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Uncertainties in conditional probability tables of discrete Bayesian Belief Networks: A comprehensive review

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28 **1 Introduction**

29 Bayesian Belief Network (BBN) has become an increasingly popular method for the analysis
30 of complex systems in various domains of application, like ecosystems (Milns et al., 2010),
31 genetics and biology (Scutari et al., 2014), agriculture (Drury et al., 2017), industry (Weber et
32 al., 2012), finance forecasting (Malagrino et al., 2018), marine safety (Hänninen et al., 2014),
33 human reliability assessment (Mkrtchyan et al., 2015), nuclear power plants (Kwag and Gupta,
34 2017), aviation risk analysis (Brooker, 2011), coastal systems (Jäger et al., 2018), structure
35 reliability assessments (Langseth and Portinale, 2007), multi-hazard risk assessments (Gehl and
36 D’Ayala, 2016), etc.

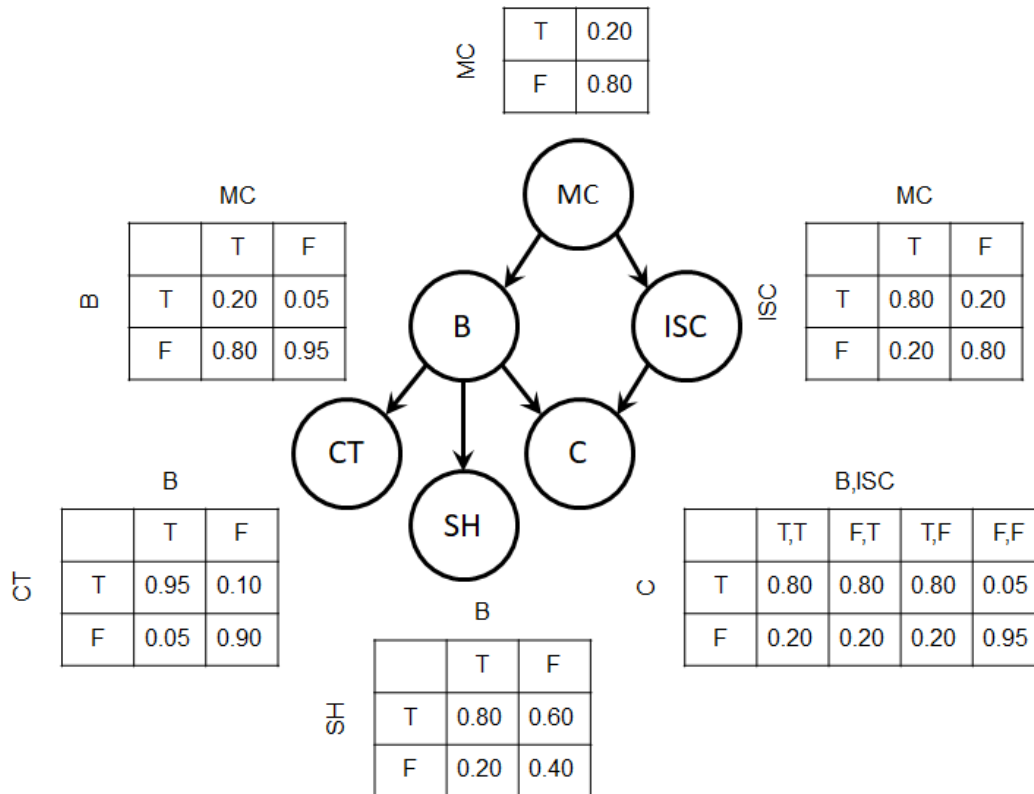
37 Its benefits are: (1) its high flexibility to model any causal relationships; (2) its capability to
38 integrate information from any kind of sources, including experimental data, historical data,
39 and prior expert opinion, and (3) its capability to answer probabilistic queries about them and
40 to find out updated knowledge of the state of a subset of variables when other variables (i.e. the
41 evidence variables) are observed.

42 Formally, a Bayesian belief Network (BBN) is a class of graphical model (see Jensen, 2001 for
43 a complete and detailed introduction to BBNs), which allows to synthetically represent relations
44 among random variables by means of a directed acyclic graph (DAG) composed of nodes (i.e.
45 the states of the random variables) and arcs (i.e. dependency between nodes). The value of the
46 nodes may be discrete or continuous, and we focus here on the former case, which is the most
47 widely used. For instance, a Boolean node representing the state of a system component can be
48 either “True” or “False”. The nodes connected by an arc are called the parent nodes and child
49 nodes respectively. One child node may have several parent nodes, meaning that this node is
50 affected by several factors. Similarly, a parent node could have several child nodes, meaning
51 that this factor may have influences on several other factors. Conditional probabilities are the
52 probabilities that reflect the degree of influence of the parent nodes on the child node. For BBNs
53 with discrete nodes, the probabilistic dependence (i.e. the cause-effect relation) is often
54 represented via a table called a Conditional Probability Table (CPT).

55 As an illustration, Fig. 1 depicts the binary BBN adapted by van der Gaag et al. (2013) from
56 Cooper (1984) in the field of oncology. The network is composed of 6 nodes and 6 arcs. Node
57 MC refers to metastatic cancer, which may potentially lead to the development of a brain tumor
58 (node B) and may give rise to an increased level of serum calcium (node ISC). The presence of
59 a brain tumour can be established from a CT scan (node CT). Another indicator of the presence
60 of a brain tumour can be related to severe headaches (node SH). A brain tumour or an increased

61 level of serum calcium are both likely to cause a patient to fall into a coma (the node C is
 62 connected to node B and node ISC). The conditional probabilistic relationships between the
 63 nodes (CPT entries) are provided in Fig. 1 next to the corresponding nodes. For instance, the
 64 probability that a patient falls into coma given brain tumor and increased level of serum calcium
 65 corresponds to the first entry of the table (1st row, 1st column), namely
 66 $P(C=True|C=True,ISC=True)=0.80$.

67



68

69 Figure 1. Binary BBN adapted by van der Gaag et al. (2013) from Cooper (1984) in the field
 70 of oncology. The tables (called CPT) next to the nodes provide the conditional probabilities
 71 values.

72

[Figure 1 about here]

73

74 Two key ingredients are necessary to build a BBN, namely (1) the graph structure with the
 75 direction of the arcs, i.e. the DAG; (2) the states of nodes and the strength of the relationships
 76 between nodes, i.e. the CPT. In the present study, we assume that the DAG model has already
 77 been determined and restrict the analysis to the quantification of the BBN relationships. The
 78 process of deriving the CPTs and its associated uncertainties is recognized in the literature as
 79 one of the most delicate part of the BBN development (e.g., Chen and Pollino, 2012; Druzdzal

80 and van der Gaag, 2000; Marcot et al., 2006; Cain, 2001, etc.). It should, however, be noted
81 that the process of DAG derivation (i.e. building the graph structure plus the directions; also
82 known as causal structure learning) has its own challenges as well, in particular when the
83 learning is based on data (see e.g., a comprehensive review by Heinze-Deml et al., 2018).

84 Depending on the available data (observations, prior knowledge, expert-based information,
85 etc.), CPTs can be evaluated in different manners, i.e. different assumptions can be made and
86 different methods are available leading to different BBN-based results, hence resulting in
87 uncertain BBN-based results. This raises the following questions: (1) how to constrain the
88 uncertainties related to CPT derivation, i.e. what are the methods that are available to minimize
89 these uncertainties? (2) how to integrate these uncertainties in the BBN-based analysis, i.e. what
90 are the methods for propagating these uncertainties? (3) how to test the robustness of the BBN-
91 based results to these uncertainties, i.e. what are the methods for identifying the most influential
92 uncertainties? These questions are addressed below through an extensive review of studies
93 performed in the past ten years by focusing on discrete BBNs that can be used for modelling
94 complex causal relationships, for merging different information sources, for prediction, and for
95 belief/evidence propagation (i.e. probabilistic queries). Continuous BBNs (i.e. BBNs with
96 continuous nodes) and dynamic BBNs (i.e. BBNs adapted to model systems evolving over
97 time) are out of the scope of the review.

98 The paper is organized as follows. The first section describes more specifically the problem of
99 populating the CPT parameters directly from data/observations. This first part highlights the
100 necessity for overcoming the lack of data by complementing with additional sources of
101 information. Sect. 3 explores an expert-based option for constraining the uncertainties related
102 to data incompleteness, namely by completing with different expert-based sources of
103 information. Sect. 4 provides an overview of the different approaches embedded in different
104 uncertainty analysis settings for evaluating the impacts of CPT uncertainties, either using
105 probabilities or imprecise probabilities. Sect. 5 further addresses the problem of screening these
106 uncertainties by describing sensitivity analysis techniques. Finally, Sect. 6 summarizes the main
107 findings and discusses the open questions.

108 **2 Learning CPT from data**

109 In this section, we address the issues related to deriving the CPT entries from data. Sect. 2.1
110 first discusses the problem of performing this task by using only data. Sect 2.2 and 2.3 further
111 discuss two practical difficulties, namely: (1) the presence of missing values and (2) the
112 problem of translating observations related to continuous variables into a limited number of

113 discrete states. Finally, Sect. 2.4 describes methods that make the most out of scarce data while
114 exploiting qualitative information provided by experts.

115 **2.1 A pure data-driven approach**

116 Let us consider a BBN composed of n discrete nodes $X_{i=1,\dots,n}$. Let us denote r_i the cardinality of
117 X_i and q_i the one of the parent set of X_i , denoted $pa(X_i)$. The k^{th} probability value of the
118 conditional probability distribution is $\theta_{ijk} = P(X_i = k | pa(X_i) = j)$ where $i=1,\dots,n$; $j=1,\dots,q_i$;
119 $k=1,\dots,r_i$.

120 In data rich contexts, CPT parameters can be evaluated by computing the appropriate
121 frequencies from data. An example is provided by Chojnacki et al. (2019) for fire safety analysis
122 where more than 1 million of numerical simulation results are used. This method corresponds
123 to the maximum likelihood estimation (MLE), which is described below.

124 Let us consider a dataset D where a total number N_{ij} of data records are available for which
125 $pa(X_i)$ is in the state j and where N_{ijk} data records are available for which X_i is in the state k and
126 $pa(X_i)$ is in the state j . MLE aims at maximizing the log-likelihood function $l(\cdot)$ of θ given D as
127 follows

$$128 \quad l(\theta|D) = \log(P(D|\theta)) = \sum_{ijk} N_{ijk} \log(\theta_{ijk}) \quad (\text{Eq. 1})$$

129 The solution is then $\frac{N_{ijk}}{N_{ij}}$.

130 The MLE method however fails to find good estimates due to data scarcity when $N_{ij} \approx 0$, i.e.
131 when training data are not sufficient in number in some specific variable state configurations.
132 Examples of such contexts are not rare in practice; see e.g. rare disease diagnostic (Seixas et
133 al., 2014), accident prevention (e.g., Hänninen, 2014), reliability analysis (e.g., Musharraf et
134 al., 2014), etc. This problem is even worsened when the number of nodes increases. Recall that
135 the number of conditional probabilities is exponential with the number of its parent nodes, i.e.
136 for a node with i states and k parent nodes and if each parent node has n states, $(i-1) \times n^k$ CPT
137 entry values have to be specified. For instance, a binary node with 2 binary parent nodes
138 imposes to specify 4 entries, whereas for a ternary node with 2 ternary nodes, this number
139 reaches 18.

140 **2.2 Dealing with missing values**

141 The process for parameter learning of discrete BBNs may be complicated in the presence of
142 missing values. This can be handled by means of different algorithms. The most popular ones
143 are Expectation Maximization (Dempster et al., 1977) and Gibbs sampling (Geman and Geman,
144 1984). Yet, they both assume that the values are missing at random. This hypothesis may not
145 always be true in practice. Alternative methods have been proposed to overcome this
146 disadvantage, like AI&M procedure (Jaeger, 2006), the RBE algorithm (Ramoni and
147 Sebastiani, 2001), and the maximum entropy method (Cowell, 1999). Other methods have also
148 been developed to speed up the learning process, like generalized conjugate gradient algorithm
149 by Thiesson (1995) or the online updating of rules (Bauer et al., 1997). To deal with both
150 missing data and qualitative influences (as described in Sect. 2.4), some initiatives have been
151 proposed like the one of Masegosa et al. (2016), who further improved the combined Isotonic
152 Regression - EM approach.

153 **2.3 Discretising continuous variables**

154 A second practical difficulty for parameter learning of discrete BBNs is inherent to the main
155 assumption introduced by discrete BBNs, namely that data should be represented by a limited
156 numbers of outcomes. This imposes to discretize continuous variables. This process might,
157 however, lead to a loss of information, and potentially to an increase of the associated
158 computational effort, because the size of discrete BBNs increases approximately exponentially
159 with the number of discrete states of its nodes. Nojavan et al. (2017) investigated the
160 implications of several mathematical methods for constructing discrete distributions in an
161 unsupervised manner. Using a simple 3-node BBN describing chlorophyll concentrations in
162 Finnish lakes, the authors evaluated the impact on the developed BBNs of the number of
163 intervals and of the choice of the type of discretization methods. Three techniques were
164 investigated, namely in which the data are divided into groups: (1) of equal length; (2) of equal
165 sample size; (3) for which the moments of the discretized distribution match with the moments
166 of the continuous data. They showed that none of the models did uniformly well in all
167 comparison criteria (sum of squared errors, accuracy, area under the receiving operating
168 characteristic curve) for the considered case. They concluded that they cannot justify using one
169 discretization method against others. Using a 4-node BBN from the domain of coastal erosion,
170 Beuzen et al. (2018) extended the tests to other types of discretization methods, namely manual
171 and supervised techniques. They showed, on their specific test case, that supervised methods

172 led to a BBN of the highest average predictive skill, followed by the one with manual
 173 discretization. They also outlined the advantages of the different methods, namely that:

- 174 - Manual methods allow ensuring physical meaningful BBNs;
- 175 - Supervised methods can autonomously and optimally discretize variables and may be
 176 preferred when predictive skill is a modelling priority;
- 177 - Unsupervised methods are computationally simple and versatile.

178 Depending on the objective, some specific discretization algorithms have also been developed;
 179 for instance, Zwirgmaier and Straub (2016) developed specific methods to deal with rare
 180 events in reliability analysis; Neil et al. (2007) proposed a dynamic discretization method to
 181 perform inference in hybrid BBNs, i.e. both dealing with continuous and discrete variables.

182 **2.4 Combining scarce data and expert judgements**

183 When data are scarce, the parameter learning may be improved by incorporating additional
 184 information provided by experts. A popular approach relies on the Maximum a Posteriori
 185 (MAP) estimation using Dirichlet priors, which express experts' belief (e.g., Heckerman et al.,
 186 1995) about θ in the absence of data. Formally, the Dirichlet distribution for CPT column θ_j is
 187 expressed as follows:

188

$$189 \quad p(\theta_{ij}) = \frac{1}{Z_{ij}} \prod_{k=1}^{r_i} \theta_{ijk}^{(\alpha_{ijk}+1)-1} \quad (\text{Eq. 2})$$

190 with $\sum_k \theta_{ijk} = 1$, $\theta_{ijk} \geq 0$, Z_{ij} is a normalisation term $\int_{-\infty}^{+\infty} \prod_{k=1}^{r_i} \theta_{ijk}^{(\alpha_{ijk}+1)-1} d\theta_{ijk} = 1$, and
 191 α_{ijk} is the parameter of the Dirichlet distribution, which can be intuitively interpreted as “how
 192 many times the expert believes he/she will observe $X_i=k$ in a sample of α_{ij} instances drawn
 193 independently at random from the distribution θ_j ” (Zhou et al., 2014). On this basis, MAP relies
 194 on the following equation:

195

$$196 \quad p(\theta|D) \propto P(D|\theta)P(\theta) \propto \prod_{ijk} \theta_{ijk}^{(\alpha_{ijk}+N_{ijk})-1} \quad (\text{Eq.3})$$

197 This equation results in the estimate of θ_{ijk} as $\frac{N_{ijk}+\alpha_{ijk}-1}{N_{ij}+\alpha_{ij}-1}$, which combines information from
 198 the data and from the experts' prior guess. In their computer experiments using twelve publicly

199 available BBNs (available at <http://www.bnlearn.com/bnrepository/>), Zhou et al. (2016a)
200 showed that MAP achieves better performances than conventional MLE, which suffers from
201 the absence of data in several state configurations in situations of limited sample size (typically
202 50).

203 Expert-based information can take several forms, and the one that corresponds to qualitative
204 constraints have given rise to several developments. Instead of directly providing the exact
205 value of the entries of binary BBN (denoted $P_{1,2}$), the expert may feel more conformable in
206 providing an ordering like “ $P_1 > P_2$ ”, “ $P_1 \approx P_2$ ”, “ $P_1 > 0.80$ ”, etc. Zhou et al. (2016a) showed that
207 incorporating such expert knowledge about the monotonic influences between nodes (translated
208 into probability constraints) further outperformed MAP and MLE and was also robust to errors
209 in labelling the monotonic influences.

210 Different methods have been developed to incorporate qualitative constraints, namely:

- 211 - Convex Optimization (Niculescu et al., 2006; Zhou et al., 2016a; de Campos and Ji,
212 2008; Liao and Ji, 2009; Altendorf et al., 2005) is an extension of the MLE by
213 incorporating constraints via penalty functions or by restricting parameter spaces;
- 214 - Constrained MAP approach has also been proposed by Yang et al. (2019) to learn BN
215 parameters by incorporating convex constraints;
- 216 - Isotonic Regression (Feelders and van der Gaag, 2005; 2006) builds on qualitative
217 information about the influences between the variables of a BBN. The most recent
218 algorithm by Masegosa et al. (2016) also enables the analyst to learn the CPT
219 parameters from incomplete data;
- 220 - Qualitative MAP (originally proposed by Chang and Wang (2010) and further improved
221 by Guo et al. (2017)) constructs Dirichlet priors from Monte-Carlo random samples of
222 the constrained parameter space, which are used by the MAP algorithm;
- 223 - Multinomial Parameter Learning with Constraints (Zhou et al., 2014; Hospedales et al.,
224 2015) rely on auxiliary BBNs, which are hybrid BBNs, to infer the posterior distribution
225 of BBN parameters.

226 **2.5 Discussion**

227 Following a pure statistical data-driven approach for populating the BBN conditional model
228 requires a large amount of statistically significant data to cover all BBN relationships. To
229 compensate the lack of data, a possible option is to complement the analysis with expert-based
230 information. Sect. 2.4 shows that a broad range of different tools/methods are available to

231 incorporate expert-based information either in the form of qualitative influences or constraints,
232 namely constraints that should be almost linear and convex (i.e. concave constraints like
233 $P_1 \neq 0.5$ cannot be accounted for). The improvement of the learning accuracy of the parameters
234 in BBNs from a small data set has been shown using each of the described methods compared
235 to conventional methods; for instance Guo et al. (2017) compared MLE, constrained MLE,
236 maximum entropy and constrained maximum entropy estimator, MAP and their qualitatively
237 MAP estimator. Yang et al. (2019) showed the higher performance of their constrained MAP
238 estimator compared to conventional parameter learning algorithms, MLE and MAP, and to
239 constrained maximum likelihood algorithm. Yet, to the author's best knowledge, no extensive
240 benchmark exercise covering all the afore-mentioned estimators (as well as their pros and cons)
241 is available yet; practical recommendations on how to implement them and their limitations is
242 currently lacking in the literature.

243 Among the possible limitations, the problem of under-fitting related to the use of prior
244 distributions (that are common ingredients of most of the methods of Sect. 2.4) is seldom
245 tackled. As described by Gao et al. (2019), imposing certain a priori knowledge on the CPT
246 parameters might decrease the likelihood of the parameters, hence a reduction of the fitness
247 between parameters and data. Azzimonti et al. (2019) proposed a hierarchical procedure to
248 improve the widely-used approach based on Dirichlet priors. Gao et al. (2019) proposed a
249 Minimax Fitness algorithm combined with an improved constrained maximum entropy method
250 to overcome this problem. They also concluded that there is a need for further investigation to
251 develop learning methods that does not require specification of prior strength.

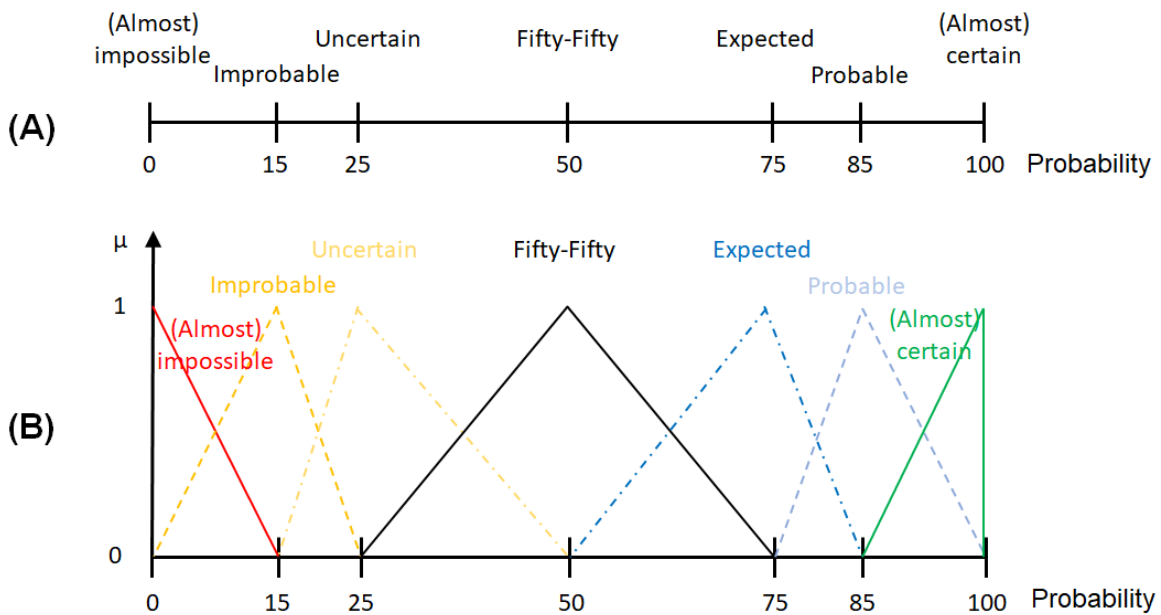
252 **3 Learning from experts**

253 In many situation, the primary source of information for learning the CPTs is not based on data,
254 but on inputs from expert domain. For instance, for rare-event situations like reliability analysis,
255 inputs from expert domain stem from questionnaires, interviews and panel discussions. Sect. 3
256 focuses on the process of deriving information from experts that is named "elicitation". The
257 issues and methods related to this task were analysed by review articles in different domains of
258 application, namely shipping accidents by Zhang and Thai (2016), human reliability by
259 Mkrtchyan et al. (2015) and more broadly regarding dependence in probabilistic modelling by
260 Werner et al. (2017). The objective is to focus the elicitation on specific pieces of information
261 to efficiently populate the CPTs by ensuring quality and consistency of the elicited result and
262 minimizing the workload on the experts owing to the large number of CPT entries. Elicitation
263 for CPT generally relies on three (possibly combined) main approaches through: (1) the

264 assessment of probabilities directly from an (or a panel of) expert (Sect. 3.1); (2) assumptions
 265 on the causal structure either by simplifying the network structure or by simplifying the causal
 266 dependence (Sect. 3.2); (3) filling-up methods (Sect. 3.3).

267 **3.1 Direct elicitation**

268 In a direct approach, experts are asked to give quantitative numbers (like frequencies or
 269 confidence intervals) using methods like probability wheel, probability scale and gambling
 270 analogy. An extensive discussion on the different types of biases are provided by Renooij
 271 (2001), and more specifically in the domain of ecology by Kuhnert et al. (2010). Overall,
 272 methods which map qualitative statements to numerical values like the probability scale (see
 273 an example in Fig. 2(A)) is preferred for its simplicity, which improves the consistency (as
 274 underlined by Wiegmann (2005), and as reported by Zhang and Thai (2016) for marine safety).
 275 Probability wheel is criticized for not being appropriate for the elicitation of small or large
 276 probabilities, and the gambling analogy is criticized for being too time-consuming.



277
 278 Figure 2. (A) Example of probability scale used to assist expert elicitation of CPTs (adapted
 279 from Knochenhauer et al. (2013)); (B) Translation of the probabilities qualified in (A) into
 280 Fuzzy sets (μ is the degree of membership).

281 [Figure 2 about here]

282
 283 As an alternative, experts are preferably asked to give qualitative statements (like categorical
 284 or relative measure). To support this indirect approach, tools from the domain of multicriteria

285 decision-making have been proposed. For instance, Chin et al. (2009) adapted the Analytical
286 Hierarchy Process method for the task of probability elicitation and semi-automatic generation
287 of the parameters of CPTs. The basic idea is to elicit paired comparisons about the relative
288 likelihood of the possible events using predefined scores (equally possible, etc.) instead of
289 directly asking the probability values. Yet, this procedure is at the expense of an increase in the
290 number of comparisons as the number of conditional probabilities increases.

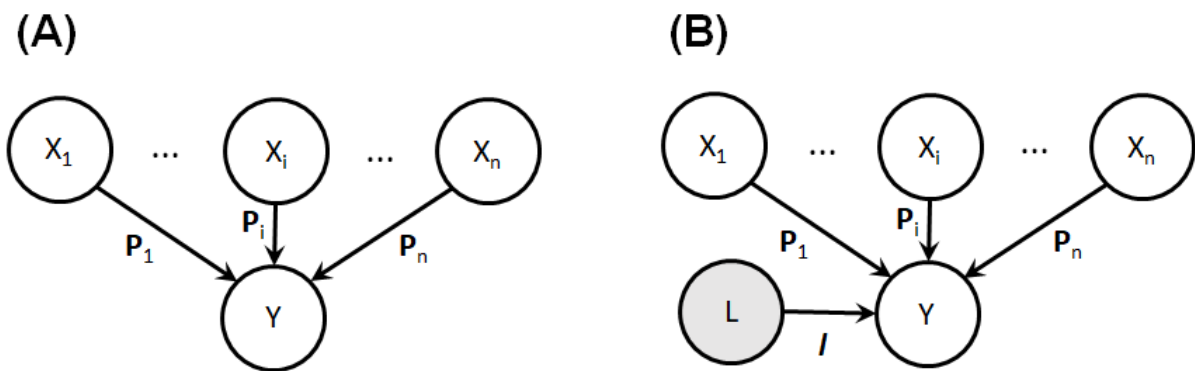
291 An alternative option proposes to directly process natural linguistic terms by mathematically
292 modelling them using for instance a Fuzzy set (Zadeh, 1975). Let us consider the concept of
293 membership function, which defines how each element x of the input space X (also named
294 “universe of discourse”) is mapped to a degree of membership (denoted μ). Under the classical
295 theory of Boolean logic, the membership function of a set A is simply defined as a binary
296 function that takes the value $\mu(x)=1$ if the element belongs to A and the value $\mu(x)=0$, otherwise.
297 The Fuzzy set theory of Zadeh (1965) introduces the concept of a set without a crisp (i.e. clearly
298 defined) boundary. Such a set can contain elements with only a gradual (partial) degree of
299 membership (μ is scaled between 0 and 1). The translation of the probability scale of Fig. 2(A)
300 into Fuzzy sets is provided in Fig. 2(B). Some successful applications cover fault detection
301 (D’Angelo et al., 2014), performance analysis of devices (Penz et al., 2012), safety risk analysis
302 (Zhang et al., 2015), human reliability analysis (~~Peng-cheng et al., 2012~~; Li et al., 2012), and
303 offshore risk (Ren et al., 2009). Two viewpoints exist in the literature on Fuzzy BBNs.
304 Fuzziness can be incorporated in the variables (nodes) or on the probabilities. For instance, Ren
305 et al. (2009) carried out studies using fuzzy probability calculations in BBNs (as illustrated in
306 Fig. 2(B)). Conversely, Tang and Liu (2007) used fuzzy events (i.e. Fuzzy node states) in BBNs
307 for a machinery fault diagnosis problem. İçen and Ersel (2019) incorporated both aspects with
308 application in medicine.

309 **3.2 Making assumptions on the causal structure**

310 To reduce the elicitation burden, the number of CPT entries to be elicited should be kept
311 “reasonable”. This can be performed by making assumptions regarding the causal structure.
312 One option is by simplifying the structure through the introduction of “divorcing” nodes
313 (Henderson et al., 2009). This involves aggregating a few of the nodes by adding a new node
314 that summarizes them provided that the aggregations are logical and no interactions are lost in
315 the procedure. Although this process adds nodes to the network, it reduces the combined size
316 of CPTs in the network (Cain, 2001). Yet, divorcing might dilute the sensitivity of the final

317 node(s) to the input nodes and might increase the uncertainty propagated through the network
 318 as underlined by Cain (2001).

319 A popular alternative aims at making some simplifications regarding the causal dependence
 320 based on the logical Noisy-OR gate (Pearl, 1988). In their typical implementation, Noisy-OR
 321 gates focus on binary BBN nodes and assume that the influence of the considered factor is
 322 independent from the presence of the other factors. This means that the probability of the
 323 outcome is the product of the probabilities of the outcome in presence of one factor at a time,
 324 with all other factors being absent. Formally, let us consider a binary variable Y with two states
 325 {False, True} and n binary parent variables $X_{i=1,\dots,n}$.



326

327 Figure 3. (A) Schematic representation of the Noisy-OR gate with $P_{i=1,\dots,n}$ the link
 328 probabilities; (B) Schematic representation of the Noisy-OR gate.

329

[Figure 3 about here]

330

331 The main principle of the Noisy-OR model is to define probabilities P_i (termed as link
 332 probability, Fig. 3(A)), which are defined as the probability that Y is False given that X_i is False
 333 and X_j is True for $i \neq j$. A Noisy-OR model is thus a disjunction “noisy” version of X_i (Pearl,
 334 1988). This means that the distribution of Y conditional on $X_1; X_2; \dots; X_n$ is $P(Y =$
 335 $F|X_1; \dots; X_n) = 1 - \prod_{i: X_i \in X_T} (1 - P_i)$ where X_T is the set of parent nodes whose states are True.
 336 The Noisy-OR model enables the analyst to specify fewer CPT parameters; the number of
 337 independent parameters being here reduced from 2^n to $2n$. The extension of Noisy-OR gate to
 338 multi-valued variables is the Noisy-MAX gate model (Diez, 1993; Henrion, 1989). If the parent
 339 node X_i has n_{X_i} states, then the total number of parameters that have to be elicited using leaky
 340 Noisy-MAX gate is $N = \sum_{i=1}^n (n_{X_i} - 1) (n_Y - 1) + 1$ to be compared to the total number
 341 without Noisy-MAX gate, namely $N = (n_Y - 1) \cdot \prod_{i=1}^n n_{X_i}$.

342 Different empirical studies have been conducted to investigate the performance of the leaky
343 Noisy-OR approach. Several authors (Oniško et al., 2001; Anand and Downs, 2008; Bolt et al.,
344 2010; among others) showed how this approach helped reducing the burden of elicitation in
345 practical real-life applications without impacting too much the performance of the network.
346 Besides, Zagorecki and Druzdzel (2012) explored to which extend the pattern of causal
347 interaction induced by Noisy-OR(MAX) gates are common in real cases. Using three existing
348 BBNs, they showed that the Noisy-MAX gate provides a good fit for as many as 50% of CPTs
349 in two of these networks.

350 The Noisy-OR structure is based however on a strong assumption, i.e. that the node of interest
351 is in the state False (considering the above illustrative case) with a probability equal to 1 if all
352 its parent variables are in the state False. Yet, in many cases, it is often difficult to capture all
353 the causes of the node of interest (e.g. for reliability purpose, it means to define all the failure
354 modes of a component). To deal with this problem, Henrion (1989) proposed an extension
355 called “leaky Noisy-OR” gate that includes a background probability that represents the
356 influence of non-modelled causes as schematically depicted in Fig. 3(B). Zagorecki and
357 Druzdzel (2004) proposed to elicit leaky and non-leaky Noisy-OR parameters as alternatives to
358 conditional probabilities using statements like “What is the probability that Y is present when
359 X_1 is present and all other causes of Y (including those not modelled explicitly) are absent?”.
360 They showed that the leaky Noisy-OR parameter was assessed as the most accurate (in terms
361 of Euclidean distance to empirical distribution).

362 The leaky Noisy-OR method was further extended by relaxing the necessity to define a crisp
363 precise leaky probability value, i.e. by introducing uncertainty on this parameter. This type of
364 uncertainty has been addressed within different uncertainty treatment settings (which are
365 introduced in more details in Sect. 4). Antonucci (2011) developed an imprecise leaky Noisy-
366 OR gate model with uncertainty on the link probabilities modelled by intervals within the
367 formalism of credal networks (see Sect. 4.2). Alternatively, Fallet-Fidry et al. (2012) (further
368 extended by Zhou et al. (2016b)) proposed an imprecise extensions of the Noisy-OR within the
369 formalism of evidential networks (see Sect. 4.3). Finally, Dubois et al. (2017) developed a
370 version of noisy logical gates within the theory of possibility (Dubois and Prade, 1988) using
371 possibilistic causal networks (as presented by Benferhat et al. (2002)) with illustration on an
372 example taken from human geography.

373 **3.3 Filling-up methods**

374 Alternative methods to Noisy-OR(MAX) gate are based on filling-up techniques. These
375 methods are typically based on extracting information on the factor effects from known
376 relationships (named anchor conditional probability distributions, denoted CPD) and
377 extrapolating to the whole CPTs. Considering two BBNs (of respectively 3 and 4 nodes) for a
378 human reliability problem, Mkrtchyan et al. (2015) tested five popular methods for CPT
379 derivation considering nodes with multiple states, namely:

- 380 - Method 1: the functional interpolation method (Podofillini et al., 2014) approximate
381 CPDs elicited at the anchor positions by functions described by parameters (e.g.,
382 Normal functions); the parameters of the missing CPDs are then obtained by
383 interpolating those corresponding to the anchor ones;
- 384 - Method 2: the Elicitation BBN method (Wisse et al., 2008) is based on piecewise linear
385 functions interpolating among the elicited CPDs, and on state influencing factors and
386 importance weights;
- 387 - Method 3: The Cain calculator (Cain, 2001) uses interpolation factors derived from
388 CPDs to populate the missing relationships in CPTs;
- 389 - Method 4: The method presented by Røed et al. (2009) is also based on functional
390 relationships between influencing factors and outcome nodes; the parameters of the
391 function (exponential) are then determined based on the elicitation of selected CPDs;
- 392 - Method 5: the ranked node method by Fenton et al. (2007) (further improved by Laitila
393 and Virtanen, 2016) is not based on interpolation of known CPDs. In this approach, all
394 the nodes are defined on the interval [0–1]. For instance, let us consider a node with 5
395 states, namely “very low”, “low”, “average”, “high”, and “very high”; each of the
396 state is assigned to an interval width of 0.2; for instance, the value “low” is assigned to
397 the interval [0.2–0.4]. To generate CPTs, the experts are asked to provide the weight
398 parameters and to choose one algorithm (the mean average, the Minimum, the
399 Maximum and the MixMinMax). Using this method, if there are m ranked nodes and
400 each node has n states, the expert will only need $m + 1$ parameter values, while it requires
401 $n \times m + 1$ values for full elicitation.

402 Mkrtchyan et al. (2015) showed that:

- 403 - All methods allow representing the different importance of the various influencing
404 factors;

- 405 - The representation of the interactions (combined effects of multiple factors) is
406 problematic for methods eliciting information on the influence of factors taken one at a
407 time (methods 2-4);
- 408 - Functional representation of the CPTs (methods 1, 5 and 4) can be traced more easily,
409 because they allow an explicit representation of uncertainty in the factor relationships;
- 410 - But methods 4 and 5 have difficulties in representing the different degrees of uncertainty
411 in the relationships;
- 412 - The method allowing the largest modelling flexibility is method 1 with respect to strong
413 factor influences (single and multi-factor) and proper uncertainty characterization, but
414 becomes too costly for large BBNs.

415 **3.4 Discussion**

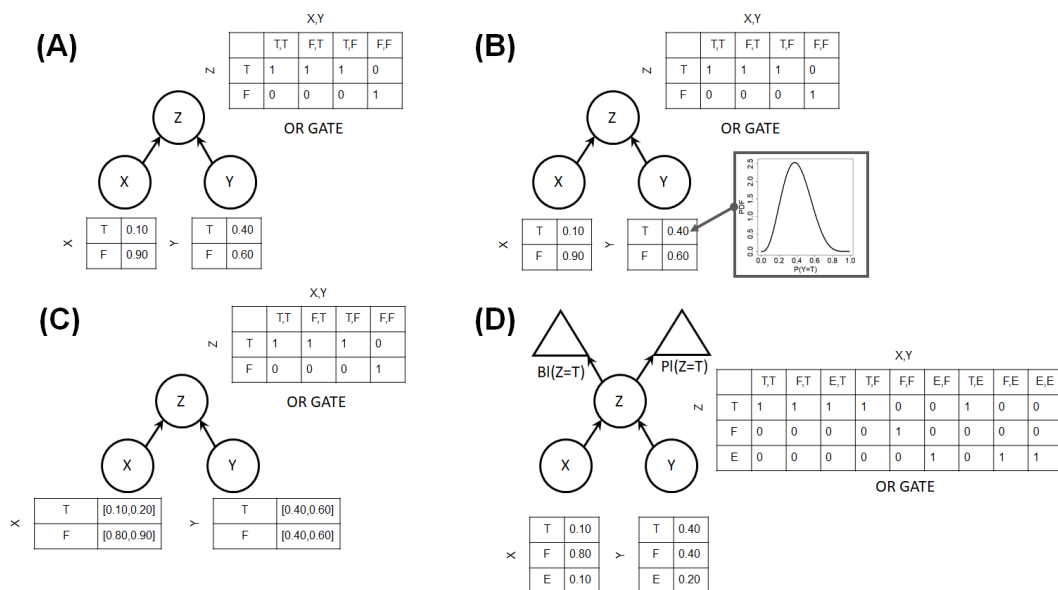
416 The conclusions drawn by Mkrtchyan et al. (2015) serve as valuable recommendations
417 regarding the use and applicability of the five most popular filling-up methods for reducing the
418 expert burden of CPT elicitation. Despite the practical usefulness of this comparative exercise,
419 it should be noted that they primarily focused, by construction, on the modelling aspects
420 important for their application domain (here human reliability analysis), namely the
421 representation of strong factor influences and interactions, and the characterization of different
422 degrees of uncertainty in the relationships. Broader exercises are needed to cover a larger
423 spectrum of methods (i.e. filling-up methods should be completed by Noisy- OR/MAX models,
424 direct elicitation among others), of contexts (different network sizes, binary versus multivalued
425 nodes, etc.), as well as of domains of application.

426 Despite the clear advantages of these methods for BBN engineering, they cannot be applied
427 uncritically, because the probability values can only be considered approximations of the true
428 probabilities and whatever the considered methods, they are all based on simplifications that
429 may hamper the BBN performance. Initiatives like the one by Woudenbergh and van der Gaag
430 (2015) for the Noisy-OR model should be intensified. They identified the conditions under
431 which ill-considered use of this method can result in large impact on output probabilities; in
432 particular, when the yet-unobserved cause variables in the mechanism have relatively skewed
433 probability distributions and/or the obtained parameter probabilities have small values. For this
434 purpose, sensitivity methods as described in Sect. 5 can play an important role. Fenton et al.
435 (2019) also dealt with the limitations of leaky Noisy-OR model for backward inference. When
436 the binary node of interest Y of the example in Fig. 3 is observed to be in the state False, the
437 normal “explaining away” behaviour fails, which means that after observing the state of any

438 parent the remaining parents become independent, and the results may not result in what BBN
 439 practitioners expected. Fenton et al. (2019) described a simple extension of the model that
 440 requires the elicitation of only one extra parameter that can solve this problem for a large
 441 spectrum of cases in practice.

442 4 Propagating the uncertainties

443 Whatever the methods used to populate the CPTs, residual uncertainties may still prevail. This
 444 residual uncertainty should be reflected in BBN-based results. This means that the uncertainty
 445 on CPT entries should be propagated in order to evaluate their consequences on the BBN
 446 results. The propagation can either rely on probabilities (Sect. 4.1), or alternative mathematical
 447 representation tools like intervals (Sect. 4.2) or a generalization of a probability distribution
 448 (Sect. 4.3), i.e. within the theory of belief functions as introduced by Shafer (1976) and
 449 Dempster (1967). Fig. 4 summarizes the main principles of the different approaches by using a
 450 simple OR-gate model.



451
 452 Figure 4. (A) Example of an OR gate model translated into a BBN with two binary parent nodes
 453 X and Y (with states corresponding to $T=$ True or $F=$ False). The truth table related to the OR
 454 gate corresponds to the table next to the child node Z . Illustration of a probability-based
 455 approach where uncertainties on CPT entries are represented by: (B) Beta probability
 456 distributions (with an example here for node Y); (C) Interval-valued probabilities (credal
 457 network approach); (D) Mass probability tables; here the truth table includes the epistemic state
 458 $E=\{T,F\}$; Two nodes were added to the network to calculate the belief and plausibility functions
 459 (see Sect. 4.3 for more details).

461 **4.1 Methods using probabilities**

462 The problem of uncertainty propagation for BBN has originally been addressed using
 463 probabilities. This approach assumes that the uncertainty on CPT entries follows a Beta
 464 probability distribution (or for more generic cases, a Dirichlet probability distribution), as
 465 schematically depicted in Fig. 4(B). Kleiter (1996) originally described a Monte-Carlo-based
 466 random simulation procedure to carry out the approximation of the spread of the probability
 467 distribution for the considered query. The method requires, however, a large number of random
 468 samples to accurately characterize the true variance. Van Allen et al. (2008) proposed an
 469 improved method by avoiding Monte Carlo sampling through the combination of bucket
 470 elimination (Dechter, 1998) with the “delta rule” that linearizes the relationship between the
 471 query probabilities and the corresponding Dirichlet conditional probabilities connecting the
 472 query variable to its parents and children. They further proved that the Beta approximation (for
 473 binary BBNs) is asymptotically valid. The conditions of the exact Beta distribution has
 474 extensively been investigated by Hooper (2008). This problem has further been formalized
 475 within the setting of subjective logic (Jøsang, 2001; 2016) as proposed by Kaplan and Ivasnoska
 476 (2018), who developed an efficient belief propagation for inference in a binary Bayesian
 477 network with a singly-connected graph. To introduce any type of probability distribution on
 478 CPTs, Fenton (2018) proposed to extend the BBN with continuous nodes corresponding to the
 479 uncertain prior probability distributions, but at the expense of a potentially large increase of
 480 computational time cost when the number of nodes and of CPTs increases.

481 **4.2 Methods using interval-valued probabilities**

482 Instead of specifying a crisp single value of each CPT entry, the formal setting of credal
 483 network, denoted CN (Cozman, 2000; 2005), integrates BBNs with credal sets, i.e. set of
 484 probability measures. A CN can be viewed as the representation of a set of BBNs, which share
 485 the same graphical structure but are associated to different conditional probability parameters;
 486 the interest being to provide a richer representation of uncertainty. In Fig. 4(C), the uncertainty
 487 in the CPTs are presented by intervals.

488 Formally, given a variable X , we denote by Ω , the possibility space of X , x a generic element
 489 of Ω , $P(X)$ the probability mass function for X and $P(x)$ the probability of x . The credal set over
 490 X is $K(X)$, which corresponds to a closed convex set of probability mass functions over X . For
 491 any $x \in \Omega$, the lower probability for x according to the credal set $K(X)$ is $\underline{P}(x) =$

492 $\min_{P(X) \in K(X)} P(x)$. Similar expression can be given for the upper probability. Within Walley's
 493 theory of imprecise probabilities (Walley, 1991), credal sets can then be represented as
 494 polytopes, where each inner point has a valid probability mass, and can be obtained by
 495 computing the convex hull of a finite number of probabilities, called vertices (Cozman, 2000).
 496 A credal set for a random variable X_i is labelled $K(X_i)$, while the set comprising its extreme
 497 points is denoted by $\text{ext}[K(X_i)]$.

498 A credal network CN (Cozman, 2000) over a set of random variables is thus a DAG where
 499 dependencies among variables are defined by a set of conditional credal sets as $K(X_i|pa(X_i))$.
 500 By analogy with BBN, it is possible to define a joint credal set as follows:

501

$$502 \quad K(X) = CH(P(X): P(x) = \prod_{i=1}^n P(x_i|pa(X_i)) \quad (\text{Eq. 4})$$

503 where $P(X_i|pa(X_i)) \in \text{ext}[K(X_i|pa(X_i))]$, CH is the convex hull operator, applied to the
 504 probabilities computed for the combination of all the vertices of all the conditional credal sets.

505 In this setting, the task of inference aims at computing the probability bounds of the largest
 506 extension that satisfies the Markov condition (i.e., independence of each node of its non-
 507 descendant non-parents given its parents) under the assumption of strong independence
 508 (Cozman, 2000). This results in the convex hull of the set containing all joint distributions that
 509 factorize the overall joint probability of the network, where the conditional distributions
 510 $P(X_i|pa(X_i)=\pi_k)$ are selected from the local sets $K(X_i|pa(X_i)=\pi_k)$. This task is a NP-hard (de
 511 Campos and Cozman, 2005), for which a number of exact and approximate algorithms have
 512 been proposed (Antonucci et al., 2015; Mauá et al. 2012; Ide and Cozman, 2008; Cano et al.,
 513 2007), but only exact inference algorithms are suitable to polytree-shape binary networks.

514 Though CN allows quantifying and integrating the uncertainty on CPTs on the BBN inference
 515 results, this increase in expressiveness comes at the expense of higher computational costs.
 516 Some real case applications of CN exist in different domains (Table 1), but the number of them
 517 remain limited (with comparison to BBN), despite the availability of some open-source
 518 solutions like OpenCossan (Tolo et al., 2018), the linear programming algorithm¹ of Antonucci
 519 et al. (2015), the GL2U-II algorithm² of Antonucci et al. (2010).

520

	Domain of application	Method	Reference
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¹ <http://ipg.idsia.ch/software.php?id=135>

² <http://ipg.idsia.ch/software.php?id=142>

1	Hazard assessment of debris flows	CN	Antonucci et al. (2007)
2	Military identification	CN	Antonucci et al. (2009)
3	Reliability analysis of a fire-detector system	EN	Simon et al. (2008; 2009; 2017)
4	Threat assessment	EN	Benavoli et al. (2009)
5	Convoy detection	EN	Pollard et al. (2010)
6	Reliability analysis of oil filter plug linked to aero engines	EN	Yang et al. (2012)
7	Railway dysfunction	EN	Aguirre et al. (2013)
8	Food processing	Dynamic CN	Baudrit et al. (2016)
9	Cyber attack analysis	EN	Friedberg et al. (2017)
10	Vulnerability analysis of Nuclear Power Plant subject to external hazards	CN	Tolo et al. (2017)
11	Reliability analysis of a safety instrumentation system for a pressurized vessel	EN	Zhang et al. (2017)
12	Medical prognostic and diagnostic	EN and Fuzzy sets	Janghorbani and Moradi (2017)
13	Fault diagnosis for railway	BBN vs EN	Verbert et al. (2017)
14	Maritime accidents	CN	Zhang and Thai (2018)
15	Terrorist attack analysis on a chemical storage plant	EN vs CN	Misuri et al. (2018)
16	Landslides	CN	He et al. (2018)
17	Risk assessment of an oscillating water column	CN	Estrada-Lugo et al. (2018)
18	Reliability analysis of a feeding control system	EN	Mi et al. (2018)
19	Human reliability for Nuclear Power Plant safety analysis	EN	Deng and Jiang (2018)
20	Safety assessment of a truss	EN	Khakzad (2019)

521 Table 1. Case studies of evidential networks (EN) and Credal Network (CN)

522 [Table 1 about here]

523

524 4.3 Methods based on Dempster-Shafer Theory

525 An alternative setting for representing imprecision is the theory of belief functions, also called
526 Dempster-Shafer Theory, denoted DST (Shafer, 1976, Dempster, 1967). Let X be a variable
527 taking values in the frame of discernment Θ composed of q mutually and exhaustive possible
528 state of X . For instance, for a binary node, the frame of discernment is $\Theta = \{\text{True}, \text{False}\}$.

529 Formally, the theory introduces the concept of basic belief assignment (BBA) based on the
 530 belief mass function $m: 2^{\Theta} \rightarrow [0,1]$ and satisfies $\sum_{A \subseteq \Theta} m(A) = 1$, and $m(\emptyset) = 0$ (which
 531 assumes that at least one element of Θ is true). Every $A \in 2^{\Theta}$ such that $m(A) > 0$ is called a focal
 532 element.

533 In classical probabilities, a probability value can be assigned to the state True or False only. By
 534 defining the belief mass function based on the powerset of the frame of discernment 2^{Θ} (which
 535 corresponds in the binary example to $\{\emptyset, \text{True}, \text{False}, \{\text{True}, \text{False}\}\}$) enables the analyst to
 536 allocate a quantity supporting an additional state termed as epistemic state $E = \{\text{True}, \text{False}\}$.
 537 Due to uncertainty, the analyst may not always be able to determine the amount of masses to
 538 attribute to each state, and the variable X may then be in both states, True or False. This means
 539 that the method allows characterizing uncertainty about the state of a given node.

540 From a mass function m , two measures can be defined (instead of one for the probabilistic case)
 541 called the belief (Bl) and plausibility (Pl) measures. The latter are respectively defined, for any
 542 event A as follows:

543

$$544 \quad Bl(A) = \sum_{E \subseteq A} m(E), \text{ and } Pl(A) = \sum_{E \cap A \neq \emptyset} m(E) \quad (\text{Eq. 5})$$

545 where Bl measures how much event A is implied by the information (it sums masses that must
 546 be redistributed over elements of A), Pl measures how much event A is consistent with the
 547 information (it sums masses that could be redistributed over elements of A). These two
 548 measures can be associated to a (closed convex) set of bound probabilities $\{P \mid \forall A \subseteq \Theta, (A) \leq(A) \leq Pl(A)\}$. It is thus possible to associate an interval-valued probability to the event A , with
 550 minimum and maximum probabilities provided by Bel and Pl , respectively. This makes the
 551 formal link with CN. Conversely, it is also possible to reconstruct BBAs from Pl and Bel
 552 functions using a Möbius Transformation (Smets, 2002).

553 As an illustration, let us assume consider a binary node for which the expert only knows that
 554 the probability of the event $\{X = \text{True}\}$ is at least 0.8. The corresponding BBA is $m(\{\text{True}\}) = 0.8$,
 555 $m(E = \{\text{True}, \text{False}\}) = 0.2$, $m(\{\text{False}\}) = 0$. This means that $Bl(\{\text{True}\}) = m(\{\text{True}\})$, and
 556 $Pl(\{\text{True}\}) = m(\{\text{True}\}) + m(E) = 0.8 + 0.2 = 1.0$. This also means that $Bl(\{\text{True}\}) = m(\{\text{True}\}) = 0.8$,
 557 and $Pl(\{\text{True}\}) = m(\{\text{True}\}) + m(E) = 0.8 + 0.2 = 1.0$. Then $0.8 \leq P(\{\text{True}\}) \leq 1.0$.

558 The evidence theory is the basis of evidential networks (EN), which is a DAG propagating
 559 belief masses. One of the first formulation by Xu and Smets (1996) is based on the Dempster's

560 rule for combining and reasoning with the belief masses. Yet, one major limitation is that the
561 inference algorithms in this formulation are less effective than the one for traditional BBNs as
562 underlined for instance by Khakzad (2019). In the domain of system reliability analysis, Simon
563 et al. (2008) proposed an alternative by mapping logical gates (like OR or AND typically used
564 for fault tree analysis), as EN with the hypothesis described by Guth (1991). Despite its
565 similarity with BBN, relations in EN between variables are not probabilities, but belief masses.
566 The truth table of gates are replaced by conditional mass tables for AND and OR gates (see an
567 example in Fig. 4(D)). To compute belief and plausibility measures in EN, specific nodes (as
568 proposed by Simon and Weber 2009) are introduced. Three types of nodes (as represented in
569 Fig. 4(D)) are thus defined (Simon and Bicking, 2017), namely:

- 570 - Root nodes to which BBA are assigned, correspond to components;
- 571 - Non-root nodes correspond to logical gates that encode its resulting states {True, False,
572 {True,False}} given the states of its parents;
- 573 - Evaluation nodes correspond to nodes that aim at providing estimates of the belief and
574 plausibility measures of the system state.

575 In the formulation by Simon and Weber (2009), the inference computation is based on the
576 Bayes theorem, which is extended to DST by specifying a mass of 1 on one of the focal elements
577 of the frame of discernment for a specific evidence (hard evidence). Non-specific evidence (soft
578 evidence) corresponds to a mass distribution on the focal elements of the frame of discernment.
579 This means that probability updating in such EN can be based on BBN inference algorithms.

580 Misuri et al. (2018) compared CN and EN with illustration on a terrorist attack analysis on a
581 chemical storage plant. They highlighted that:

- 582 - When used for uncertainty propagation, EN and CN give the same results;
- 583 - In terms of implementation, EN is simpler to use, because they can be built using
584 existing codes for BBN, whereas CN requires specific codes;
- 585 - In terms of interpretation, Misuri et al. (2018) concluded that EN is more intuitive,
586 because experts directly assign some weight to the epistemic state (e.g. $E=\{\text{True, False}\}$
587 for a binary node), whereas they have to specify interval-valued probabilities for CN,
588 which can become tricky for multivalued nodes.

589 Khakzad (2019) further filled the gap between CN and EN by proposing some heuristic rules
590 to determine prior belief masses based on imprecise probabilities. They further modified Simon
591 and co-authors' EN formulation to both improve the propagation and updating of the belief

592 masses using BBNs. In order to deal with linguistic variables for the network node' states, the
593 EN method can be combined either with Fuzzy sets (Zadeh, 1975) as applied by Janghorbani
594 and Moradi (2017) for medical prognostic, or with a Naive Bayes classifier model as applied
595 by Zhang et al. (2017) for safety analysis for nuclear power plant.

596 **4.4 Discussion**

597 Different settings are available to help the BBN analyst to deal with the problem of uncertainty
598 propagation. A natural question is the justification for using approaches that are alternative to
599 classical probabilities. A first argument often highlights the epistemic nature of the CPT
600 uncertainties. Contrary to aleatory uncertainty (also referred to as randomness), which
601 represents the variability of the physical environment or engineered system under study,
602 epistemic uncertainty mainly stems from the incomplete/imprecise nature of available
603 information (e.g. Hoffman and Hammonds, 1994). While tools from the probabilistic setting
604 can appropriately handle aleatory uncertainties, it is the second type, which raises several
605 problems in practice. In our situation, probability distribution cannot be inferred from
606 data/observations, and should therefore be assumed; the procedure described in Sect. 4.1 is
607 mainly based on the assumption that the uncertainties on the CPTs are described by a Beta (or
608 for more generic cases, a Dirichlet probability distribution) probability distribution. Yet, this
609 assumption may influence the final results of the BBN-based analysis (see. e.g., Ditlevsen, 1994
610 for an extensive discussion in reliability analysis); Relying only on probabilities masks this
611 problem and might induce an appearance of more refined knowledge with respect to the existing
612 uncertainty than is really present (Klir, 1989; 1994). Sect. 4.2 and 4.3 describe alternative non-
613 probabilistic frameworks to represent uncertainty in situations characterized by limited
614 available pieces of information, which are mainly restricted to expert judgements. Both
615 approaches allow improving the expressiveness with respect to uncertainty representation (as
616 shown by the few tens of application studies using these techniques, see Table 1), in particular
617 by enabling the BBN analyst to translate his/her uncertainty on the node states or his/her
618 imprecision on the CPT parameters by avoiding the need for specifying a probability model.

619 Yet, extra-probabilistic approaches (whatever the considered methods, CN, EN or networks
620 combined with linguistic variables or based on alternative uncertainty theories like possibility
621 theory, see Dubois et al. (2017)) might come at the expense of higher level of sophistication
622 and of complexity of the inference algorithms (and potentially higher computational costs). The
623 danger is to add more confusion than insights as discussed by Aven and Zio (2011) with the
624 viewpoint of decision making for risk management. The question of selecting the most

625 appropriate approaches for representing and characterizing the risk and uncertainties (in
626 particular with application on BBNs) still remains open (see e.g., an extensive discussion by
627 Flage et al. 2014).

628 **5 Characterizing the uncertainties**

629 Methods presented in Sect. 4 allows evaluating the impacts of CPT uncertainties on the BBN
630 results. But, this tells nothing about the respective contribution of the different CPT entries on
631 the total uncertainty, i.e. the influence of the different uncertainties. This is the purpose of
632 sensitivity analysis (SA), which can be used, in the construction phase of the BBN model, to
633 study how the output of a model varies with variation of the CPT parameters. Subsequently,
634 the results from SA can be used as a basis for parameter tuning, as well as for studying the
635 robustness of the model output to changes in the parameters (Coupé and van der Gaag, 2002;
636 Laskey et al., 1995).

637 **5.1 Description of the methods**

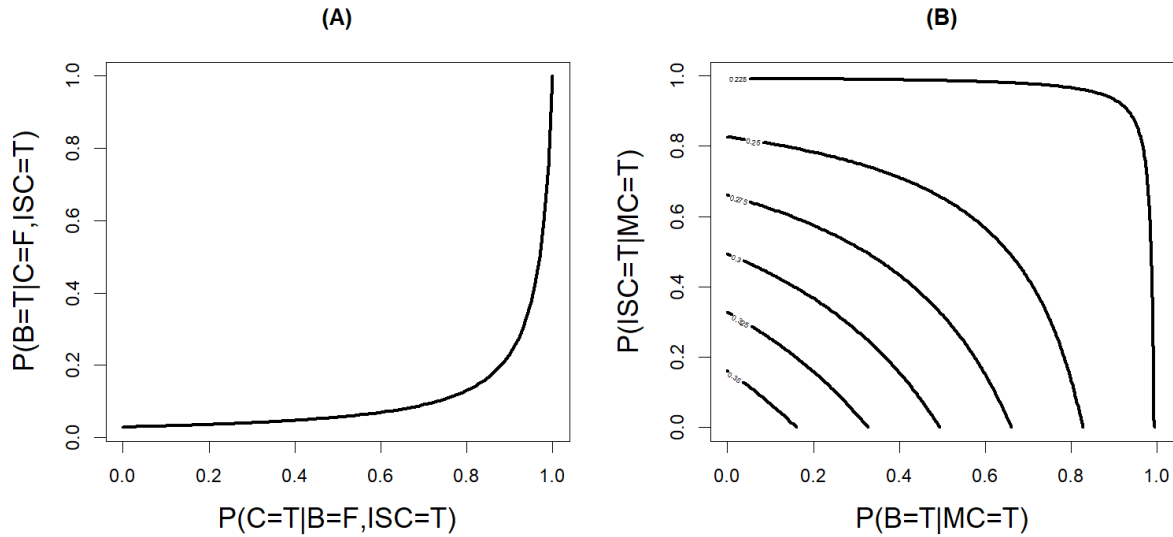
638 For discrete BBNs, a widespread SA method relies on the use of sensitivity functions (Coupé
639 and van der Gaag, 2002; Castillo et al., 1997), which describe how the considered output
640 probability varies as one CPT entry value is changed. An example of application in the domain
641 of marine safety is provided by Hänninen and Kujala (2012). Formally, consider the conditional
642 probability $P(Z=k|e)$, where e denotes the available evidence, and a CPT entry $x=P(X=i|\pi)$ where
643 i is a value of a variable X and π is a combination of values for the parents of X . The sensitivity
644 function then corresponds to a quotient of two functions that are linear in x of the following
645 form:

646

$$647 \quad f(x) = \frac{c_1x+c_2}{c_3x+c_4} \quad (\text{Eq. 6})$$

648 where the constants c_i are built from the values of the network's non-varied parameters. The
649 numerator of Eq. 6 expresses the joint probability $P(Z=k|e)$ as a function of x , and its
650 denominator describes $P(e)$ in terms of x . Using the example described in Fig. 1, we focus on
651 the probability of having brain tumor given absence of coma but increased level of serum
652 calcium, i.e. $P(B = T|C = F, ISC = T)$. Van der Gaag et al. (2013) estimated the sensitivity of
653 this probability of interest to the probability of having coma given absence of brain tumor but
654 increased level of serum calcium, $x = P(C = T|B = F, ISC = T)$. The sensitivity function

655 was established as $\frac{-0.03}{x-1.03}$ (as depicted in Fig. 5(A)). This type of function shows that the
 656 probability of interest steeply increases when x exceeds 0.80, i.e. above the original
 657 parametrization given by Cooper (1984).



658
 659 Figure 5. (A) One-way sensitivity function for the BBN described in Fig. 1; (B) Two-way
 660 sensitivity function for the BBN described in Fig. 1 considering the probability $P(C=T)$ as the
 661 targeted probability.

662 [Figure 5 about here]

663
 664 Two-way sensitivity functions can be expressed in a similar form as a quotient of two bi-linear
 665 functions. Consider the sensitivity function of $f(x, y)$ that expresses $P(Z=k|e)$ as a function of
 666 the parameter probabilities $x = P(X = i|\pi_X)$ and $y = P(Y = j|\pi_D)$, where i and j are values of
 667 the variables X and Y , and π_X and π_Y are combinations of values for the parents of X and of Y .
 668 The function holds as follows:

669
 670
$$f(x, y) = \frac{c_1x.y+c_2x+c_3y+c_4}{c_5x.y+c_6x+c_7y+c_8} \quad (\text{Eq. 7})$$

671 where the constants c_i are estimated from the values of the network's non-varied parameters.
 672 In the tumor BBN example (Fig. 1), we focus on the probability of having a cancer $P(C=T)$ and
 673 its sensitivity to the simultaneous variation of the conditional probabilities $x=P(B=T|MC=T)$
 674 and $y=P(ISC=T|MC=T)$, which was established by van der Gaag et al. (2013) as $0.374 +$

675 $0.15 \cdot x \cdot y - 0.15 \cdot x - 0.15 \cdot y$ (Fig. 5(B)). This type of function shows that despite the large
676 variation of x and y (from 0 to 1), the probability of interest varies over a moderate range of
677 values of only ~15%.

678 A complementary approach for SA involves the study of the Chan–Darwiche (CD) distance
679 (Chan and Darwiche, 2002; 2005), which is a measure for bounding probabilistic belief change.
680 It is complementary in the sense that it gives insight in the effect of parameter changes on the
681 global joint distribution, rather than on a specific (posterior) output probability of interest (as
682 sensitivity functions do). In practices, the CD distance can be used to identify parameter
683 changes, which lead the closer distance between the original and the varied BBN distributions
684 (Chan and Darwiche, 2005). It should however be noted that the choice of the type of distance
685 is rather arbitrary as outlined by Renooij (2014) and other distances like the KL-divergence
686 (Kullback and Leibler, 1951) or the ϕ -divergences (Ali and Silvey, 1966) could also be of
687 interest.

688 Recent studies have focused on the properties of the SA methods. Renooij (2014) thoroughly
689 investigated the different schemes for varying a probability from a (conditional) distribution,
690 while co-varying the remaining probabilities from the same distribution; the proportional co-
691 variation scheme being the most popular one. Leonelli et al. (2017) further formalized the SA
692 problem for discrete BBNs within the generic setting of multilinear models. They developed a
693 unifying approach to sensitivity methods via the interpolating polynomial representation of
694 discrete statistical models in the context of “BBNs single full CPT analyses”, i.e. where one
695 parameter from each CPT of one vertex of a BBN given each configuration of its parents is
696 varied. This approach based on multilinear probabilistic models enabled them to address the
697 problem of multi-way SA (with dimension ≥ 2). Furthermore, they proved the optimality of
698 proportional covariation by showing that the CD distance is minimized when parameters are
699 proportionally co-varied.

700 **5.2 Discussion**

701 Since the nineties, the BBN community has seen the developments of SA methods that are
702 specifically dedicated to their respective needs regarding the BBN use and application. Though
703 simple and efficient to implement, the approach based on sensitivity functions (combined with
704 CD-distance analysis) remains local, because one parameter values are varied, while the other
705 ones are kept constant. Multi-way SA methods have been proposed, but can rapidly become
706 intractable. Interestingly, outside the BBN community, the problem of SA is commonly
707 addressed with alternative tools; variance-based global SA techniques being the most popular

708 one (Iooss and Lemaitre, 2015). Such techniques were adapted by Li and Mahadevan (2018) to
 709 bridge the gap between both communities. Their approach has the advantage to be global i.e.
 710 in the sense that all CPT parameters' values are changed all together. Besides, this approach
 711 can be applicable to any types of BBN (discrete, hybrid or continuous), i.e. it is model-free.

712 **6 Concluding remarks**

713 **6.1 Summary**

714 The current survey has investigated how to deal with uncertainties related to the specification
 715 of CPTs for discrete BBNs. Three questions were addressed, namely: (1) how to constrain the
 716 uncertainties related to CPT derivation; (2) how to integrate these uncertainties in the BBN-
 717 based analysis; (3) how to test the robustness of the BBN-based results to these uncertainties.
 718 Table 2 provides a summary of the main methods/approaches (together with their advantages
 719 and limits) to answer these questions.

720

Question	Approach	Advantages	Limits	Section
1	Learning CPT by combining data and expert prior knowledge via MAP estimation	<ul style="list-style-type: none"> - It improves the MLE-based fitting when the number of data is limited. 	<ul style="list-style-type: none"> - The representation of expert belief is restricted to the use of Dirichlet priors; - There is a possible problem of “under-fitting” in sparse situations. 	Sect. 2.4-2.5
1	Learning CPT by combining data and qualitative constraints	<ul style="list-style-type: none"> - The accuracy of the MLE/MAP-based fitting is largely improved when data are scarce; - The experts may feel more conformable in providing ordering than precise CPT values. 	<ul style="list-style-type: none"> - Many new estimators are available, but many lack practical recommendations; - There is a possible problem of “under-fitting” depending on the chosen priors. 	Sect. 2.4-2.5
1	Direct elicitation using qualitative statements	<ul style="list-style-type: none"> - The experts may feel more conformable in providing qualitative statements than quantitative estimates. 	<ul style="list-style-type: none"> - Mathematical modelling of linguistic terms may lead to information loss or increased computation burden. 	Sect. 3.1
1	Use of “divorcing” nodes	<ul style="list-style-type: none"> - The number of nodes is decreased through aggregation of nodes. 	<ul style="list-style-type: none"> - Care should be paid to avoid the loss of interactions in the procedure; - It may dilute the sensitivity of the final node(s) to the input nodes; 	Sect. 3.2

			<ul style="list-style-type: none"> - It might increase the uncertainty propagated through the BBN. 	
1	Simplification of the causal structure using logical gates (e.g. Noisy-OR gate)	<ul style="list-style-type: none"> - The number of nodes to be elicited is largely decreased (e.g. from 2^n to $2n$ for a binary node with n parents). 	<ul style="list-style-type: none"> - The assumptions on the causal relationships might not always be valid in real life applications; - The simplifications may hamper the BBN performance. 	Sect. 3.2
1	Extracting information on the factor effects from known relationships and extrapolating them	<ul style="list-style-type: none"> - A large variety of different “filling-up” methods exist to relieve the elicitation burden; - Some feedbacks on real case applications exist (e.g. for human reliability analysis). 	<ul style="list-style-type: none"> - Simplifications are introduced and the derived probabilities can only be considered approximations of the true probabilities. 	Sect. 3.3
2	Uncertainty propagation using probabilities	<ul style="list-style-type: none"> - The degree of confidence in the BBN-based results can be quantified. 	<ul style="list-style-type: none"> - The uncertainty representation is restricted to the use of Beta/Dirichlet probability distributions; - It can become computationally intensive. 	Sect. 4.2
2	Uncertainty propagation using intervals with credal networks (CN)	<ul style="list-style-type: none"> - It avoids selecting a probability model to represent the uncertainty; - The experts may feel more comfortable in assigning intervals than probabilities. 	<ul style="list-style-type: none"> - The specification of interval-valued probabilities can become tricky for multivalued nodes; - It needs specific sophisticated inference algorithms and software solutions (with potential high computational costs). 	Sect. 4.3
2	Uncertainty propagation within the Dempster-Shafer Theory by using evidential networks (EN)	<ul style="list-style-type: none"> - The expressiveness is improved like for CN; - EN is more intuitive than CN, because experts directly assign some weight to the epistemic state; - It can be implemented with existing BBN softwares. 	<ul style="list-style-type: none"> - The translation of interval-valued probabilities within this setting can become difficult for multivalued nodes; - The inference algorithms for combining joint/disjoint belief masses are not so effective as those based on probability theory. 	Sect. 4.4
3	Sensitivity Analysis (SA) using sensitivity functions	<ul style="list-style-type: none"> - The theory is well-established; - It is simple to implement; 	<ul style="list-style-type: none"> - It focuses on the influence of one (or multiple) CPT parameters while the 	Sect. 5.1

		- The graphical representation is straightforward to interpret.	<ul style="list-style-type: none"> other ones are kept constant; - It requires specific co-variations schemes; - Multi-way SA can rapidly become intractable. 	
3	Sensitivity Analysis using Chan–Darwiche distance	- It complements the sensitivity functions by giving insight in the effect of parameter changes on the global joint distribution.	<ul style="list-style-type: none"> - It presents the same disadvantages than the sensitivity functions; - The choice of the distance can be rather arbitrary. 	Sect. 5.1

721 Table 2. Summary of the advantages and limits of the main approaches

722 [Table 2 about here]

723 Considering the first question, we described methods for deriving CPT entries from different
724 sources of information (observations, prior knowledge, expert-based information, etc.).
725 Traditional estimators like MLE and MAP (or new ones) were proposed to make the best use
726 of the data available even in scarce situations when completed by qualitative constraints like
727 knowledge about the monotonic influences between nodes. For rare-event situations like
728 reliability analysis, the main source of information relies on inputs from expert domain using
729 different elicitation techniques; the main challenge being the minimization of the workload on
730 the experts owing to the large number of CPT entries while preserving the quality and
731 consistency of the elicited result. Elicitation for CPTs generally relies on three (possibly
732 combined) main approaches: (1) through the assessment of probabilities directly from an expert
733 or a panel of experts; (2) through a simplification of the causal structure using the popular
734 Noisy-OR(MAX) model (and its improved versions like the leaky one); (3) through filling-up
735 methods, which have in particular been thoroughly benchmarked on test cases in the domain of
736 human reliability analysis.

737 The second question can be addressed using different approaches, either using probabilities, or
738 imprecise probabilities either using interval-valued probabilities within the setting of credal
739 networks or within the Dempster-Shafer theory within the setting of evidential networks.
740 Though the latter approach enables an increase in expressiveness with respect to uncertainty
741 representation (as shown by the few tens of application studies using these techniques, see Table
742 1), this might come however at the expense of higher complexity of the inference algorithms
743 (and higher computational costs). Finally, the third question is investigated by methods
744 specifically developed for sensitivity analysis of BBN; in particular through the use of one- or
745 multi- way sensitivity functions.

746 **6.2 Discussion and open questions**

747 BBN is now viewed as a suitable tool for overcoming data gaps, estimating uncertainties, and
748 visualizing complex causal relationships. Despite its clear advantages, it cannot be applied
749 uncritically, and addressing the question of uncertainties in its construction, and more
750 specifically in the CPT derivation, should become standard practices to increase the confidence
751 in its use. The analysis of the literature (Table 2) shows that any analyst is now equipped with
752 a handful of different tools/methods to address the question of uncertainties. This contributes
753 to the minimization of the concern of Neil et al. (2000): “In the literature much more attention
754 is given to the algorithmic properties of BBNs than to the method of actually building them in
755 practice”.

756 Yet, the developments of these techniques is only one part of the problem, and effort should be
757 intensified to bring them to an operative state. To this purpose, the implementation of these
758 techniques within commonly-used BBN software packages (like Beuzen and Simmons 2019
759 for the widely-used Netica software, Norsys Software Corp., 2006 or Tolo et al. (2018) who
760 proposed an open-source software package OpenCossan) should be strengthened. Second many
761 methods lack practical recommendations. Therefore, more benchmark / comparative exercises
762 are needed to cover broader situations and to serve as best practices for selecting the most
763 appropriate tools depending the characteristics of the considered situation. For instance, the
764 filling-up methods benchmarked by Mkrtchyan et al. (2015) should be completed by Noisy-
765 OR/MAX models, direct elicitation among others, and applied in different contexts (different
766 network sizes, binary versus multivalued nodes, etc.), as well as domains of application.
767 Similarly, there is a need for comparing the pros and cons of using alternative frameworks for
768 uncertainty representation and propagation in BBNs, i.e. comparing approaches using
769 probabilities, or interval-valued or Dempster-Shafer structures or possibility distributions or
770 Fuzzy sets, for instance by following the initiatives conducted for probabilistic risk analysis
771 (e.g., Pedroni et al., 2013, Loschetter et al., 2016).

772 The current work has focused on CPT derivation for discrete BBN development. The second
773 key ingredient of BBNs is the DAG specification, whose learning from data has been
774 investigated in numerous studies (e.g., Heinze-Deml et al. (2018), Scutari et al. (2018), Beretta
775 et al. (2018), etc.). To address the whole spectrum of uncertainties in BBN building, studies
776 both covering DAG and CPT learning would be beneficial. To integrate both sources of
777 uncertainty, possible lines of future research may either focus on the improvement of existing
778 algorithm like the structural expectation-maximization algorithm (Benjumbeda et al., 2019) to
779 simultaneously learn the structure and parameters of a BN from incomplete data, or on the

780 combination/aggregation of multiple BBNs, each of them being based on a different set of
781 assumptions either regarding structure or CPT parametrisation (Kim and Cho, 2017; Feng et
782 al., 2014).

783 Finally, it should be underlined that BBN modelling is a rapidly advancing field (see e.g.,
784 Marcot and Penman, 2019) that covers new applications and features (like the incorporation of
785 the time and space dimension, the improvements in the treatment of discrete and continuous
786 variables, its links with artificial intelligence, among others). The research on the uncertainty
787 treatment for these new developments is active (see e.g., recent advances for sensitivity analysis
788 of a wide array of graphical models by Leonelli (2019)), and the scope of the current work
789 should be broadened in the future to include them.

790

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794

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