciplines and policies.

- BNs are good for classification based on observations.
- A BN can do unsupervised learning from a dataset and allow the learning algorithm to find both structure and probabilities. This means the evaluator does not need to know how to create a BN, although it is possible to aid the learning algorithm with a priori knowledge about relations and probabilities.
- Dealing with uncertainty when evaluating policy is a challenge that can be addressed using BNs because they allow one to safely ignore some uncertain probabilities of variables to get to the desired probabilistic quantity of a random variable.
- BNs engage directly with subjective data in a transparent way. It is better to think of the method as a tool to explore beliefs, evidence and their logical implications, than as a means to 'prove' something in some absolute sense. They, therefore, are also useful in producing the balanced judgements required for evaluation in a Value for Money (VfM) context.
- BNs can be used privately to structure and inform the evaluator's understanding or publicly in a participatory process to stimulate and challenge collective views.



What advantages do BNs offer?

BNs in addition to their simple causal graphical structure have some other appealing properties:

- The ability to update initial beliefs about the values of each variable (prior probabilities) in the face of new evidence via Bayes' theorem.
- They can perform three types of inference: deductive (top-down, forward, predictive), diagnostic (bottom-up, inverse, explantory), and intercausal (bi-directional "explaining away"). This is useful since the same BNs can be used for both policy assessment and policy evaluation.
- Analysts can make probability judgments consistent with the direction of causality.
- Evidence can be entered into the model, and the effect on the other variables (nodes) can be observed (improving or worsening, and by what magnitude).
- BNs are able to work with data of different types and sources: they handle a mix of subjective and objective data, and therefore can supplement traditional experimental and statistical methods.
- BNs are user-friendly, practical and can present intuitively and graphically the 'story' behind a finding.

What are the main weaknesses of BNs?

In spite of their remarkable potential for addressing the dependency between the variables and their conditional probabilities, there are some inherent limitations to BNs:

- Conducting full Bayesian learning is computationally very expensive. This even holds true when the network structure is already given.
- BNs need data and perform poorly with very small data sets. When a data set is small, many conditioning cases are represented by too few or no data records, so they do not offer sufficient basis for learning conditional probability distributions.

Example: A DBN to evaluate bovine tuberculosis eradication policy and risk factors in England's cattle farms, 2008 to 2015

The spread of bovine tuberculosis (bTB) disease is an ongoing problem in cattle farms in England despite the current government's policy on bTB control in England including cattle herd testing, quarantine, and slaughter practices (Defra, 2019). The following definitions are essential for this example:

- Officially TB free (OTF): herds with a clear test history.
- Officially TB suspended (OTS): the OTF status of a herd is suspended when there is a suspicion of TB infection within that herd.
- Officially TB withdrawn (OTW): the OTF status of a herd is withdrawn when evidence proposes that infection does exist.
- Officially TB unclassified (OTUC): not currently OTW, but where testing was still underway and could become OTW if tests revealed any bTB.
- New herd incidents (NHI): herds which were previously OTF but either had cattle that reacted to a tuberculin test or had a tuberculous animal disclosed by routine meat inspection at slaughter.
- Movement restriction: there is no movement into or out of the herd and cattle can only leave the herd to move straight to slaughter.
- Skin test: the main screening test for bTB in cattle in Great Britain, commonly known as the tuberculin skin test.
- Edge risk area: the buffer zone between the high risk areas and low risk areas. The level of bTB in the majority of the edge risk area is much lower than in the high risk areas, but higher than in the low risk areas.
- Failed test: where at least one animal tests positive during any test herd-level (routine, whole-herd, follow up).
- Breakdown: A failed test on an OTF herd, not currently subject to movement restriction.

There are a number of risk factors related to bTB in cattle farms including (i) environmental biosecurity from farm waste and management, and foodstuff storage, (ii) herd characteristics such as age of cattle, herd size and animal movements, (iii) contact between cattle and badgers, and (iv) animal management including stocking densities, isolation, feeding and grazing regimes. Key factors considered in our model are: manure storage, silage, age of cattle, badgers, and stock density.

We designed a BN to identify which risk factors have the highest impact in England's cattle farms in spreading bTB (Table 1). We created a DBN to explore the spread of the disease over the period 2008-2015 using monthly data about reported changes to the risk factors. The DBN examines the effect of risk factors in cattle farms on available measures of bTB spread: Number of herds OTF, OTS, OTW, OTUC and NHI.

Relevance of risk factors	Official TB status: Suspended (OTS)	Official TB status: Unclassified (OTUC)	Official TB status: Withdrawn (OTW)
High	Manure storage more than 6 months ≈ 17.5%	Manure storage more than 6 months ≈ 23%; Stock density more than 3 heads per hectare ≈ 22%	Manure storage more than 6 months ≈ 19%
Low	Badger density ≈ 3.5%	Silage ≈ 6%; Number of purchased cattle ≈ 10%	Badgers density ≈ 4%; Silage ≈ 4.6%

Table 1 | The effect of different risk factors on bTB in high-risk areas of England cattle farms obtained from designed BN (Figure 3).

The model evaluates the effect of the policy's movement restrictions and skin tests upon different classes of risk area: high, low and edge risk. Each risk area has different probabilities for risk factors and resulting New Herd Incidents. The structure of the BN appears in Figure 3.

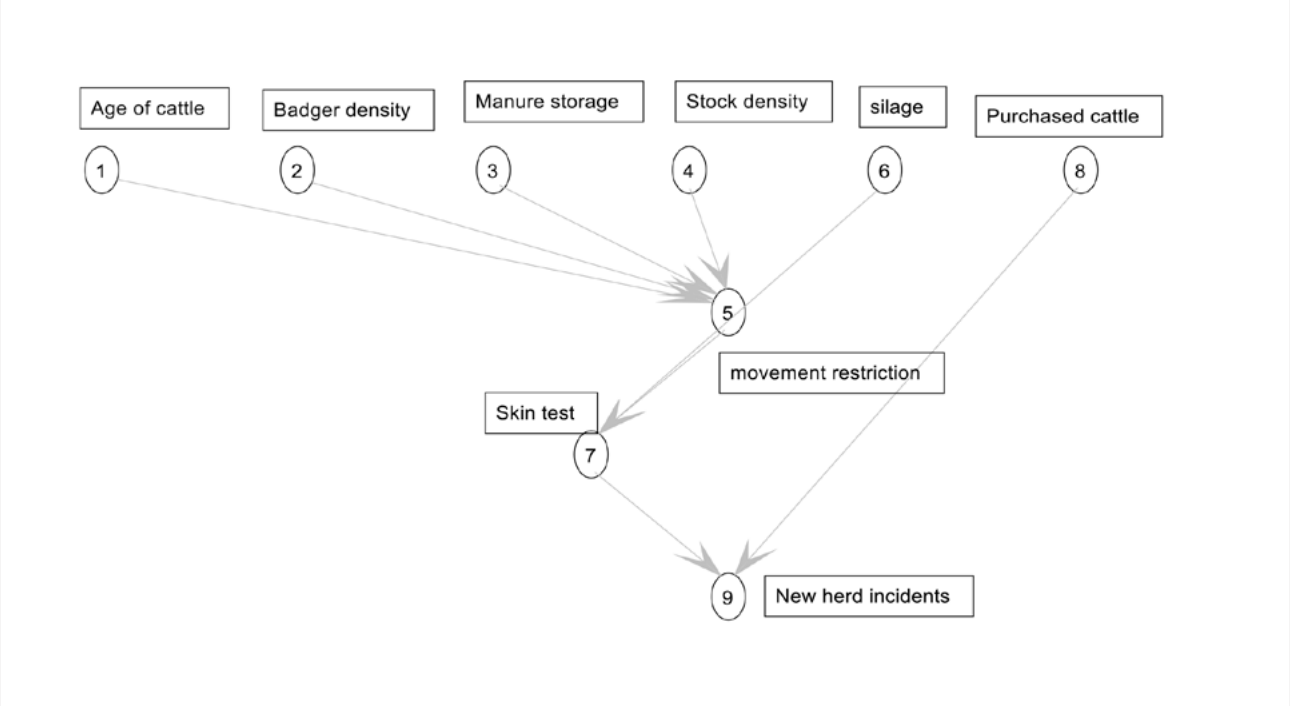
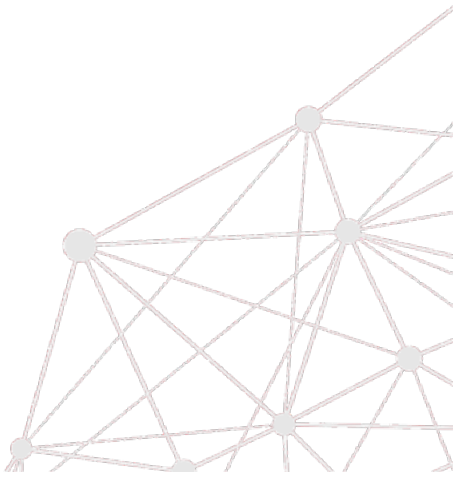


Figure 3 | Static BN model. This network is used to represent the probabilistic relationships between root causes or risk factors and symptoms or evidences. Given evidence about new herd incidents (NHI), the network can compute the probabilities of the strength of various root causes of bTB.

The DBN is able to replicate corresponding new herd incidents from 2008 until 2015 (see Figure 4). Nodes 10-18 are a copy of the nodes in the static model. The red links indicate the interslice dependencies between the corresponding temporal/continuous nodes in the two different time slices that can enable users to monitor and update the system as time proceeds, and even predict further behaviours of the system. The temporal nodes with influence between time slices (dynamic), are: a) the skin tests; b) movement restrictions; and c) new herd incidents.

A significant advantage of this approach is that it represents the government's policy on bTB control in England as a dynamic process capturing the data from experience, testing and infection over time.



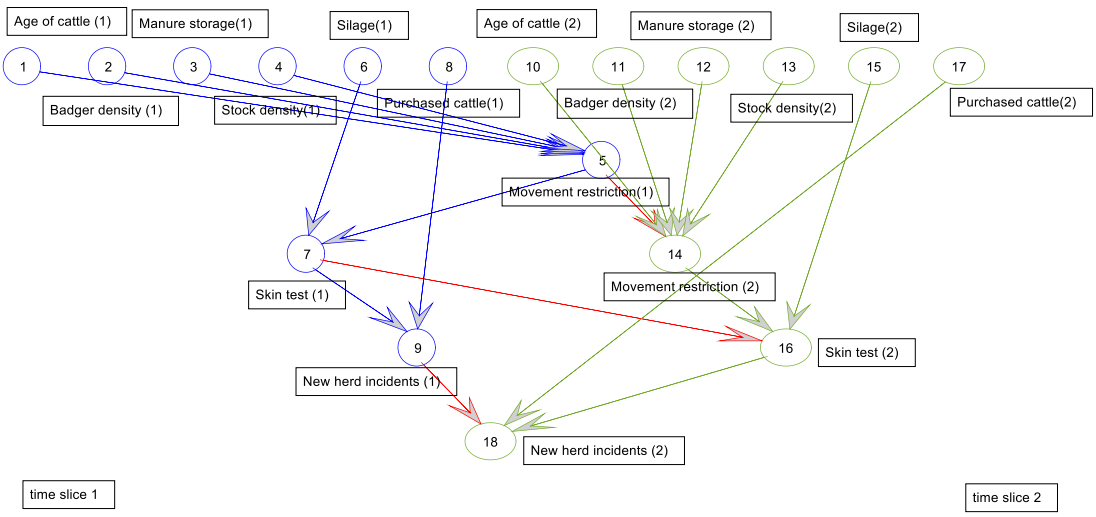


Figure 4 | In this figure, cycles over time can be represented for figure 2, using an underlying acyclic DBN. In this DBN, skin test results at time t influences the skin test results at time t+1.

Our results for high risk and edge risk areas suggest that biosecurity is a key risk factor that requires improved control. As shown in Figure 5, the probability of NHI: OTW was increasing (≅37%) in the presence of badgers and silage fed cattle at the same time. This is because the mechanisms of disease transmission from badgers to cattle are likely to involve cattle foodstuffs and/or environmental contamination from Mycobacterium bovis (a slow-growing aerobic bacterium and the causative agent of tuberculosis in cattle) in urine, faeces or sputum. Controls could involve consideration of the type and length of storage of food, as well as limiting contact between cattle and infected badger sources by fencing, building maintenance and design.

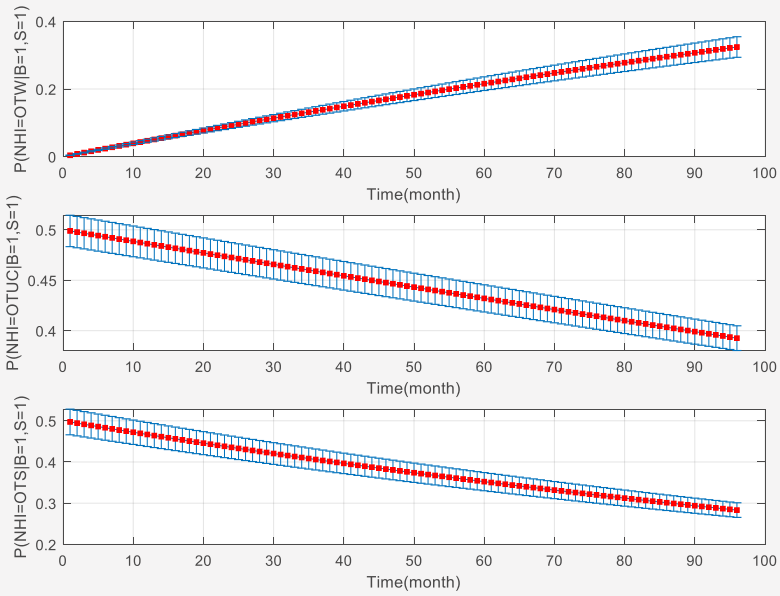


Figure 5 | The probability of new herd incident (NHI) (officially TB free status withdrawn (OTW), officially TB free status unclassified (OTUC), officially TB free status suspended (OTS)) in high-risk areas of England where B indicates badgers density is more than 3 setts/ha and S indicates silage fed cattle.

Regarding low risk areas, acquired cattle are the source of the majority of breakdowns in herds previously free of disease (NHI: OTW was increasing ≅17%). Hence, Pre-movement testing which was recently introduced to prevent the spread of bTB infection from purchased cattle can reduce the risk of breakdowns in the low risk areas. Finally, it is concluded that applying the DBN modelling approach can reduce investment and policy risks associated with cattle farms' husbandry interventions within three risk areas of England. Moreover, it could act as a decision support tool for some of the private, public and community sector stakeholders, key decision makers and policymakers.

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This Evaluation Case Study Policy and Practice was written by Tabassom Sedighi, with contributions and comments from Liz Varga.

CECAN has developed a set of co-produced case studies, working with government departments and agencies to tackle their intractable evaluation challenges in complex policy area. These case studies have involved sustained dialogue and an orchestrated succession of activities and relationship building. They are providing experiments in bringing together the expertise of evaluation practitioners, methods and domain specialists, social and natural scientists and policy analysts to develop shared understandings of evaluation challenges and to identify evaluation needs and solutions.

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