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A method for root cause analysis with a Bayesian belief network and fuzzy cognitive map

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ABSTRACT

People often want to know the root cause of things and events in certain application domains such as intrusion detection, medical diagnosis, and fault diagnosis. In many of these domains, a large amount of data is available. The problem is how to perform root cause analysis by leveraging the data asset at hand. Root cause analysis consists of two main functions, diagnosis of the root cause and prognosis of the effect. In this paper, a method for root cause analysis is proposed. In the first phase, a causal knowledge model is constructed by learning a Bayesian belief network (BBN) from data. BBN's backward and forward inference mechanisms are used for the diagnosis and prognosis of the root cause. Despite its powerful reasoning capability, the representation of causal strength in BBN as a set of probability values in a conditional probability table (CPT) is not intuitive at all. It is at its worst when the number of probability values needed grows exponentially with the number of variables involved. Conversely, a fuzzy cognitive map (FCM) can provide an intuitive interface as the causal strength is simply represented by a single numerical value. Hence, in the second phase of the method, an intuitive interface using FCM is generated from the BBN-based causal knowledge model, applying the migration framework proposed and formulated in this paper.

1. Introduction

Identifying the root cause and effect of an event has become a very important issue in some domains such as security, medical, mechanical and others. Root cause analysis (RCA) is able to identify the relationship between the causes and effects of an event and perform diagnosis and prognosis. Diagnosis means finding the cause and prognosis means predicting the effect. The fuzzy cognitive map (FCM) and the Bayesian belief network (BBN) are the two major frameworks used in RCA. BBN is a powerful modelling tool in data-rich domains. It has an ability to learn from data. In addition, it supports an efficient evidence propagation mechanism, which is very useful in the RCA process. Moreover, BBN is a more mature framework than other RCA frameworks because many BBN software tools have been introduced to and commercialised in today's market, such as Hugin, Netica, BayesiaLab and others.

After the causal model of a domain is constructed, the presentation of causal knowledge is the next concern in this study. Representing causal knowledge in an intuitive way is vital, especially for knowledge acquisition and information sharing. FCM is simpler and more intuitive in interpreting causal knowledge than BBN (Cheah, Kim, Yang, Choi, & Lee, 2007). A good understanding of causal knowledge enables us to make successful causal reasoning and strategic decisions manually. A method which integrates the BBN and FCM is proposed in this paper to leverage the merits of both causal modelling approaches within a unified framework. The reasons for the integration are to reduce the human effort by learning the causal model from the data automatically and to present the model in an intuitive way. BBN is used to learn the causal model and to perform the RCA because of its expressiveness and powerful causal reasoning capability. FCM is used to present the causal knowledge in an intuitive way because of its simplicity.

In order to provide a powerful RCA capability using BBN and an intuitive presentation of causal knowledge using FCM, a method to migrate BBN to FCM is proposed. Although BBN and FCM are causal knowledge approaches which share some common features in their representation, there are also some differences between them. Hence, some modifications need to be made before the migration takes place. The first step of the method involves discovering the individual causal effects from a conditional probability table (CPT) as CPT represents the combination of multiple causal effects. Therefore, migration of BBN to FCM involves transforming a quantitative to a qualitative representation. A conditional probability equation

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is used to discover the probability of the increase for an event when the cause event has increased. The value is stored in a new CPT and the combination of positive influences calculated for subsequent use. The next step of the method generates an FCM-compatible BBN to address the range of difference between BBN and FCM by using Pearson's correlation coefficient equation. Once the fuzzy-compatible probability has been constructed and reorganised, the transformation from probability to possibility by adoption of Klir's equation will be performed. The causality sign will be determined at the last stage to generate a proper FCM.

2. Literature study

2.1. Root cause analysis (RCA)

There is a cause behind every problem. To avoid the problem persisting, localisation and elimination of its cause is of the utmost significance. RCA is there to address the problem or non-conformance by localising the true cause and implementing corrective action to prevent recurrence of the problem (Rooney & Heuvel, 2004). In the past, RCA was well-known in industrial psychology and was utilised in the analysis of many important industrial accident cases. RCA is alternatively referred to as error analysis, root cause localisation, root cause diagnosis, fault localisation, causal reasoning, causal discovery and problem determination (Reason, 2000). Kiciman and Subramanian (2005) claimed that the process of localising the root cause is extremely important, especially in large-scale systems. The evolution of communication systems has contributed to unprecedented growth in the number of internet users, which has in turn produced a large amount of data flow. As a result, identifying the cause of a system which fails to function properly is a very challenging task. In addition, identification of the root cause in today's enterprise systems is still usually performed manually (Wong & Debroy, 2009). Identifying the causes manually in such a data-rich domain is very time-consuming and experienced technical experts are needed. Moreover, the reliability and performance of a system are always a prerequisite in the globalised world. Detection and diagnosis of causes or faults must be accurately performed and completed in a short period of time.

2.2. RCA with BBN and FCM

Though BBN and FCM have been applied in various domains, BBN is selected by many researchers for building causal models because of its soundness and expressiveness. A causal model can be built by two methods, manual and automated (Korb & Nicholson, 2003). Manual construction of a causal model is a way to acquire knowledge from experts in a particular domain. Construction of BBN by hand involves several development stages. First, the relevant variables of the event need to be selected and captured by interviewing experts in particular domains. In the second stage of the construction, the conditional independence or dependence relationships among the variables will be identified and represented in a graphical structure. The causality relationships obtained are based on the interviews with the domain experts and represented in a graph by taking the causality sign to determine the arcs direction between the variables. Next, the assessment and verification of the probabilities needed for the network under development will be facilitated because the probabilistic and logical constraints among the domain variables are known. Once the graphical structure has been constructed, the CPT for each variable needs to be built. The conditional probabilities can be obtained from the domain expert. Finally, an assessment of the completed BBN will be done by performing a sensitivity analysis.

The automated method of BBN construction involves learning the BBN causal model from data. This method significantly reduces the effort required for eliciting causal knowledge from the domain experts. There are two stages of learning in BBN, structure learning and parameter learning. In BBN, the DAG is called the structure and the values in the conditional probability distribution are called the parameters (Neapolitan, 2003). Structure learning in BBN is a harder problem algorithmically than parameter learning. BBN parameter learning means learning the strength of dependencies as encoded by the entries in the CPT.

A new method for acquiring probabilities from domain experts has been designed to elicit big number probabilities in reasonable time and tested in oesophageal cancer analysis (Van der Gaag, Renooij, Witteman, Aleman, & Taal, 2002). Though the assessment rate by the domain expert can hit 150 probabilities per hour with the proposed method, the accuracy of probabilities is not absolute. Furthermore, finding an expert in a particular domain is always a big challenge, especially unpopular domains. However, Yet, Perkins, Marsh, and Fenton (2011) presented a method of building causal BBN by knowledge elicitation with a clinician as domain expert. Three stages of knowledge modelling are outlined to decrease the semantic mistakes in the final BBN model and provide understandable immediate models. However, the method proposed has not been completely developed and is only applicable to a few attributes. Other than that, causal probabilistic graphical models can be built with an expert system approach. Athanasiou and Clark (2009) built a causal model based on the rule-based DIMITRA system for the caring procedure to be followed for wheelchair users with spinal injury. Eleven qualified staff nurses participated in the elicitation of the conditional probabilities of signs and symptoms given specific diagnoses. The diagnostic performance tested by the causal BBN built is equally promising but each expert may have different assumptions and this could lead to bias when the diagnostic performance test is performed. Moreover, manual construction of BBN needs to elicit knowledge from human experts and could be very time-consuming.

The data mining approach is the other method which is commonly used in BBN without explicit access to the knowledge of human experts. However, several requirements need to be fulfilled in order to construct a good BBN with this approach. The domain has to be a data-rich domain which can provide enough data and valuable information for the analysis and construction of the causal model. The data must be collected very carefully to permit reliable identification of likelihood relationships. Moreover, the missing values in the dataset have to be filled in based upon estimated probabilities of these values or amputated from the dataset. Learning BBN from data involves two stages which are structure learning and parameter learning. Medina-Oliva, Iung, Barberá, Viveros, and Ruin (2012) integrated several RCA methods to identify the bad physical actors which cause performance deviations in an industrial system. They compared BBN with other RCA methods and concluded that BBN is able to deal with issues such as prediction or diagnostic optimisation, data analysis of feedback, experience, deviation detection and model updating and multi-state elements. Jiang, Neapolitan, Barmada, and Visweswaran (2011) designed a combinatorial epistasis learning method called BNMBL to construct BBN epistatic models. They concluded that representing epistatic interactions with BBN models and scoring them with a BBN scoring criterion holds promise for identifying epistatic genetic variants in data. The data mining approach allows BBN to learn structure from a large number of variables in the shortest time (Cussens, 2012) compared with knowledge-based BBN. Although the data mining approach has been widely applied in BBN, the capability of BBN has not been fully exploited. This literature applied BBN only in the structure learning process, which is only a part of BBN's capabilities. The powerful root cause analysis capability of BBN has not been fully utilised. Furthermore, the causal representation in BBN is unable to provide immediate understanding to the non-expert user.

Some researchers apply FCM in RCA to identify the root cause in certain scenarios. White and Mazlack (2011) identify suicidal tendencies in writing by only analysing word frequency patterns. Those patterns are then converted into input values for FCM to determine those who intend to commit suicide. Words frequently used by the suicidal can be easily identified in the FCM causal model, which is learnt from data. However, the correctness of such models has not been verified. Maitra and Banerjee (2014) use FCM for decision-making to improve the production and maintenance of mining and plant machinery. FCM provides immediate understanding and identification of the root cause. It is very helpful in decision-making processes. However, constructing an FCM causal model by means of a knowledge engineering approach, which is the most widely applied approach, has some disadvantages: knowledge acquisition from experts is time-consuming and finding an expert in certain domains is challenging.

Abele et al. (2013) used both knowledge engineering and machine learning approaches to reduce alarm floods in industrial systems. The knowledge engineering approach provides accurate decision-support and reduces alarm floods and machine learning approaches using BBN provide fast modelling and accurate parameterisation of alarm dependences. However, the manual combination of the two approaches consumes a lot of time and effort. In addition, expert knowledge is limited in the knowledge engineering approach. A comparison of the methods is shown in Table 1 below.

BBN and FCM are knowledge representation and RCA frameworks which have been used extensively in constructing causal models for various domains (Liu, Zhang, Han, Zhang, & Bhargava, 2007; Sedki & De Beaufort, 2012). In most cases, researchers applied the two frameworks separately. Only a few combined the two approaches and applied them simultaneously in a specific domain. A new approach using Bayesian causal maps was proposed by Nadkarni and Shenoy (2001) for probabilistic inference in causal maps. Later, they also proposed a cognitive map (CM) for constructing BBN (Nadkarni & Shenoy, 2004). Lee and Jo (2011) then proposed a new method called the cognitive Bayesian network (CBN) in which software maintenance effort (SME) professionals draft the causal map for the target SME problem first and then translate the draft into the corresponding general Bayesian network. Recently, Sedki and De Beaufort (2012) proposed a method called the Bayesian cognitive map (BCM), in which CM was first built by eliciting knowledge from experts and then transforming it into BBN. However, none of these papers embraces FCM. The idea common to all of them is eliciting knowledge from domain experts with a less complicated framework and the resultant causal model is then migrated into a framework which has more powerful automated reasoning ability. All these papers aim to handle the complexity of BBN construction by constructing CM before the elicitation of probability distributions. Nevertheless, such approaches are unable to reduce the complexity caused by the sheer magnitude of probability distributions and the constructed causal model by using the knowledge engineering approach. Only a few papers about the migration of FCM and

Table 1
Comparison of methods for RCA using BBN and FCM.

Existing method	Research papers	Pros	Cons	Our proposed method
RCA using BBN knowledge engineering approach	Van der Gaag et al. (2002)	Acquire large number of probabilities from domain expert in reasonable time	Difficulty in finding domain expert	Learn causal network from data using data mining approach
	Yet et al. (2011)	Semantic mistakes decrease	Not completely developed and only applicable to a few attributes	No difficulty in finding domain expert or inconsistency in experts' opinions
		Provide understandable immediate models		
	Athanasiou and Clark (2009)	The causal BBN is reliable as the result of diagnostic performance tests using BBN is promising	Each expert may have different assumptions and it is time-consuming	
RCA using BBN data mining approach	Medina-Oliva, Iung, Barberá, Viveros, and Ruin (2012)	BBN is able to deal with issues such as prediction or diagnostic optimisation, data analysis of feedback experience, deviation detection, model updating and multi-state elements	Causal model is not intuitively presented and other factors should be incorporated in the model such as human and latent causes	Causal model is intuitively presented through BBN to FCM transformation
				Fully utilise capability of BBN with diagnostic, prognostic and hybrid RCA
	Cussens (2012)	Learn BBN causal structure from data in shortest time	Capability of BBN not fully utilised	
	Jiang et al. (2011)	A learning method called BNMBL which will construct BBN model	Causal model is not intuitively presented	
		Root cause identification result is promising		
RCA using FCM	Maitra and Banerjee (2014)	Provide immediate understanding and identification of the root cause	Knowledge acquisition from experts is time-consuming and may have bias	Learn causal model from data and provide intuitive causal representation
	White and Mazlack (2011)	Provide immediate understanding and identification of the root cause	Correctness of the FCM learned from data has not been verified	Correctness of the causal model learned from data in BBN has been verified
RCA using BBN hybrid approach	Abele et al. (2013)	Provide accurate decision-support and reduce alarm flood	Expert knowledge is limited	Learn causal network from data, using data mining approach and transform the causal model into an intuitive way
		Fast modelling and accurate parameterisation of alarm dependences	Manual combination of the two approaches is highly time- and effort-consuming	Make decision -making task easier for people

BBN can be found. Cheah et al. (2007) is the first to apply the FCM and BBN together in a domain and to propose a migration method from FCM to BBN. FCM is used at the front end to elicit knowledge from experts for the construction of the causal model, and a method for converting the FCM representation to BBN is presented.

3. Learning BBN causal model from data

Causal reasoning is natural and easy to understand. It gives explanations of conclusions drawn, and this is very useful in decision-making. It is convincing as it explains why a particular conclusion has been inferred. BBN is a well-established and efficient tool for building causal models. However, elicitation of causal knowledge from domain experts through the specification of conditional probabilities is both unnatural and tedious. Learning a BBN causal model from data is an alternative to the knowledge engineering approach. Since the 2000s a number of BBN learners have been proposed by the research community. Recently, several commercially available BBN tools have incorporated the learning component. However, the potential of causal model discovery through machine learning of BBN is still not well studied. The correctness of the BBN causal model needs to be carefully verified and its diagnostic performance thoroughly evaluated. The reliability of BBN learners and the correctness of a BBN causal model discovered from data will be tested in this section.

To evaluate the performance of BBN learners, two typical examples representing two different categories are used. The Bayesian Network Power Constructor (BNPC) is a product of the University of Alberta, Canada (Cheng's Bayesian Belief Network Software). It is based on the analysis of conditional independence relationships among attributes and it uses them as constraints to construct BBN. Causal Minimum Message Length (CaMML), on the other hand, is a product of Monash University, Australia (MDMC Software-CaMML). It uses search and scoring tests. The search is based on the Markov chain Monte Carlo and the scoring test is based on a trade-off between simplicity and goodness of fit. An existing knowledge-engineered BBN, in a domain familiar to the authors is used as a benchmark for performance comparison. Simulated cases are generated from the BBN and these cases are used by the machine learners to perform causal discovery. There are two major tasks in learning a BBN, learning the graphical structure and then learning the parameters (i.e., conditional probability table entries). As it is trivial to learn the parameters for a given structure (one simply uses the empirical conditional frequencies from the data), only learning the structure will be considered.

3.1. Benchmarked knowledge-engineered BBN

The Chest Clinic network or Asia network, a simple BBN introduced by Lauritzen and Spiegelhalter, is a famous knowledge-engineered representation used in the research community (Lauritzen & Spiegelhalter, 1988). This network consists of eight variables connected by eight arcs. Each of the variables has two states, as shown in Fig. 1. The figure shows BBN before any evidence is added. Fig. 2 shows the complete set of CPTs for all the random variables in the problem domain. The random variables represented in this network are medical parameters such as lung cancer, dyspnoea, bronchitis, tuberculosis, and others.

3.2. Simulated cases and data pre-processing

Simulated cases are generated from the Chest Clinic BBN described above with Hugin (Hugin Expert Software). To make the simulated data as faithful as possible to the data collected from real surveys, the procedure for the simulation of raw data is

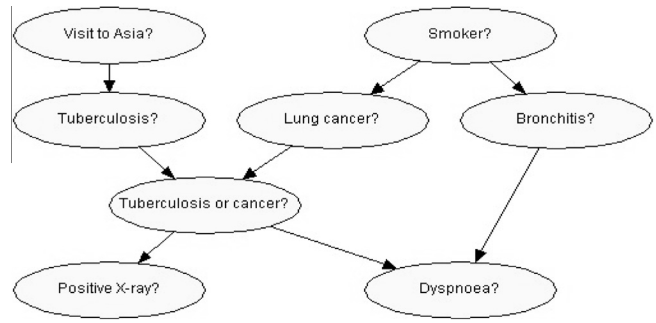


Fig. 1. BBN for chest clinic (adopted from Lauritzen and Spiegelhalter (1988)).

supplemented with the random introduction of artificial errors in the set of generated data. The user can control the impact on the data of artificial errors by specifying the error rate. There are two error models available in Hugin. The Missing Completely At Random (MCAR) model generates missing values on the basis of a Missing Completely At Random mechanism that is the probability that a missing value is independent of the values in the hypothetical complete data set (Heitjan & Basu, 1996). The Missing At Random (MAR) model generates missing values on the basis of a Missing At Random mechanism which is that the probability of an item being missing does not depend on the value of the item itself although it can depend on the observed data of other variables (Heitjan & Basu, 1996).

3.3. Results and discussion

In this experiment, three datasets are generated for testing. A dataset with no missing value is generated, and the other two datasets are generated using MCAR and MAR for 5% missing values. All the three datasets are tested using BNPC and CaMML, and all the links are recorded in a table. BNPC is represented by 'B' and CaMML is represented by 'C'. The recovery of links is categorised into five possible situations as below:

(1) Link + direction: correctly predicted link and direction.
(2) Link – direction: correctly predicted link in opposite direction.
(3) Link 0 direction: correctly predicted link without direction.
(4) Missing link: missed the link prediction.
(5) Added link: wrongly predicted link.

CaMML is able to recover almost all the eight links correctly with only two links in the wrong direction as shown in Fig. 3. Though the two links are recovered, CaMML shows a strong capacity for learning causal model from data, and it can discover the relationship for A → T and S → L though the causal effects of these two links are very weak and hard to identify. Furthermore, the model learned is almost exactly the same as the original underlying structure. The BNPC learned model is slightly inferior to CaMML by using the same dataset. BNPC recovered only four links in the correct direction out of a possible eight links, and two links with no direction as shown in Fig. 4. Besides, BNPC failed to identify two links in the causal network, A → T and E → D, and added one extra link, L → D. This implies that BNPC is unable to discover weak relationships between the variables in a network and it may find a wrong relationship. A comparison of the two learning methods using 10,000 cases with 0% missing value is shown in Table 2.

For a dataset with 5% of missing values generated using MCAR, CaMML recovered six links in correct direction, one link in the wrong direction and one missing link as shown in Fig. 5. However, CaMML still outperforms BNPC by using the same dataset. BNPC

CPT for T

A	T = Y	T = N
Y	0.05	0.95
N	0.01	0.99

CPT for B

S	B = Y	B = N
Y	0.6	0.4
N	0.3	0.7

CPT for E

T	L	E = Y	E = N
Y	Y	1	0
Y	N	1	0
N	Y	1	0
N	N	0	1

CPT for D

B	E	D = Y	D = N
Y	Y	0.9	0.1
Y	N	0.8	0.2
N	Y	0.7	0.3
N	N	0.1	0.9

CPT for L

S	L = Y	L = N
Y	0.1	0.9
N	0.01	0.99

CPT for X

E	X = Y	X = N
Y	0.98	0.02
N	0.05	0.95

CPT for S

S = Y	S = N
0.5	0.5

CPT for A

A = Y	A = N
0	1

Abbr	Name of Variable
X	Positive X-Ray?
T	Tuberculosis?
D	Dyspnea
S	Smoking?
A	Visit to Asia?
L	Lung Cancer?
B	Bronchitis
E	Tuberculosis or Cancer?

Fig. 2. CPTs for the chest clinic BBN.

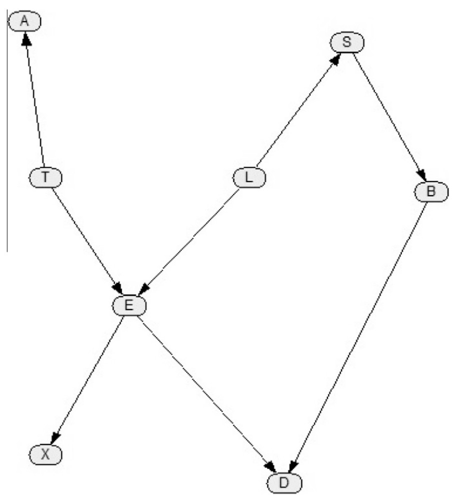


Fig. 3. CaMML learned model (10 K cases with 0% missing value).

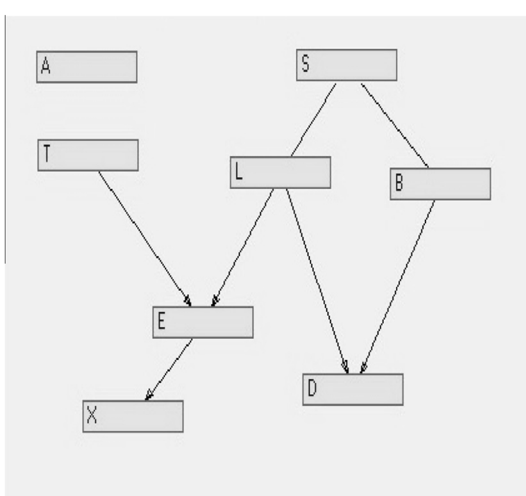


Fig. 4. BNPC learned model (10 K cases with 0% missing value).

can only identify four links in the correct direction and it has added one link, L → D, as shown in Fig. 6. A comparison of the two learning methods using 10,000 cases generated by MCAR with 5% missing value is shown in Table 3.

By using the dataset with the same percentage of missing values but generated by MAR method, CaMML remains the same network model as that generated by MCAR as shown in Fig. 7. Conversely, the BNPC learned model is better than the model learned from the MCAR dataset; it is able to recover five links in the correct direction as shown in Fig. 8. A comparison of the two learning methods using 10,000 cases generated by MAR with 5% missing value is shown in Table 4.

The evaluation statistics for each learned model of different datasets for BNPC and CaMML are summarised in Table 5. According to the results, CaMML apparently outperforms BNPC in terms of the accuracy of the model learned. The model learned (in the case of no missing values) is almost exactly the same as the original structure for benchmarking, and it is able to identify even very weak relationships between the variables. Hence, this confirms the assumption that root cause analysis performed by learning a BBN causal model from data is applicable in real-life problems.

3.4. Root cause analysis with BBN

RCA is able to diagnose the root cause and then predict the future outcome of an event in an application. RCA can be performed after BBN is completely learned from data including both structure and parameters. BBN is used in RCA because of its expressiveness in representation and soundness in reasoning. The evidence propagation mechanism in BBN allows forward prognostic reasoning and backward diagnostic reasoning to be done. The belief propagation algorithm was first proposed by Pearl (1988) to overcome the limitation of the node elimination technique, which is computationally expensive, provides no insight into the impact of evidence on hypotheses, and can create spurious dependences by the removal of variables through marginalisation.

In the propagation process, the prior probability for each node needs to be calculated before the reasoning process is performed. Posterior probability or belief of variable $X = x$ is denoted as $Bel(x)$. The types of propagation of evidences that influence variable X are split into two $\pi(x)$ and $\lambda(x)$. $\pi(x)$ indicates that the evidence passes through the arc between X and its children, and $\lambda(x)$ indicates that the evidence propagates from X to its parents. The belief, $Bel(x)$, can be written as in Eq. (1) below.

$$Bel(x) = \alpha\lambda(x)\pi(x) \tag{1}$$

where α is a normalisation constant, independent of x, which can be obtained by using Eq. (2) as follows.

$$\alpha = \left[\sum \pi(x)\lambda(x)\right]^{-1} \tag{2}$$

$\lambda(x)$ is the likelihood representing the diagnostic reasoning support for X, and $\pi(x)$ represents the predictive reasoning support for X. $\lambda(x)$ and $\pi(x)$ could be obtained by Eqs. (3) and (4) on the basis of Fig. 9.

Table 2
Links of learned model (10 K cases with 0% missing value).

No	Links	Link + direction		Link – direction		Link 0 direction		Missing link		Added link	
	BBN learner	C	B	C	B	C	B	C	B	C	B
1	A → T			✓					✓		L → D
2	T → E	✓	✓								
3	E → X	✓	✓								
4	L → E	✓	✓								
5	S → L			✓			✓				
6	S → B	✓					✓				
7	B → D	✓	✓								
8	E → D	✓							✓		

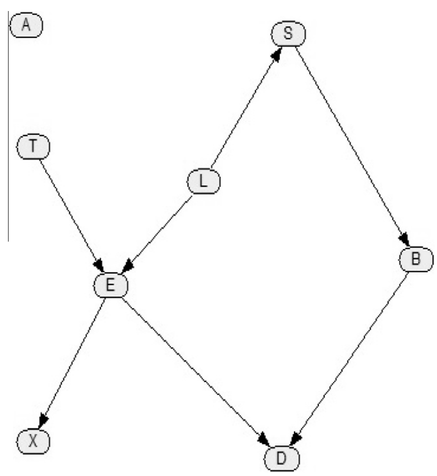


Fig. 5. CaMML learned model (10 K cases using MCAR with 5% missing values).

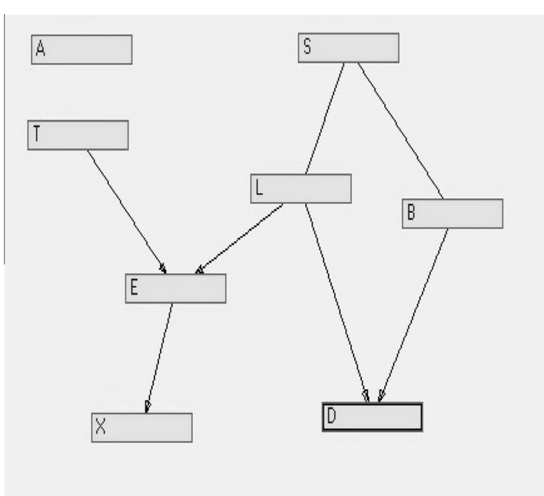


Fig. 6. BNPC learned model (10 K cases using MCAR with 5% missing values).

$$\lambda(x) = \prod_{j=1}^{n} \lambda_{Zj}(x) \tag{3}$$

$$\pi(x) = \sum_{w} P(x|W) \prod_{k=1}^{n} \pi_x(Wk) \tag{4}$$

As in Fig. 9, X consists of multiple child nodes and more than one parent node. Therefore, the total $\lambda(x)$ message which passes from the child nodes to X is acquired by combining the λ_z, as X has two child nodes. Other than that, the evidence at X splits the λ messages between multiple parent nodes and it combines the π messages from multiple parent nodes. λ_z and π_z are calculated from Eqs. (5) and (6).

$$\lambda_x(Wi) = \beta \sum_{x} \lambda(x) \sum_{Wk;k\neq i} P(x|u) \prod_{k\neq i} \pi_X(Wk) \tag{5}$$

$$\pi_{Zk}(x) = \alpha \prod_{k\neq j} \lambda_{Zj}(x)\pi(x) = \alpha \frac{\mathrm{Bel}(x)}{\lambda_{Zk}(x)} \tag{6}$$

where β denotes an arbitrary constant and α denotes a normalisation constant.

In this section, the Chest Clinic BBN is used to demonstrate the evidence propagation in a causal network. Fig. 10 shows the path of evidence propagation in the Chest Clinic BBN. Before the evidence propagation can be done, the prior probability of each node needs to be calculated. An initialisation step is needed. For nodes without parents, the $\pi(x)$ value is equal to the prior probability of $P(x)$, and for nodes without children, the $\lambda(x)$ value is set to one. In addition, λ and π values are set to one wherever $x_i = e_i$ for all $V_i = e_i$ in evidence node and zero otherwise.

First of all, the prior probability for S and A is (0.5, 0.5) and (0.01, 0.99) respectively as neither node has parents. The λ value for D and X is (1, 1) as they do not have any child node. Eqs. (3) and (5) result in all the other λ values being unit vectors as well. $\pi(b)$ can be calculated by using Eq. (2). $Bel(b)$ is calculated with Eq. (1) after the value of $\pi(b)$ is identified. The same steps are repeated for the remaining nodes until no change occurs. The λ, π and Bel values are shown in Table 6.

3.4.1. Predictive RCA

Predictive RCA is able to forecast the future outcome when evidence of an event is found. In BBN, the propagation of evidence of a variable allows an update of the probability distribution of the other variables in the network in the light of the newly found evidence. Hence, the assumption of the outcome can be confirmed by applying the predictive RCA. When evidence is set on the S node, the evidence will propagate downwards to the child nodes and cause the prior probability of the affected nodes to change. Fig. 11 shows the propagation route when evidence is set on S. Note that the evidence does not propagate to A and T nodes.

As mentioned in the initial steps above, $\lambda(s)$ is set as (1, 0). The probability of A and T nodes remains unchanged as no evidence has been propagated to either node. By using Eq. (3), we note that the λ value does not change in any of the nodes except for node S. The π value of each node can be calculated by using Eq. (4). The same process is repeatedly applied to the remaining nodes and the Bel value is obtained by using Eq. (1). The probability values of each node are calculated by the equation above and are shown in Table 7.

Table 3
Links of learned model (10 K cases using MCAR with 5% missing values).

No	Links	Link + direction		Link – direction		Link 0 direction		Missing link		Added link	
	BBN Learner	C	B	C	B	C	B	C	B	C	B
1	A → T							✓	✓		L → D
2	T → E	✓	✓								
3	E → X	✓	✓								
4	L → E	✓	✓								
5	S → L			✓			✓				
6	S → B	✓					✓				
7	B → D	✓	✓								
8	E → D	✓							✓		

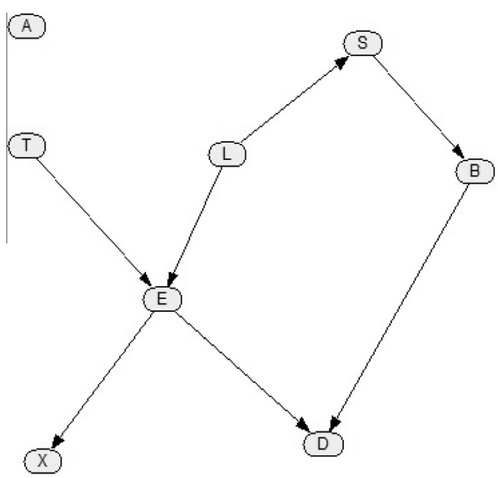


Fig. 7. CaMML learned model (10 K cases using MAR with 5% missing values).

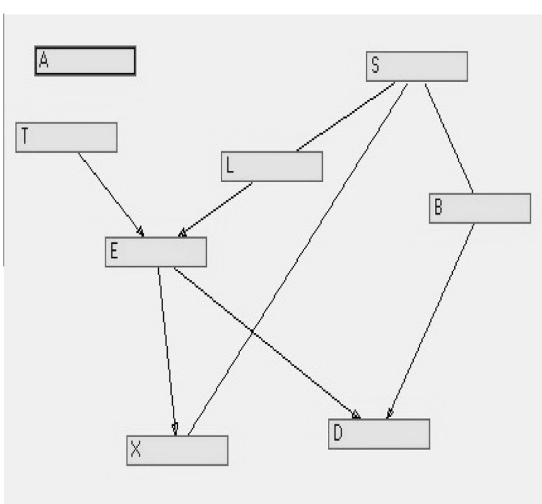


Fig. 8. BNPC learned model (10 K cases using MAR with 5% missing values).

3.4.2. Diagnostic RCA

BBN is also used to identify the possible root cause(s) of an event. Setting evidence on a domain variable may affect the probability distribution of domain factors by propagating backwards against the direction of the link. In this way, BBN is able to diagnose the possible root cause(s) and influence by identifying the change of posterior probability of the ancestor nodes. The propagation route, when evidence is found on X node, is shown in Fig. 12. It can be seen that all the nodes are affected as evidence is propagated to them. $\lambda(E)$ can be obtained by using Eqs. (3) and (5). $\pi(e)$ is acquired by using Eqs. (4) and (6) as mentioned above. However, normalisation is needed to calculate $Bel(e)$ and the normalisation constant is obtained by using Eq. (2). The change of probability for each node is shown in Table 8. $Bel(e)$ is calculated from Eq. (1) once the α value is obtained.

3.4.3. Hybrid RCA

Hybrid RCA allows the combination of predictive and diagnostic inferences at the same time. The combination of the inferences will cause either a cumulative or a cancellation effect on the probability of a particular state of the other variables in the domain. The cumulative effect will increase the state probability to a higher value, as compared with the individual probabilities obtained separately for predictive RCA and diagnostic RCA. Conversely, the cancellation effect will trim down the probability value. Fig. 13 shows the propagation route when hybrid reasoning is performed.

Hybrid reasoning combines the predictive and diagnostic propagation effects. From Fig. 13, node L is affected by both evidence of X which propagates upwards and evidence of S which propagates downwards. Hence, the π value of node L is the same as $\pi(L)$ in Table 7 under the predictive reasoning section, and the λ value of node L is the same as $\lambda(L)$ in Table 8 under the diagnostic reasoning section. Thus, the Bel value of L has changed and it shows the cumulative effect caused by hybrid reasoning as the probability of node L is higher than the probability value of node L in either the diagnostic or the predictive reasoning. The probability value for other nodes is calculated and recorded in Table 9.

Table 4
Links of learned model (10 K cases using MAR with 5% missing values).

No	Links	Link + direction		Link – direction		Link 0 direction		Missing link		Added link	
	BBN learner	C	B	C	B	C	B	C	B	C	B
1	A → T							✓	✓		S–X
2	T → E	✓	✓								
3	E → X	✓	✓								
4	L → E	✓	✓								
5	S → L			✓			✓				
6	S → B	✓					✓				
7	B → D	✓	✓								
8	E → D	✓	✓								

Table 5
CaMML vs BNPC learned models evaluation statistics by percentage.

Dataset	BBN learner	Correct link (%)	Link X direction (%)	Link 0 direction (%)	Missing link (%)	Added link (%)
0% MV	CaMML	75	25	–	–	–
	BNPC	44.4	–	22.2	22.2	11.1
MCAR with 5 % MV	CaMML	75	12.5	–	12.5	–
	BNPC	44.4	–	22.2	22.2	11.1
MAR with 5% MV	CaMML	75	12.5	–	12.5	–
	BNPC	55.6	–	22.2	11.1	11.1

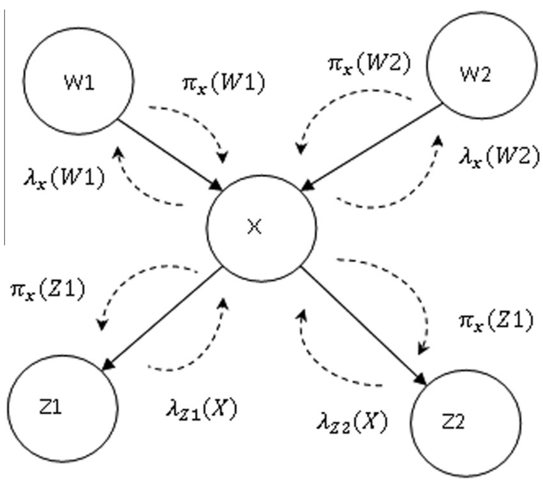


Fig. 9. Propagation of evidence.

4. Migration from BBN to FCM

The BBN model is represented by two components, a directed acyclic graph (DAG) and CPT. DAG represents the structure and direction of the causal relationships, and CPT represents the causal strength between them. The DAG of BBN only shows the direction and the connection between the variables, whereas the graphical structure of FCM shows the direction and the influence strength between the variables, and offers an intuitive understanding of the map and the influence between the variables. Though BBN and FCM are causal frameworks used in RCA, there are some differences between the approaches. Hence, several processes need to be performed to modify BBN into FCM-compatible BBN before moving to the actual conversion process. FCM-compatible BBN ensures BBN is in compliance with the requirements of FCM. A BBN in the assembly design decision support domain is used in this section for the explanation of the conversion process. Fig. 14 shows such a BBN, before any evidence is set.

The BBN has 11 variables and 18 links between the nodes. Each variable contains two states, a positive state represented by the symbol '+' and a negative state represented by the symbol '–'. The reasoning processes discussed in the previous section can be done here by setting evidence in any state of a variable.

Besides the graphical structure, BBN has a complete set of CPTs, one for each variable. A CPT is a table that records the joint probability distribution for a variable and it is used as the basic element for the migration of BBN to FCM. The main differences between BBN and FCM are that FCM does not show causal strength in CPT format and it is based on possibility rather than probability. The strength of each causal connection between the variables in FCM is calculated and transformed by using the probability distribution in CPT. The set of CPTs for the variables in Fig. 14 is shown in Fig. 15 below. The abbreviations used in Fig. 15 are described in Table 10.

4.1. Discovering the individual causal effects of CPT

Discovering the individual causal effects is an essential step in the migration of BBN to FCM. The combination of multiple effects in CPT needs to be resolved into individual causal effects. In FCM, each arc represents a causal relationship between the variables

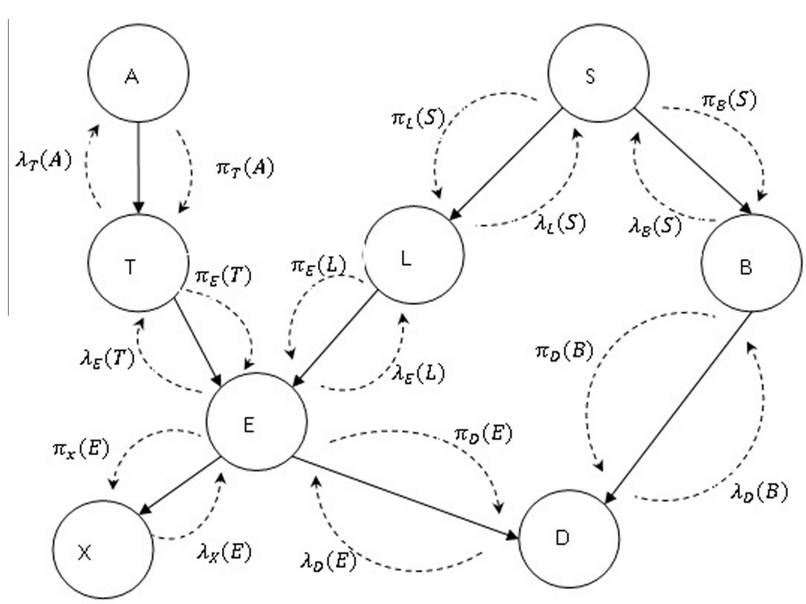


Fig. 10. Chest clinic BBN with evidence propagation route.

Table 6
Prior probability of each node in chest clinic BBN.

	$Bel(x)$	$\pi(x)$	$\lambda(x)$
S	**(0.5, 0.5)**	**(0.5, 0.5)**	**(1, 1)**
B	(0.45, 0.55)	(0.45, 0.55)	(1, 1)
L	(0.055, 0.945)	(0.055, 0.945)	(1, 1)
E	(0.0648, 0.9352)	(0.0648, 0.9352)	(1, 1)
X	(0.1103, 0.8897)	(0.1103, 0.8897)	(1, 1)
D	(0.436, 0.564)	(0.436, 0.564)	(1, 1)
A	**(0.01, 0.99)**	**(0.01, 0.99)**	**(1, 1)**
T	(0.0104, 0.9896)	(0.0104, 0.9896)	(1, 1)

The bold values represent initial values which remain unchanged from the prior probabilities.

Table 7
Probability values of each node after setting evidence on *S* node.

	$Bel(x)$	$\pi(x)$	$\lambda(x)$
S	**(1, 0)**	**(0.5, 0.5)**	**(1, 0)**
B	(0.6, 0.4)	(0.6, 0.4)	**(1, 1)**
L	(0.1, 0.9)	(0.1, 0.9)	**(1, 1)**
E	(0.1094, 0.8906)	(0.1094, 0.8906)	**(1, 1)**
X	(0.1517, 0.8483)	(0.1517, 0.8483)	**(1, 1)**
D	(0.5528, 0.4472)	(0.5528, 0.4472)	**(1, 1)**
A	**(0.01, 0.99)**	**(0.01, 0.99)**	**(1, 1)**
T	**(0.0104, 0.9896)**	**(0.0104, 0.9896)**	**(1, 1)**

The bold values represent initial values which remain unchanged from the prior probabilities.

and each graph node represents a domain variable. The numeric value that appears between two nodes indicates the total causal influence of the occurrence of an event on the occurrence of another event. However, CPT in BBN represents the combination of multiple causal effects, which indicates the probability of the effect event influenced by the multiple causal events. Therefore, causal strength between variables in FCM can be obtained from CPT in BBN.

The conditional probability concept and equation are used to resolve the combination of multiple causal effects in the constituents. The equation is used to calculate the probability of the positive state of a variable knowing the other variable has occurred (represented by a positive state) and the probability of the negative state knowing the other variable has not occurred (represented by a negative state). The conditional probability of *B*, given *A*, denoted by *P* (*B*|*A)* is defined in Eq. (7) below. The following equation is called the conditional probability definition.

$$P(B|A) = \frac{P(A \bigcap B)}{P(A)} \quad \text{if } P(A) > 0 \tag{7}$$

The equation above can be explained as the probability that *B* will occur given that *A* has occurred. An example of resolving the combination of the multiple causal effects of assembly quantity (AQ) into its individual causal effects is described below. AQ contains a CPT with two causal effects, quality control (QC) and assembly design (AD). However, knowing that the probability of QC increases, given that AQ has occurred, is of interest in the experiment rather than knowing the probability of AQ given that QC and AD have occurred together.

In this experiment, the conditional probability is required. Being derived from Eq. (7) $P(A \bigcap B)$ can be calculated from Eq. (8) below. The following equation is called multiplicative law.

$$P(A \cap B) = P(B|A)P(A) \tag{8}$$

However, *AQ* as in Fig. 16 is connected with two nodes, *AD* and QC. So, *AQ* has a CPT with eight states, which are $P(AQ{=}+|AD{=}+, QC{=}+)$, $P(AQ{=}+|AD{=}-, QC{=}+)$, $P(AQ{=}+|AD{=}+, QC{=}-)$, $P(AQ{=}+|AD{=}-, QC{=}-)$, $P(AQ{=}-|AD{=}+, QC{=}+)$, $P(AQ{=}-|AD{=}-, QC{=}+)$, $P(AQ{=}-|AD{=}+, QC{=}-)$, $P(AQ{=}-|AD{=}-, QC{=}-)$.

The probability value obtained will be stored in a new four-state table as in Table 11. A Joint Probability Table (JPT) consists of four possible situations that can happen, which are $P(A{=}+ \cap B{=}+)$, $P(A{=}+ \cap B{=}-)$, $P(A{=}- \cap B{=}+)$ and $P(A{=}- \cap B{=}-)$.

After all the multiple causal effects for all the CPTs have been resolved into individual causal effects, Pearson's correlation coefficient (PCC) (Rodgers & Nicewander, 1988) is used to calculate the causal influence between variables in BBN. PCC is the measurement of correlation between two variables and has been widely applied in statistics. It is used to measure the strength of a linear relationship between paired data in the range between −1 and +1. Furthermore, a positive value of the PCC reveals a positive linear correlation, a negative value reveals a negative linear

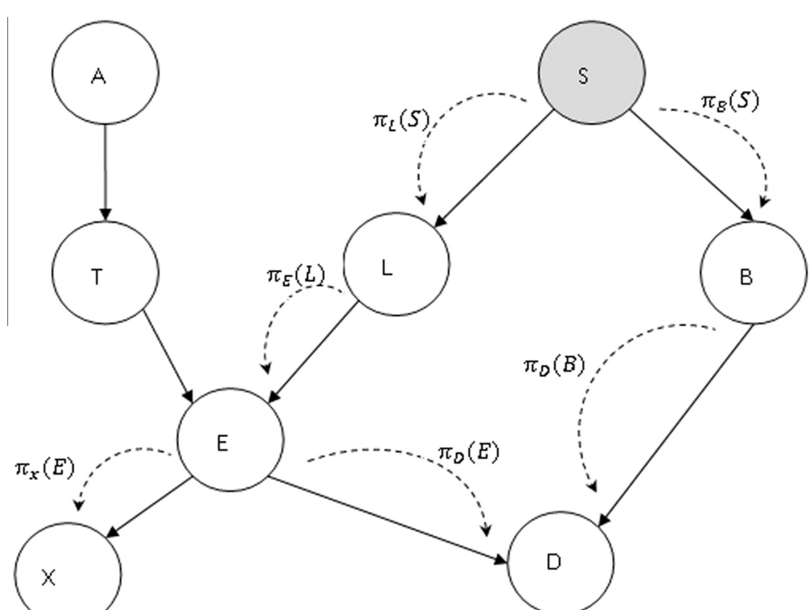


Fig. 11. Evidence propagation route after setting evidence on *S* node.

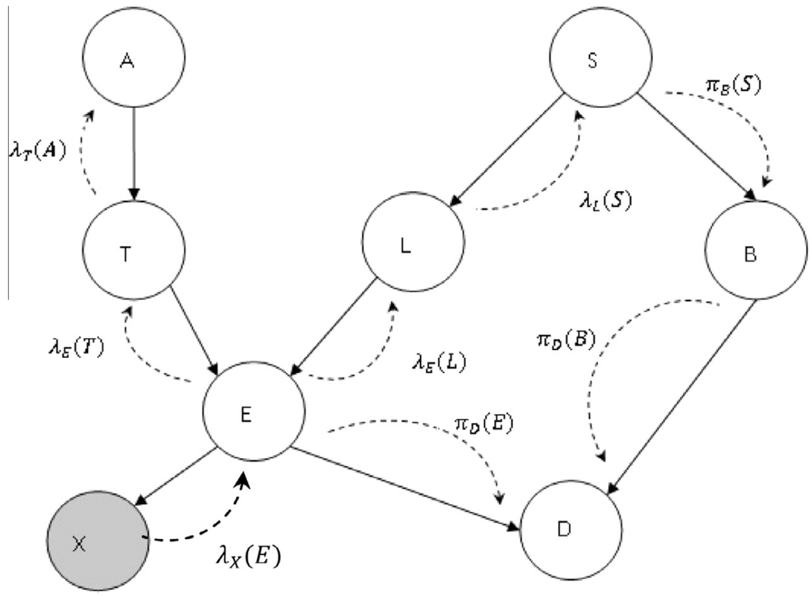


Fig. 12. Evidence propagation route after setting evidence on *X* node.

Table 8
Probability values of each node after setting evidence on *X* node.

	Bel(x)	$\pi(x)$	$\lambda(x)$
S	(0.6878, 0.3122)	**(0.5, 0.5)**	(0.152, 0.069)
B	(0.5063, 0.4937)	(0.5063, 0.4937)	**(1, 1)**
L	(0.4887, 0.5113)	**(0.055, 0.945)**	(0.98, 0.05967)
E	(0.576, 0.424)	**(0.0648, 0.9352)**	(0.98, 0.05)
X	**(1, 0)**	**(0.1103, 0.8897)**	**(1, 0)**
D	(0.6408, 0.3592)	(0.6408, 0.3592)	**(1, 1)**
A	(0.0132, 0.9868)	(0.01, 0.99)	**(0.1451, 0.11)**
T	(0.0924, 0.9076)	(0.0104, 0.9896)	(0.98, 0.1012)

The bold values represent initial values which remain unchanged from the prior probabilities.

Table 9
Probability values of each node after setting evidence on S node and X node.

	Bel(x)	$\pi(x)$	$\lambda(x)$
S	**(1, 0)**	**(0.5, 0.5)**	**(1, 0)**
B	(0.6, 0.4)	(0.6, 0.4)	**(1, 1)**
L	(0.646, 0.354)	(0.1, 0.9)	(0.98, 0.05967)
E	(0.7065, 0.2935)	(0.1094, 0.8906)	(0.98, 0.05)
X	**(1, 0)**	**(0.1103, 0.8897)**	**(1, 0)**
D	(0.7319, 0.2681)	(0.7319, 0.2681)	**(1, 1)**
A	(0.0122, 0.9878)	**(0.01, 0.99)**	(0.185, 0.151)
T	(0.0672, 0.9328)	**(0.0104, 0.9896)**	(0.98, 0.143)

The bold values represent initial values which remain unchanged from the prior probabilities.

correlation, and no linear correlation between the paired data is indicated by a value of zero. Despite some similarities, FCM and PCC are fundamentally different. PCC is calculated as probability value, whereas FCM is based on possibility.

Though PCC is applied in many domains, it can be interpreted in many ways (Rodgers & Nicewander, 1988). Pearson's product-moment correlation coefficient, *r*, between variables *X* and *Y* is depicted by Eq. (9) below.

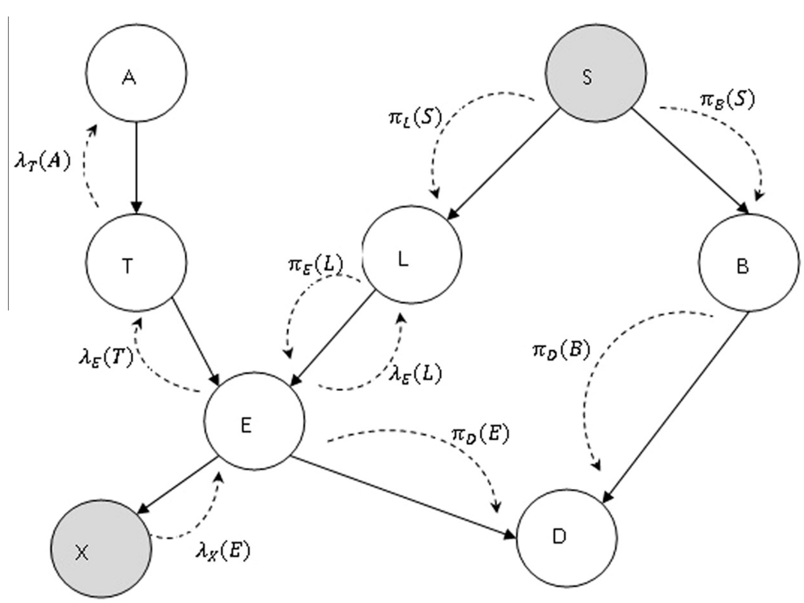


Fig. 13. Evidence propagation route after setting evidence on *S* node and *X* node.

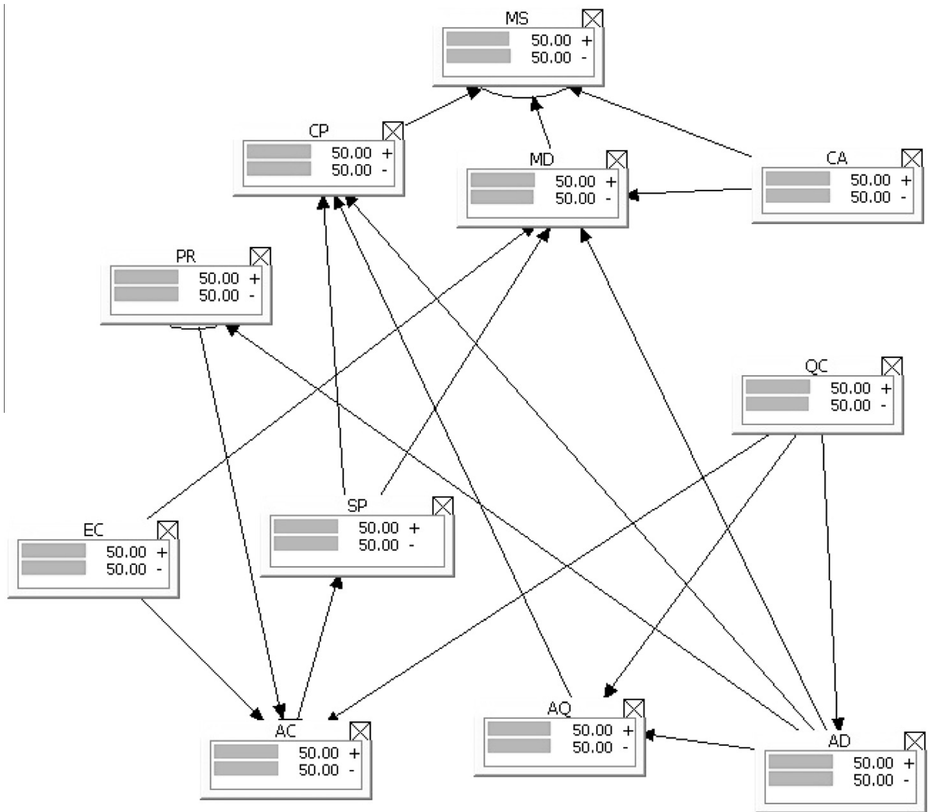


Fig. 14. BBN in assembly design decision support domain.

CP	MD	CA	MS +	MS -
+	+	+	0.62	0.38
+	+	-	0.84	0.16
+	-	+	0.47	0.54
+	-	-	0.75	0.26
-	+	+	0.26	0.75
-	+	-	0.54	0.47
-	-	+	0.16	0.84
-	-	-	0.38	0.62

SP	AQ	AD	CP +	CP -
+	+	+	0.79	0.22
+	+	-	0.47	0.53
+	-	+	0.47	0.53
+	-	-	0.19	0.82
-	+	+	0.82	0.18
-	+	-	0.53	0.47
-	-	+	0.53	0.47
-	-	-	0.22	0.78

SP	EC	CA	AD	MD +	MD -
+	+	+	+	0.79	0.21
+	+	+	-	0.38	0.62
+	+	-	+	0.72	0.28
+	+	-	-	0.30	0.71
+	-	+	+	0.67	0.34
+	-	+	-	0.25	0.76
+	-	-	+	0.58	0.43
+	-	-	-	0.18	0.82
-	+	+	+	0.82	0.18
-	+	+	-	0.43	0.58
-	+	-	+	0.76	0.25
-	+	-	-	0.34	0.67
-	-	+	+	0.71	0.30
-	-	+	-	0.28	0.72
-	-	-	+	0.62	0.38
-	-	-	-	0.21	0.79

QC	AD +	AD -
+	0.65	0.35
-	0.35	0.65

AD	PR +	PR -
+	0.31	0.70
-	0.70	0.31

AC	SP +	SP -
+	0.72	0.29
-	0.29	0.72

QC	EC	PR	AC +	AC -
+	+	+	0.70	0.30
+	+	-	0.76	0.24
+	-	+	0.51	0.49
+	-	-	0.60	0.40
-	+	+	0.40	0.60
-	+	-	0.49	0.51
-	-	+	0.24	0.76
-	-	-	0.30	0.70

QC	AD	AQ +	AQ -
+	+	0.85	0.15
+	-	0.58	0.42
-	+	0.42	0.58
-	-	0.15	0.85

Fig. 15. CPTs of BBN.

$$r = \frac{cov(X, Y)}{(\sigma X)(\sigma Y)} \tag{9}$$

where $cov(X, Y)$ denotes the covariance of X and Y, and both σX and σY in the denominator imply the unique variance of X and Y respectively. In statistics, the equation derived from Eq. (7) is shown in Eq. (10).

$$r = \frac{\sum xy - \frac{\sum x \sum y}{N}}{\sqrt{\left(\sum x^2 - \frac{(\sum x)^2}{N}\right)\left(\sum y^2 - \frac{(\sum y)^2}{N}\right)}} \tag{10}$$

where $\sum xy$ indicates the summation of the product of x and y, and $\sum x$ and $\sum y$ indicate the summation of x and the summation of y respectively. N denotes the total number of data.

Table 10
Abbreviations in Figs. 14 and 15.

Abbreviation	Name	Abbreviation	Name
MS	Market Share	PR	Productivity
CP	Competitiveness	AC	Assembly Cost
CA	Competitor's Advertisements	SP	Sales Price
MD	Market Demand	AD	Assembly Design
QC	Quality Control	AQ	Assembly Quality
EC	Economic Conditions		

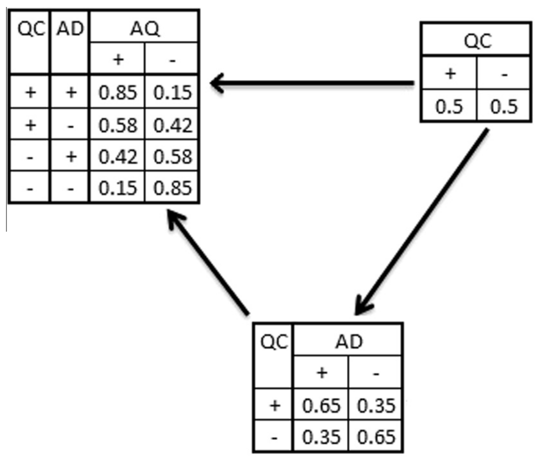


Fig. 16. CPTs of the three connected nodes.

Table 11
Four-state table of *QC* to *AQ*.

QC	*AQ*		Total
	+	–	
+	0.37775	0.12225	0.5
–	0.12225	0.37775	0.5
Total	0.5	0.5	1

However, when PCC values are represented in the conditional probability as shown in Table 11, they can be interpreted in different ways. In BBN, probability is always represented as a positive value [0,1] but PCC is in the range of –1 to +1. Rodgers and Nicewander (1988) claim that non-negative *r* is interpreted as the geometric mean of the two slopes of the regression lines. However, non-negative *r* is used here to fulfil the requirements of BBN and it does not imply the geometric mean of the two conditional probabilities. The sign of the causal strength will be determined in the following sections. The equation of PCC for a four-state table is shown below in Table 12.

$|r_{xy}|$ is the absolute value of Pearson's correlation coefficient.

$$|r_{xy}| = \frac{(P_{x=T,y=T} \cdot P_{x=F,y=F}) - (P_{x=T,y=F} \cdot P_{x=F,y=T})}{\sqrt{P_{x=T} \cdot P_{x=F} \cdot P_{y=T} \cdot P_{y=F}}} \qquad (11)$$

where $P_{x=T,y=T}$ is the conditional probability when *X* is true and *Y* is true; $P_{x=F,y=F}$ is the conditional probability when *X* is false and *Y* is false. Probability *r* value can be calculated from Eq. (11). After the calculation, the probability *r* value is stored in a table and sorted in descending order, as shown in Fig. 17. In this figure, QC has the strongest correlation with AQ, with the probability value of 0.51.

Table 12
Probability distribution.

X	Y		
	T	F	Total
T	TT	FT	X = T
F	TF	FF	X = F
Total	Y = t	Y = F	1

i	Relationship	|r|
1	QC -----> AQ	0.51
2	AC -----> SP	0.44
3	AD -----> CP	0.42
4	AQ -----> CP	0.42
5	AD -----> MD	0.41
6	AD -----> AQ	0.4
7	AD -----> PR	0.38
8	CP ----> MS	0.36
9	QC ----> AD	0.3
10	QC -----> AC	0.3
11	CA -----> MS	0.24
12	EC -----> AC	0.17
13	MD ----> MS	0.16
14	EC -----> MD	0.13
15	PR -----> AC	0.11
16	CA -----> MD	0.08
17	SP -----> CP	0.004
18	SP -----> MD	0.004

Fig. 17. PCC value for causal strength.

4.2. Generation of FCM from FCM-compatible BBN

In this section, the transformation process from the probability value described in previous section to possibility value is discussed. After that, the causality sign of the strength is determined and FCM is built.

4.2.1. Probability to possibility transformation

After the causal strength for each link has been calculated, the fuzzy-compatible probability value for each relationship which fulfils the fundamental requirements of FCM is ready to be used. Fuzzy-compatible probability value is used to represent the causal value in FCM after the transformation process. Probability to possibility transformation can be very useful in many problems as probability enables sound reasoning and possibility facilitates the intuitive understanding of the end-user. Nevertheless, some information will be lost in the conversion of probability to possibility as it goes from point-valued probability to interval-valued (Dubois & Prade, 1982). Even though the problem of transformation from probability to possibility and vice versa has received much attention from the research community, only a few works have tried to determine the practical transformation between the two (Yamada, 2001). The transformation between probability and possibility has roots in the consistency principle of Zadeh (1965). He claims that an event must be possible prior to being probable and the degree of possibility must be higher than the degree of probability.

Let $p = (p_1, p_2, \ldots p_n)$ and $\pi = (\pi_1, \pi_2, \ldots \pi_n)$ denote a probability distribution and a possibility distribution on a finite set *X* with *n* or more elements. According to Klir (2005), the transformation of probability to possibility and vice versa should be based on three assumptions. First, assume that certain properties (such as the ordering or proportionality of values) are preserved during the transformation as p and π are connected by a scale. This scaling assumption can be ratio-scale, interval-scale, log-interval-scale, ordinal-scale transformation, etc. Second, assume an uncertainty invariance according to which the Shannon entropy, $S(p)$, should be numerically equal to the measure of the information, $E(\pi)$, contained in the transform π of p. In order to be coherent with the probabilistic entropy, $E(\pi)$ can be the logarithmic imprecision index of Higashi and Klir (1982), for instance. Lastly, assume a consistency condition $\pi(x) \geqslant p(x)$, $\forall x$ that stating what is probable must be possible should be obeyed. In this research, the log-interval scale transformation by Klir will be adopted for the probability to possibility transformation process. Log-interval scale transformation is adopted as it satisfies the assertion in both directions, i.e., the total uncertainty of the non-specificity, and the body of evidence must be preserved in the transformation between probability and possibility (Klir, 1999).

Log-interval scale transformations have the form $\pi_i = \beta p_i^{\alpha}$ for all $i \in \mathbb{N}_n$, where β and α are positive constants. The equation for all $i \in \mathbb{N}_n$ is obtained by determining the value of β from the possibility normalisation where $\pi_1 = 1$ is shown as follows:

$$\forall\ i \in \mathbb{N}_n, \quad \pi_i = \left(\frac{p_i}{p_1}\right)^{\alpha} \tag{12}$$

As α must be a positive constant and derived from Eq. (12), Eq. (12) has been rewritten as:

$$\forall\ i \in \mathbb{N}_n, \quad \pi_i = \left(\frac{p_i}{p_1}\right)^{|\alpha|} \tag{13}$$

First of all, the value of α needs to be determined. Eqs. (14) and (15) are used to calculate the value of α. $S(p)$ is the Shannon measure (Klir, 1999) applied to uncertainty formalised in terms of a probability distribution. The Shannon measure is used here to calculate the value of α in Eq. (13). Eq. (15) is used to obtain the value of $S(p)$. The value of $S(p)$ will then be substituted in Eq. (14) to acquire the value of α. The α value will be substituted in Eq. (13) for all the probability values to calculate the value for possibility.

$$S(p) = \sum_{i=2}^{n} \left(\frac{p_i}{p_1}\right)^{\alpha} \log_2 \frac{i}{i-1} \tag{14}$$

p1 denotes the first probability value.

$$S(p) = -\sum_{x \in X} p(x) \log_2 p(x) \tag{15}$$

The corresponding possibility values obtained from Eq. (13) are listed in Fig. 18 below.

i	Relationship	π
1	QC -----> AQ	1
2	AC -----> SP	0.92
3	AD -----> CP	0.89
4	AQ -----> CP	0.89
5	AD -----> MD	0.88
6	AD -----> AQ	0.87
7	AD -----> PR	0.84
8	CP ----> MS	0.82
9	QC ----> AD	0.74
10	QC -----> AC	0.74
11	CA -----> MS	0.65
12	EC -----> AC	0.53
13	MD ----> MS	0.51
14	EC -----> MD	0.46
15	PR -----> AC	0.41
16	CA -----> MD	0.35
17	SP -----> CP	0.06
18	SP -----> MD	0.06

Fig. 18. Table of possibility.

4.2.2. Causality sign determination

The causality sign in FCM represents the causal direction from one event to another event. The positive sign represents the promoting effect in FCM whereas the negative sign represents the inhibitory effect. In FCM, three types of effect obtained by assuming an increase of a variable and how it affects another variable:

- Promoting effect: the connected variable tends to increase.
- Inhibitory effect : the connected variable tends to decrease.
- No effect: the other variable neither increases nor decreases.

The promoting effect is represented by a positive sign, the inhibitory effect is represented by a negative sign, and no effect is represented by a zero value in the range of -1 to +1, where -1 implies the strongest inhibitory effect and +1 implies the strongest promoting effect.

As in the four-stage table mentioned in Section 4.2, $P(Y = T \cap X = T)$ and $P(Y = F \cap X = F)$ will be represented as the promoting effect and $P(Y = T \cap X = F)$ and $P(Y = F \cap X = T)$ will be represented as the inhibitory effect. Therefore, it is a promoting effect when the total probability value of $P(Y = T \cap X = T)$ and $P(Y = F \cap X = F)$ is larger than the total probability of $P(Y = T \cap X = F)$ and $P(Y = F \cap X = T)$. On the other hand, it is an inhibitory effect when it is smaller. The total probability values for positive influence and negative influence are calculated by Eqs. (16) and (17).

$$\text{Total positive influence} = P(Y = T \cap X = T) * P(Y = F \cap X = F) \tag{16}$$

$$\text{Total negative influence} = P(Y = T \cap X = F) * P(Y = F \cap X = T) \tag{17}$$

Then, the causality sign can be obtained from the equation below by comparing the total negative influence with total positive influence as follows.

```
If  Total negative influence > Total positive influence
    Causality sign = '–';
Else
    Causality sign = '+';
```

4.2.3. Construction of FCM

Lastly, with all the requirements ready, FCM can be built as in Fig. 19 below.

Compared with the BBN of assembly design decision support in Fig. 14, the FCM of assembly design decision support provides an intuitive causal representation for the end-user. For example, from Fig. 19, an immediate observation could be made as CA has an inhibitory effect on MS. An increase in CA is very likely (i.e., high possibility) to cause a decrease in MS. Furthermore, conclusion can be made instantly as among the three causes of MS, CP has the strongest promoting effect to MS, which means an increase

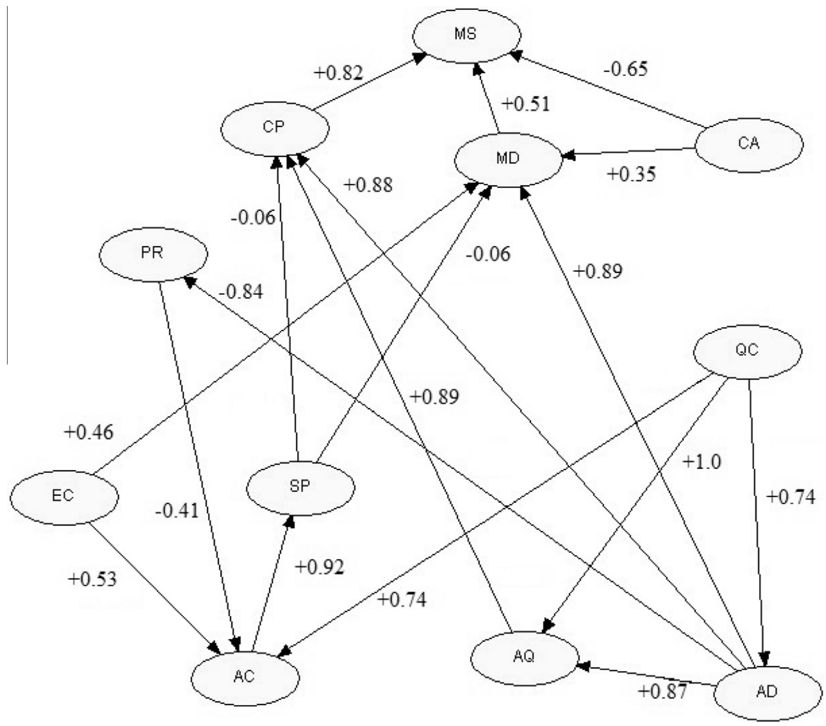


Fig. 19. FCM of assembly design decision support.

in CP is very likely to cause an increase in MS. Therefore, FCM is more intuitive than BBN in terms of causal knowledge representation.

5. Case study

To validate the proposed method as mentioned above, a case study related to an automobile start-up problem is used. A common reason why a car cannot start is a dead battery. However, there may be other reasons as an automobile consists of multiple parts, and a series of complicated steps is needed to start it. There are three main reasons, however: ignition, compression and fuel/air problems (Al-Taani, 2005). Thousands of minor things can cause failure to start an automobile. Table 13 below shows some of them.

5.1. Learning BBN causal model from data

Learning a BBN causal model from data involves three main steps: data pre-processing, structure learning and parameter learning, as shown in Fig. 20. At this stage, the purpose is to discover the relationship between variables (data elements) by using appropriate BBN learning tools and constructing a causal model. The most arduous process is the structure learning.

Table 13
Reasons for automobile start-up failure.

Component	Condition
Ignition Switch	Faulty ignition switch
Starter	Poor starter motor and connection fail to turn the engine over
Battery	Dead battery can cause the engine not to crank; lights and radio fail to work
Bearings	Worn out bearings can cause the crankshaft not to turn
Valves	Opening and closing at the wrong time mean the air is unable to get in and exhaust unable to get out
Tailpipe	Clogged pipe means the exhaust cannot exit the cylinder so the engine will not run
Oil	Piston cannot move up and down freely in the cylinder and engine will seize up if running out of oil

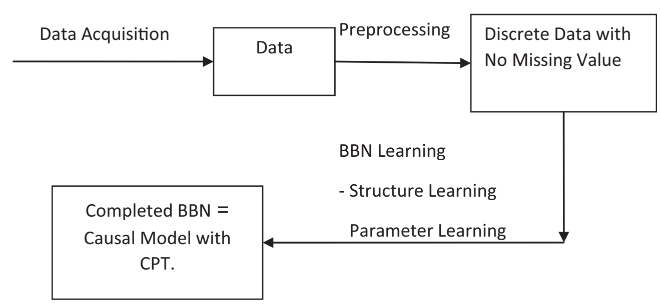


Fig. 20. Process of learning BBN causal model from data.

5.1.1. Data pre-processing

Most BBN freeware does not accept continuous or missing data. Hence, some data pre-processing steps need to be carried out before learning of the BBN causal model takes place. For the variables which consist of continuous data or missing data, discretisation is needed. There are several mechanisms available for discretising continuous variables, such as the minimum descriptive length (MDL) proposed by Fayyad and Irani (1993), class-attribute interdependence maximisation (CAIM) (Kurgan & Cios, 2001), the class-attribute contingency coefficient (CACC) (Tsai, Lee, & Yang, 2008) and others. A few methods are available for handling missing values such as ad hoc methods which ignore missing data by filtering, replacing them with mean/modal values; inferring them using static completion; and others. Ad hoc methods are used in this experiment as it is simple and the dataset at hand only contains a few missing values.

The automotive fault diagnosis dataset was introduced in JavaBayes (Car-starts dataset). The reason why an automobile is

Table 14
Attributes in car start dataset.

No	Attribute	Domain	No	Attribute	Domain
1	Alternator	OK, faulted	10	Lights	Work, no light
2	Fan belt	OK, broken, slipping	11	Radio	Works, dead
3	Leak	No leak, leak	12	Starter	OK, faulted
4	Charge	Good, low	13	Leak2	False, true
5	Battery age	Old, new	14	Engine cranks	Cranks, no crank
6	Battery state	OK, weak	15	Fuel pump	OK, faulted
7	Battery power	Good, poor	16	Distributor	OK, faulted
8	Gas in tank	Gas, no gas	17	Spark plug	OK, bad
9	Gas gauge	Gas, no gas	18	Starts	Yes, No

unable to start is presumed to relate to the engine crank, alternator, fan belt and others. This database consists of eighteen variables as in Table 14 and all variables of the database take discrete values. Some of the variables take three discrete states and the others take two discrete states. The entire dataset is in a discrete format. Hence, no discretisation is needed. The total number of instances in the database is 10,000 and one instance has a missing attribute value. The instance with a missing value will be removed from the database and the remaining 9999 instances used in this experiment.

5.2. RCA with BBN

BBN is completed when the structure and parameters of the network have been learned. In the following experiment, a BBN causal model has been tested to show its ability to do the causal reasoning. Usually, BBN will only show the structure of the causal model with the states of each variable. CPT will remain at the rear end for probability calculation purposes. Fig. 21 is the graphical model of the initial BBN without any evidences set.

5.2.1. Predictive RCA

Prognostic/predictive RCA is the ability to predict the future outcome. In BBN, the probability of other variables will be affected if the value of certain variables in the network is changed. The evidence propagation in the network will produce updated posterior probability values for all the variables in the network. An assumption can be made based on the results of prognostic reasoning. Assuming that there is evidence of poor battery power, and referring to Fig. 22, what-if analysis and prediction suggest that there is an 80.2% chance that the engine will not crank. In addition, the chances of radio and lights not working will be increased to 90% and 100% when the battery power is poor. This indicates that battery power has a huge influence on engine, radio and lights. In addition, the prediction is correct because those assumptions are consistent with the knowledge of experts in this domain, as shown in Table 13. The impact will further propagate to other variables which have direct or indirect relationships with the *BatteryPower* variable. The impact flows further down to the *Starts* variable, which suggests there is an 80.23% chance that the car cannot be started if battery power is poor. That being the case, the *Starts* variable's changes come from its indirect dependence on battery

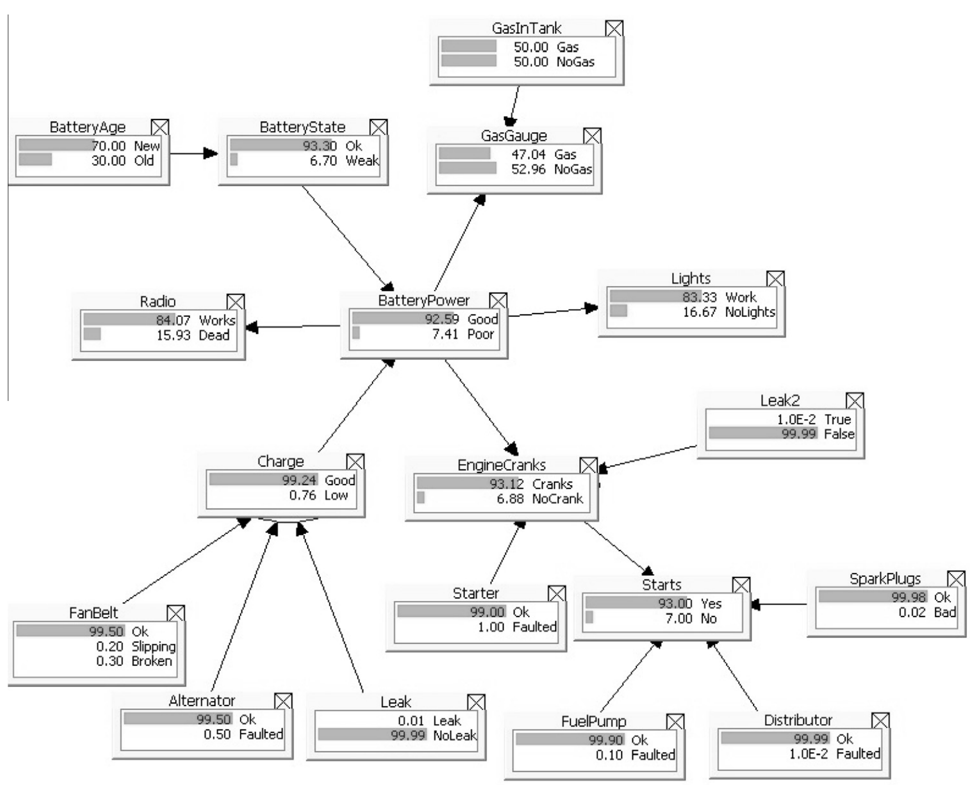


Fig. 21. Graphical model of initial BBN.

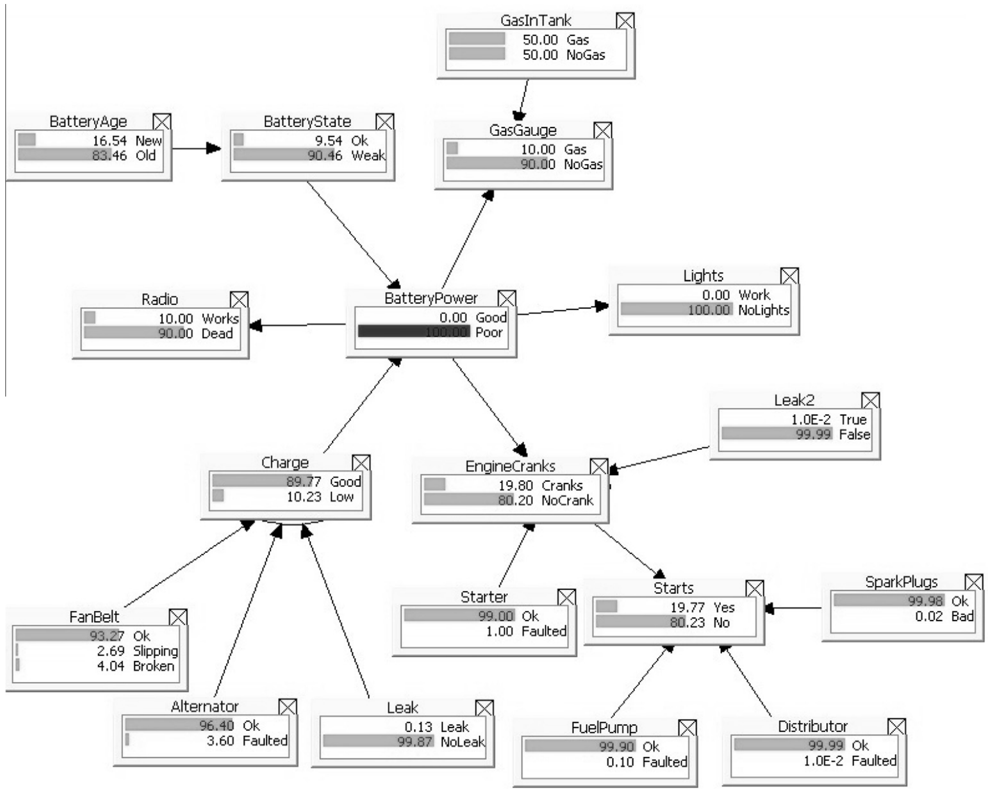


Fig. 22. Predictive RCA – setting evidence in *BatteryPower* node.

power. Generally, because of a dead battery the engine does not crank, and as a result the automobile fails to start.

5.2.2. Diagnostic RCA

Besides prognostic reasoning, BBN provides another usage, which is diagnostic reasoning. This is the ability to diagnose the root cause of an event. Sometimes, people want to know the factor(s) that will influence a target variable. In this case, BBN is used to diagnose the possible root cause by changing the probability for a variable of interest. For example, if there is evidence that a car cannot start, as in Fig. 23, an observation is made that there is a 98.27% chance the engine crank is not working, a 0.29% chance the spark plugs are in bad condition, a 0.14% chance the distributor is faulty and a 1.43% chance the fuel pump is faulty. These four variables are regarded as direct factors or causes. In this context, an assumption can be made that the main reason why an automobile cannot be started is that the engine will not crank. The assumption is pretty accurate as the engine is the main part in an automobile and it plays an important role in automotive functioning. Moreover, spark plugs and fuel pumps are also a direct cause of malfunction, as mentioned in Section 5.1. Diagnostic reasoning is able to trace not only the direct causes but also the indirect causes. Battery power, starter, and leakage are possible reasons why an engine will not crank. Obviously, battery power is the main reason, as the probability in the *BatteryPower* node has the greatest value. Extending the analysis to all the ancestor nodes, there is a 74.76% chance that the battery is old if a car cannot start. Though the charge system will also affect the battery power as there is a causal link between the two variables, the battery age is a more likely cause. As a result, both the *Charge* and *BatteryState* variables will affect the battery power. However, the causal network will identify the most likely cause of an automobile failing to start as the engine failing to crank.

5.2.3. Hybrid RCA

Hybrid reasoning combines prognostic and diagnostic inferences. It allows us to perform the diagnosis and prognosis mentioned above at the same time. Setting the value for both nodes will affect the probability of the remaining nodes either continuously increasing or continuously decreasing. For example, the chance an engine will not crank is 80.20% affected by poor battery power, as shown in Fig. 22. It has, however, become a 98.27% cause, as shown in Fig. 23. If there are both poor battery power and engine failure, the effect is cumulative. As shown in Fig. 24, the combination of the prognostic and diagnostic inferences will push up the probability of the engine not cranking to 99.97%. However, some variables will retain the same probability value as in predictive or diagnostic reasoning, as those variables are only affected by a node. Hence, setting the evidence in both nodes will not have a cumulative or cancellation effect on them.

5.3. Transformation of BBN to FCM

After a complete BBN has been learnt, the migration of BBN to FCM will be carried out. Each node in the BBN is attached to a joint probability distribution CPT, as in Fig. 27. The CPT of *BatteryPower* (BP) shown in Fig. 25 is modified from its original joint probability distribution CPT consisting of eight states. This is done because only the probability of BP being in good condition and in poor condition need to be used in the subsequent calculation for causal strength of the link from BP to *GasGauge* (GG). The modification is aimed at better interpretation of the migration process.

To discover the individual effect of *GasInTank* (GIT) on GG, a conditional probability equation is applied. Once the new four-state table, consisting of $P(GG = Gas,\ GIT = Gas)$, $P(GG = No\ Gas,\ GIT = Gas)$, $P(GG = Gas,\ GIT = No\ Gas)$, $P(GG = No\ Gas,\ GIT = No\ Gas)$, has been constructed, a PCC equation is used to calculate the causal strength of GIT towards GG in terms of probability. Those steps will

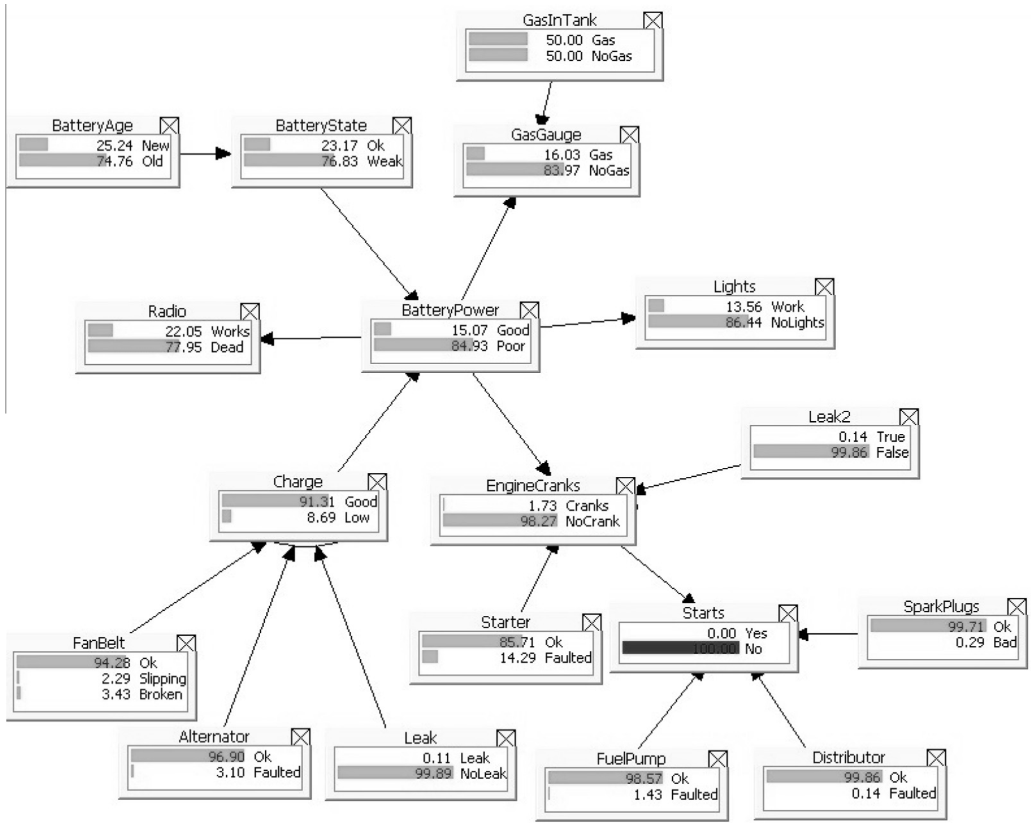


Fig. 23. Diagnostic RCA – setting evidence in *Starts* Node.

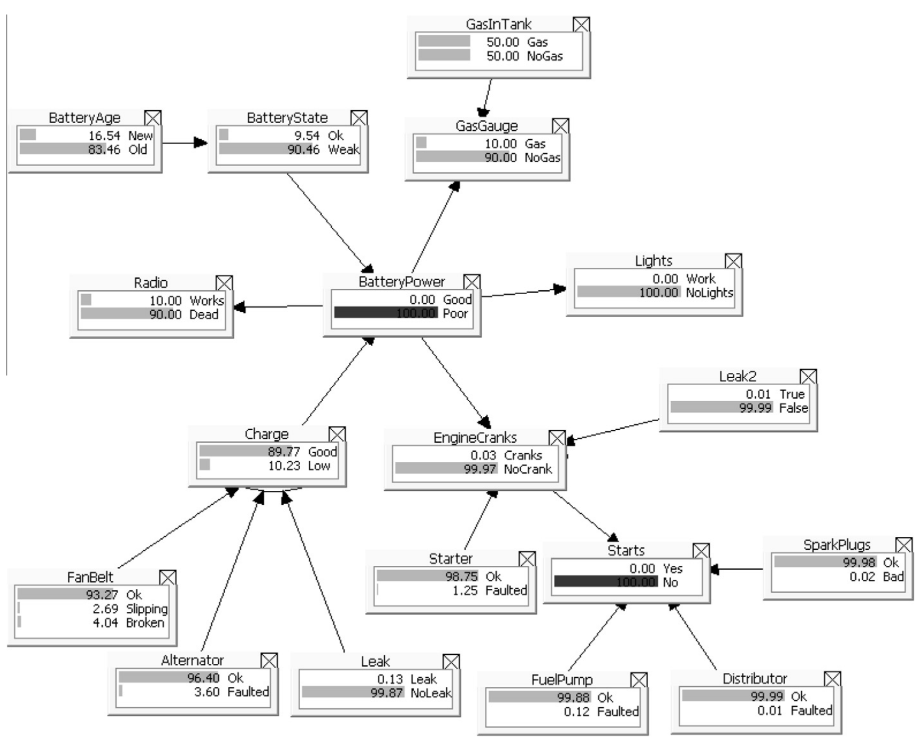
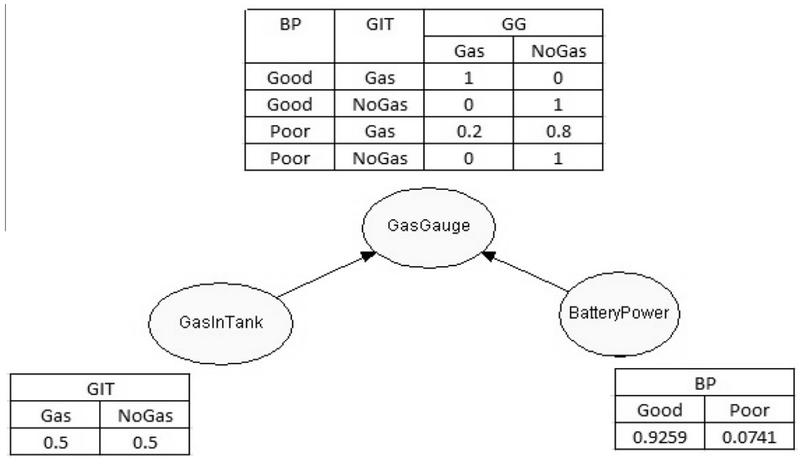


Fig. 24. Hybrid RCA – setting evidence in *BatteryPower* node and *Starts* node.

be repeated for the whole network until all causal strengths in probability have been calculated. After that, the causal strength in probability for each relationship is stored in a table for the probability to possibility transformation. The FCM is completed when the causal strength in possibility is calculated and attached to a causal model, as shown in Fig. 26. In FCM, a causal relationship



BP	GIT	GG	
		Gas	NoGas
Good	Gas	1	0
Good	NoGas	0	1
Poor	Gas	0.2	0.8
Poor	NoGas	0	1

GIT	
Gas	NoGas
0.5	0.5

BP	
Good	Poor
0.9259	0.0741

Fig. 25. Illustrative partial automotive fault diagnosis BBN graphical structure and CPTs.

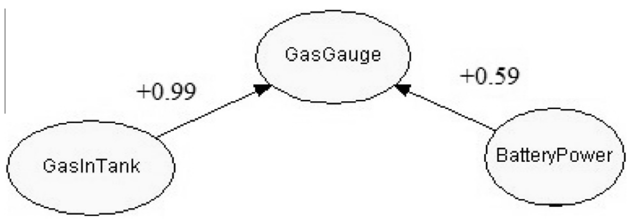


Fig. 26. Illustrative partial automotive fault diagnosis FCM graphical structure.

is assigned a single value, representing causal strength. For example, in Fig. 26, the causal strengths +0.99 and +0.59 are attached to the causal links (GIT → GG) and (BP → GG) respectively. In BBN a causal relationship is not represented as a single value attached directly to the causal link. Instead, it is represented indirectly as multiple probabilistic values in a CPT attached to the effect (child) node of the link. For example, in Fig. 27, the causal strength of the link (GIT → GG) is represented in the CPT for GG as conditional probability values for the gas and no gas states of GG, given the gas and no gas states of GIT, together with good and poor states of BP. Obviously, it is more intuitive for causal strength to be represented as a single value, directly attached to the causal link itself. However, it is less intuitive for causal strength to be represented as the multiple probabilistic values in a CPT attached to the effect node.

With the steps in Section 4, a BBN causal model can be transformed to FCM as shown in Fig. 27. Representation of the causal

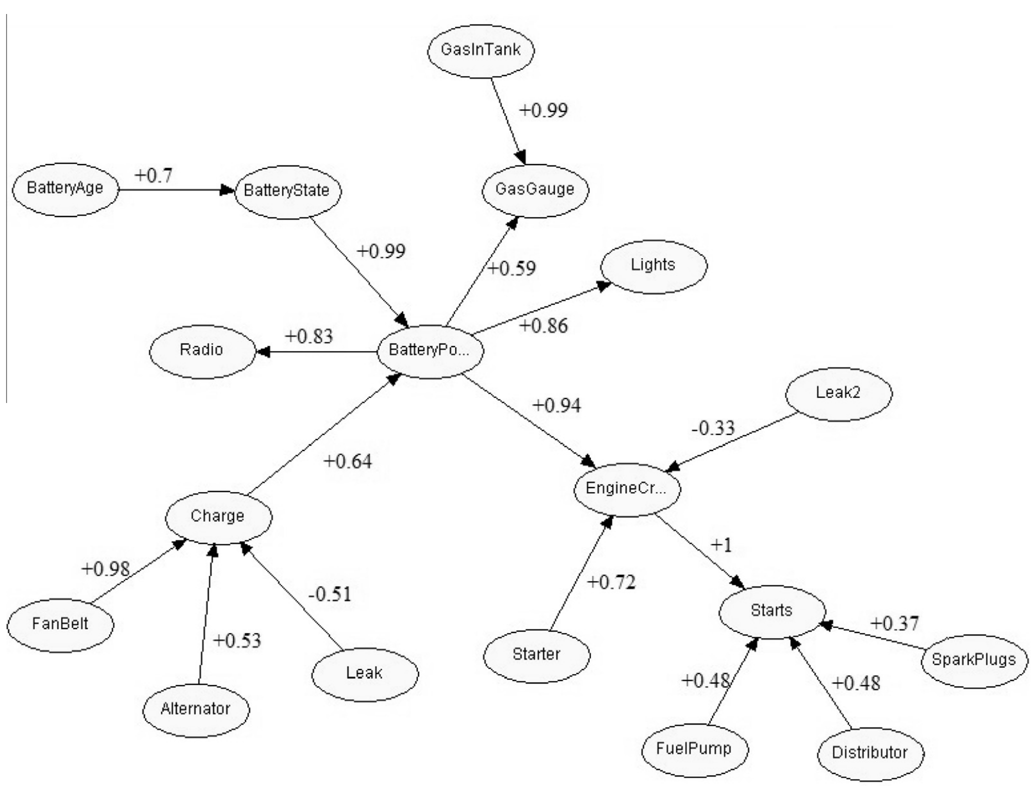


Fig. 27. Graphical representation of the automotive fault diagnosis FCM.

model in FCM provides an intuitive explanation to the end-user. An immediate explanation can be obtained by referring to the representation in Fig. 26, but not by referring to Fig. 21. An instantaneous assumption can be made that when battery power is good, the possibility of lights and radio working well is very strong. In addition, an assumption can be made immediately as *EngineCranks* has the strongest effect on the *Starts* variable, and *BatteryPower* has the strongest effect on the *EngineCranks*. This is very convenient and simple for those users who are not experts in the domain in which they want to identify the root cause of an event.

6. Conclusions and future study

In this paper, a method has been proposed for RCA using BBN and FCM. The paper has two main parts. First, BBN learning as well as the correctness and accuracy of the model learnt from data is tested. The results are positive as BBN is able to recover most of the relationships among the variables correctly. Apart from that, BBN can perform many other tasks such as causal reasoning, classification and feature selection. The performance of each task is presented and discussed. After the reliability of BBN learning is verified, it is used to construct a causal model from a database.

Next, the causal knowledge model constructed in BBN by the data mining approach is used to perform RCA for decision-making. BBN offers powerful reasoning capability as well as minimum human intervention and effort. The prognostic RCA is able to predict the future outcome and the diagnostic RCA is able to diagnose the root cause of an event. However, the representation of causal knowledge in BBN is not intuitive compared with FCM. In the second part of this study, a migration method of BBN to FCM is proposed and presented. The purpose of the migration is to take advantage of the simplicity of FCM, which shows causal strength in an intuitive way.

The final output of this research work is a simple and cost effective method for developing causal reasoning model, which is significant in many expert system application domains, such as stock analysis, intrusion detection, medical diagnosis, and machine fault localisation. Overall, there are two main contributions of this article. The first contribution is described in Section 3. It constitutes an experimental set-up. The purpose is to test and to verify the reliability of BBN in learning a causal model from data through an innovative set-up of a series of experiments. Experimental results show that BBN has correctly learned the causal model from data with sufficiently high accuracy.

The next contribution, a theory, is described in Section 4. The purpose is to propose an integration method for BBN and FCM. The method involves the migration of BBN to FCM for more intuitive and simpler causal representation. An intuitive causal representation is extremely important for enabling the immediate understanding of the end-users who need to make strategic decisions, especially those who are non-experts. FCM, which represents causal knowledge in a qualitative format, reveals a clear picture. Thus, the novel migration from BBN to FCM can bridge the gap between the two approaches.

The proposed method is better than many existing RCA methods because the causal networks are learnt from data using data mining approach. This approach eliminates the difficulty in finding domain experts, inconsistency in experts' opinions, and human errors in the knowledge engineering process. The representation of causal models using both BBN and FCM allows powerful automated RCA as well as intuitive manual analysis of the causal knowledge. However, the proposed method requires a data-rich domain to work effectively, which unfortunately is not always practical in many application domains.

This work is the first step towards the development of a methodology for the migration of BBN to FCM. Testing the methodology by using larger data sets in complex and practical domains such as industrial RCA is planned. Moreover, formalisation of the transformation process needs to be performed to affirm each step in the migration methodology. One of the limitations of this work is the use of static BBN which, unlike dynamic BBN, does not have much in common with FCM. In future work, dynamic BBN is proposed to enhance the migration methodology and further improve the methodology by extending the migration method to a two-way migration between dynamic BBN and FCM.

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