Cluster-Based WSA for Decision Support Bayesian Systems: Case of Prognostic in Maintenance Management

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Abstract: A knowledge representation and reasoning from data have produced many models. Probabilistic graphical models, specifically the Bayesian Network (BN) have proved its worth. It is considered to be a very useful tool for representing uncertain knowledge and decision-making support. This presupposes availability of knowledge problem in the conditional probabilities form. However, one is often in a critical situation because of data are insufficient, partially unavailable or heterogeneous. Developing methods and techniques to reconstruct the corpus of data needed for decision making, especially via BN is called the "knowledge elicitation". Several elicitation methods exist but they are not always applicable, too demanding in expert knowledge or presenting limits. The most generic and useful is the Weighted Sum Algorithm (WSA) but it presents two major issues concerning the compatible parental configuration. In the present paper, we discuss what the literature proposes for the first one, then we develop the solution for the second and validate it via a case of pump failure prognostic tool based on Bayesian support decision.

1 INTRODUCTION

A knowledge representation and reasoning from data have produced many models. Probabilistic graphical models, specifically the BN, initiated by Pearl in the 1980s, have proved its worth. It is considered to be a very useful tool for representing uncertain knowledge and reasoning from incomplete information. It also allows providing effective solutions with compact graphical representations of real problems in short time. In general, using as a decision support tool presupposes availability of problem knowledge in the conditional probabilities form. However, in many real applications, we are often in a critical situation where data are insufficient, partially unavailable or heterogeneous. Indeed, to definitively establish a conditional probability table (CPT), availability of a large quantity of data is required. In addition, the descriptive knowledge of a problem is sometimes qualitative and we have to transform them to quantitative knowledge in order to build the related CPT. In these situations, learning parameters of BN using expert knowledge to estimate the conditional probabilities is the most reliable way. Developing methods and techniques to reconstruct the corpus of information needed for decision making, especially via BN is called the "knowledge elicitation". This is a branch of artificial intelligence and most of the elicitation methods come from Knowledge management techniques and they are detached from the tool used to guide the decision maker. Among these methods is the Weighted Sum Algorithm (WSA) which is for all purpose. This method allows us to reduce the information number to elicit with the expert but in the field of application, it presents gaps concerning the compatible parental configurations. One of them has no scientific contribution thus it has been solved in this paper by proposing a clustering approach.

This paper is organized as follows: in the next section, we will introduce the BN, its structure and parameters. In section 3, we will classify and discuss various Bayesian-based elicitation methods found in literature. In section 4, we will deal with the WSA and its limits. Then, we will propose our clustering approach as a method to remedy the scientific issue encountered. In section 5, we will apply our method on the "Shutdown Pump" case study and we are going to use some tools to facilitate the task for the expert. Then, we will compare our method with WSA and the Raw method of elicitation and give thereafter our results. Finally, in section 6, we will summarize the paper and draw some conclusions about further works.

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2 BAYESIAN NETWORK

A BN according to (Pearl, 2014) is a graphical model representing the joint probability distribution $P(X)$ on a set of random variables $X = \{X_1, ..., X_n\}$ defining probabilities $P \in [0,1]$ for each possible state $(x_1, , x_n) \in X_{1,dom}, ..., X_{n,dom}$ where $X_{i,dom}$ is the domain of definition of each variable X_i. It is a directed acyclic graph, in which nodes represent random variables, arcs symbolize the relationships between these variables and by the set of CPTs of each node in the graph given its parents. They encode the joint probability over all the nodes as the product of these conditional probabilities. The joint probability distribution on all the variables X of this model is written as follows:

$$P(X_1, ..., X_n) = \prod_{i=1}^{n} (P(X_i|pa(X_i))) \quad (1)$$

2.1 Structure and Parameters

BN is a mix of probability and graph theories. In other words, it require a combination between expert knowledge and data (Fenton and Neil, 2012). But, it is not very common to combine both sources of information. In practice, many BNs models have been learnt only with data however others have been built solely on expert knowledge. It can be explained by the difficulty to combine knowledge with data. BN users should have a strong background in both data mining and expert systems, as well as to have access to, and time for, the actual domain expert elicitation (Constantinou et al., 2016). For building a BN, we should:

- Determining the structure of the network

According to (Naïm et al., 1999), the human intervention in the first step of construction is important. We have to determine all the variables that characterize the system. Then we must specify the states of each variable, that is to say all of its possible values. After identifying the different variables and their state spaces, we proceed thereafter to identify links between these variables. In short, the variables involved (or parent) and effect variables (or child) must be defined (Figure 1).

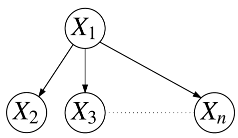

Figure 1: Example of Bayesian network.

- Determining the conditional probabilities tables

Once the BN is established, we assign to each state of each node (Variable) a conditional probability given the statements of the parents to determine CPTs associated with different nodes. According to (Nguyen, 2007), expert knowledge on variable probability distributions is included in the model. Specifically, there are two cases according to the position of a variable X_i in the BN: X_i has no parent variable: experts must identify the marginal distribution X_i (See Table 1).

Table 1: CPT of X_1.

X_1	x_1	...	x_n
	$P(X_1 = x_1)$	...	$P(X_1 = x_n)$

X_i has parental variables: experts must express the dependence of X_i function of the parent variable, either by means of conditional probabilities, or by deterministic equation, which subsequently allows the calculation of conditional probabilities (See Table 2).

Table 2: CPT of X_n.

X_n	X_1	x_1	...	x_n
	x_1	$P(X_n = x_1 \mid X_1 = x_1)$	...	$P(X_n = x_1 \mid X_1 = x_n)$
	...	...	...	...
	x_n	$P(X_n = x_n \mid X_1 = x_1)$	...	$P(X_n = x_n \mid X_1 = x_n)$

2.2 Parameter Sourcing Problem

A BN's direct acyclic graph and CPTs can be learnt automatically from data, or by domain expert elicitation, or using the combination of both. However, in most cases we do not found the necessary information and data is not available for the determination of probabilities. So, we need expert knowledge as source of probabilities. Using expert's beliefs to assign conditional probabilities is called expert elicitation.

According to (Cooke and Goossens, 2000), the main steps of the elicitation process are:

- determine what the experts need to elicit,
- select experts,
- expert elicitation, where the experts may use an elicitation method to assign probabilities,
- if there are several experts, combine their assessments,
- document the process and the result.

We suppose that we have a simple BN, referred to as a naive BN, where there is just one child and two parent nodes with four and three states respectively. The number of probabilities required for each node is represented by equation 2.

$$NP = (m-1) \prod_{i=1}^{k} n_i \quad (2)$$

Where NP = the number of probabilities needed to build a CPT of the child node ; m = the number of states of the child node; and n = number of states of parent node i = 1...k.

If a node has no parents, the product term drops from the equation (it does not take the value of zero) and only the prior probabilities $(m-1)$ are needed. In its simplest form with all nodes binary, $NP = 2^k$ (Tang and McCabe, 2007). So and in this case, the expert must elicit to us $(4-1) \times 3^2 = 27$ probabilities to fill the CPT of the child node.

Due to the structure of a BN the number of probabilities in CPT grows exponentially with the number of parent nodes and their states related to that CPT. For example, if we add another parent node with 4 states and an additional state to other nodes (parent and child). Then, CPT size would increase from 27 to 256 parameters. Thus, the elicitation becomes extremely laborious and very time consuming. For an expert, it can be particularly difficult to assign probabilities for events that are very rare. Therefore, different methods to help the expert and to systematize the elicitation have been developed (Knochenhauer et al., 2013) which will be detailed in the next section.

3 KNOWLEDGE ELICITATION FOR DECISION SUPPORT

When developing BNs for practical applications, we must incorporate expert knowledge of factors which are important for decision analysis where historical data is unavailable or difficult to obtain (Constantinou et al., 2016). The involvement of expert elicitation is a big challenge. First, the design of the elicitation process itself, which includes the determination of experts and elicitation techniques, might be a daunting process (Kuhnert et al., 2010). Moreover, the demanding of large number of conditional probability entries not only put great workload on the experts but also poses challenges to the quality or consistency of the elicited result. Therefore, as to experts elicitation, many of the previous literature were working on two aspects: one is to reduce the burden of the experts by reducing the number of conditional probabilities to elicit while the other is to facilitate the elicitation of individual probability entry (Knochenhauer et al., 2013). The difficulties are related to expert reliability and pertinence. By the way and to facilitate the elicitation, it is possible to provide expert tools linking qualitative and quantitative concepts to associate a probability to the various events.

3.1 Facilitation Methods

We found various methods to facilitate the elicitation when we should elicitate one probability like Gamble Like Methods originate from the standard gamble introduced by (Von Neumann and Morgenstern, 2007) as an indirect method for utility elicitation. The basic idea behind a gamble like method is that the expert is presented with a choice between two lotteries (Burgman et al., 2006). In addition, there is Probability Wheel method which is an indirect method that is not influenced by risk attitudes. It is usually a circle divided into two sections. The sections are altered until the expert believes he can spin a pointer and the probability that it will stop in a section is equivalent to the probability being assessed (Renooij, 2001). Also, we found Probability Scale which is the best known and one of the various easiest methods to work. The basic idea of this scale is to facilitate to the expert the determination of probabilities in CPTs by allowing them to use information both textual and numeric to assign a level of achievement to a particular assertion (Druzdel and Van Der Gaag, 2000) and (Renooij and Witteman, 1999).

3.2 Reduction Methods

For reducing the number of conditional probabilities to elicit, we present five of the most frequently used methods:

1. Node divorcing which allows as to simplify the model structure by introducing a mediating node to reduce the number of parent nodes (Zhang and Thai, 2016).
2. Likelihood method where the experts are asked about the influence weight instead of the direct conditional probability numbers (Kemp-Benedict, 2008).
3. EBBN method (an Elicitation method for Bayesian Belief Network) uses on piecewise linear interpolation based on the ranks of the parent nodes' states to determine the CPT (Wisse et al., 2008), (Knochenhauer et al., 2013), (Mkrtchyan et al., 2016).
4. Exploit the causal independence between the parent nodes. The most widely used way is to exploit the Noisy-OR role (for binary variables) and its extension Noisy-Max (for nominal variables) (Bolt and van der Gaag, 2010), (Kraaijeveld et al., 2005). However, this method often make fundamental assumptions about the BN: assume that parent nodes must be independent, their states must

be ordered according to a criterion or express a degree or gradient of a variable and that each node must have an absent state. In reality, these assumptions cannot often be satisfied.

5. Weighted Sum Algorithm(WSA) is a method which solve many constraints of the previous method. In fact, what makes this algorithm special compared to other techniques, is that it allows us to ask experts questions that are easy to visualize and simulate (Baker and Mendes, 2010). Also, using the WSA will make the number of assessments of a CPT linear instead of exponential (Das, 2004). That's why our choice is converged towards this method to more explore and apply it to a case study. We develop it more in the next section.

4 CLUSTER-BASED WSA ELICITATION

The use of the WSA method is indeed practical in terms of reducing the information to elicit but sometimes in some situations experts can't objectively provide probabilistic data. In what follows, we will detail the method as it has been presented with (Knochenhauer et al., 2013) to better explain and we will give his limits. In next subsections, we explain WSA method and then solve the main of these limits for which we don't find literature contribution.

4.1 WSA Elicitation Method

According to notation used with (Knochenhauer et al., 2013), this method consists of an algorithm that estimates the $k_1 \times ... \times k_n$ conditional probabilities : $P(X_c = x_c^m | X_{p_1} = x_{p1}^{j_1}, X_{p_2} = x_{p2}^{j_2}, ..., X_{p_n} = x_{p_n}^{j_n})$ that form a CPT. With X_c as the child node with l states and $\{X_{p_i}\}_{i=1}^{n}$ as the parent nodes with k_i states each the algorithm takes the following form:

$$P(x_c^m | x_{p_1}^{j_1}, ..., x_{p_n}^{j_n}) = \sum_{i=1}^{n} w_i P(x_c^m | \{Comp(X_{p_i} = x_{p_i}^{j_i})\}) \quad (3)$$

where $m = 1, 2, ..., l$ and $j_i = 1, 2, ..., k_i$.

This method requires the expert to elicit two things:

- the relative weights $w_1, ..., w_n$ for the parent nodes, where $0 \le w_i \le 1$ and $\sum_{i=1}^{n} w_i = 1$.
- the $k_1 + ... + k_n$ probability distributions over X of
$$P(x_c^m \left| \{Comp(X_{p_i} = x_{p_i}^{j_i})\} \right.) \quad (4)$$
for compatible parental configurations.

Compatible parental configurations refer to the term $\{Comp(X_{p_i} = x_{p_i}^{j_i})\}$ which has the following definition: The state $X_{p_n} = x_{p_n}^{j_n}$, for the parent X_{p_n}, is compatible with the state $X_{p_i} = x_{p_i}^{j_i}$, if according to the expert's mental model the state $X_{p_n} = x_{p_n}^{j_n}$ is most likely to coexist with the state $X_{p_i} = x_{p_i}^{j_i}$. Then $\{Comp(X_{p_i} = x_{p_i}^{j_i})\}$ denotes the compatible parental configuration where X_{p_i} is in the state $x_{p_i}^{j_i}$ and the rest of parents are in states compatible with $X_{p_i} = x_{p_i}^{j_i}$. And then the WSA is used to generate the probabilities of a child node's CPT.

In literature, they frequently say that we need only the 3^{rd} term of equation n°5 as information from expert (Das, 2004). In reality, there is more information to solicit from him: the relative weights for the parent nodes (the 1^{st} term) and the parental compatible configurations (the 2^{nd} one). Hence, the total number of informations (NI) that we will need from the expert to form the CPT will be:

$$NI = k + \sum_{i=1}^{k} n_i + \sum_{i=1}^{k} (n_i.(m-1)) = k + m.\sum_{i=1}^{k} n_i \quad (5)$$

where k the number of parent nodes.

This method presents two major issues when we ask an expert to give us the compatible parental configuration. The first issue is when the expert is confronted to many compatible parental configuration for a given parental state and he can't select one of them. To solve this problem, (Baker and Mendes, 2010) propose an extension for the WSA method by averaging the probabilities of valid compatible parental configurations that expert might select. The second issue is when the expert is unable to give compatible parental configuration since there are states of the nodes that are not coherent with each other. To remedy this issue, we propose a clustering approach detailed below.

4.2 Clustering Approach

The blocking situation is when the expert considers that the compatible parental configuration of all parent nodes is irrelevant and he is unable to give all the compatibilities as shown in the Figure 3. Indeed, the expert explains that the nodes 2, 3, 4, 5 explained in Table 3, make sense from the point of view of compatibility since they contribute to define, somewhere the notion of cavitation (see the detail in the case study section). That it is not objective to amalgamate them with the nodes 1 and 6. This recurrent situation inspired us to propose the solution hereafter. We propose to suggest to the expert, in elicitation phase, to choose the most coherent group to define a compatibility. For this, he will propose a "**Cluster**" (like the one in Figure 4 grouping the nodes from 2 to 5) whose notion of compatibility is plausible and insert an intermediate node. In other words, we introduce the Node Divorcing method (Fenton and Neil, 2012). Subsequently, we can apply the WSA for this cluster to obtain the CPT of the intermediate node. As for the rest of nodes, they will be used for elicitation independently. Of course, it is possible that we have to define several clusters. In this paper, only the case of a single cluster will be treated to illustrate our method.

The Figure 2 illustrate a general example of a Bayesian network where the child node x_c has a set of parent nodes P from X_{P_1} to X_{P_k}. By applying our method, we obtain a cluster P' grouping the nodes X_{P_6}, X_{P_7} and X_{P_8} with an intermediate node noted x_{Int}.

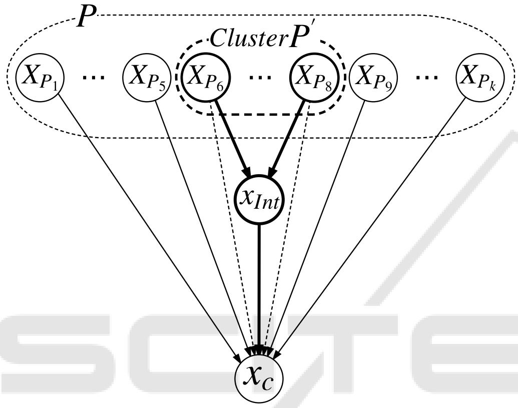

Figure 2: Bayesian network showing cluster Approach.

With our clustering approach, the total number of informations (NI') needed to elicit from the expert is calculated with our equation 6 bellow:

$$NI' = k' + m'.\sum_{i \in P'} n_i + (m-1).m' \prod_{i \in P-P'} n_i \qquad (6)$$

Where:

- k': the number of parent nodes of the intermediate node (*cluster size*), with $k' \in [2, k-1]$.
- m': the number of states of the intermediate node, with $m' \in \left[2, \prod_{i=1}^{k'} n_i\right]$.
- P: set of the parent nodes index of the original structure.
- P': set of the parent nodes index of the intermediate node.

After presenting our method, we will develop it more in the next section with case study and we detail our results.

5 CASE STUDY

We relaunched our research work from a real case of a petroleum company. Due to its importance in contribution to the national economy and specifically in the energy sector, the goal of this company is to decrease the waste of time and money. Thus, a sudden and instant stop in one of its production equipment can cause enormous material damage with very high maintenance costs, knowing that the acquisition of new equipment will be too expensive. Since 2004, the stopping frequency and maintenance interventions of the P-0701 pump have increased remarkably. The cost of maintenance is too expensive and requires qualified staff. However, they are uncertain to know immediately the main causes for this judgment. In short, they will waste time for the diagnosis, search for causes and finally to repair them. In addition, if the failure requires a spare part, it would be unavailable on the market and must be ordered. To import this piece, there will be a waste of time and the whole process will be paralyzed. This will negatively influence the volume of production and subsequently a large expense. Moreover, the pump played a significant and critical role because it ensures the transfer of gas from the field to its customers. So, if there is a break or shutdown in the pump it will generate a complaint and dissatisfaction of its customers.

To avoid these different consequences of stopping the pump, it is useful to develop maintenance plans as little as possible. To do this, we need a model with a capacity of integrating technical and statistical data of pump as well as knowledge expert. By the way, we chose to model this problem by a model derived from a probabilistic approach by the Bayesian networks to estimate the causes that provide the shutdown of this pump which will be used for decision making, rapid diagnosis of the failure and prognostic in future. For this, we made several meetings with the experts. We used the method of 5 Why, the Ishikawa Diagram and various questionnaires. The purpose was to build up a body of knowledge and practices of maintenance personnel that would produce strategies and plans for maintenance operations of the pump system. The finding of this study was the important number of information which is needed from experts to parameterize the Bayesian structure successfully. It is at this point that the usefulness of facilitation and reduction methods for the elicitation of the model has become unavoidable.

After validation with the experts, a small representative part of the Bayesian structure is presented in Figure 3. For reasons of simplification, we have reduced ourselves to the first level of causes of failure.

This allowed us to identify six main causes that can lead to the sudden shutdown of the pump with two possible states for each of them (Yes, No), (see Table 3).

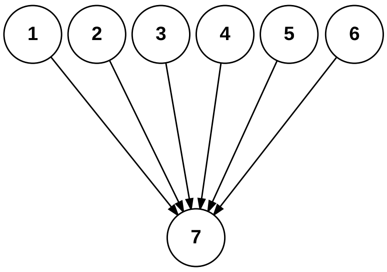

Figure 3: Part of Bayesian network of Pump P-0701 Shutdown.

Table 3: Dictionary of nodes information.

Ref.	***Nodes***
1	HUMAN_FAULT
2	HYDRAULIC_INSTABILITY
3	STEAM_BUBBLE
4	TEMPERATURE
5	PRESSURE
6	PREMATURE_WEAR
7	SHUTDOWN_PUMP

Then, the expert must provide us the CPT of the node 7. In this case, he must elicit, according to the equation 2, $NP = (2-1)\prod_{i=1}^{6} n_i = 64$ probabilities which is important and very hard to expert to give us. In order to reduce the number of probabilities to elicit and facilitate the task to the expert, we use the WSA method detailed in previous section. Through this method, we will go from 64 probabilities to elicit to $NI = 6 + 2 \times \sum_{i=1}^{6} n_i = 30$ either a reduction of 53,12% which illustrates the linear growth of the input information required by the method, compared to the exponential growth of manual elicitation. However, when we asked the expert to give us the 12 probability distributions, he can't do that. He is unable to give all the compatibilities since there are states of the nodes that are not coherent with each other. Indeed, he can't give the compatible parental configuration including nodes 1 and 6 because they have no relation with other nodes. To solve this problem, we introduce our method and we ask the expert if he could propose grouping or aggregation variables. So, he gives us a grouping by introducing an intermediate node CAVITATION noted 8 with three states (Low, Average, Important) as indicated in Figure 4.

Now, the expert is able to give us $2+2+2+2$ probability distributions of parents nodes of the cavitation node. For that, we gave him the Table 4 below

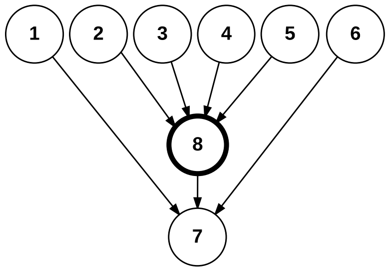

Figure 4: Part of Bayesian network of Pump P-0701 Shutdown after divorcing node method.

as the tool to facilitate the task which present the combination of all states of parent nodes and we asked him just to check those who coexist the most with a given state to make the compatible parental configurations.

Table 4: Compatible parental configurations.

		2		3		4		5	
		Yes	No	Yes	No	Yes	No	Yes	No
2	Yes			x		x		x	
	No				x		x		x
3	Yes	x				x		x	
	No		x				x		x
4	Yes	x		x				x	
	No		x		x				x
5	Yes	x		x		x			
	No		x		x		x		

After that, we asked him to give us for each parent nodes the relative weights w_1, w_2, w_3 et w_4. For this, we gave him a scale of weights (Figure 5 (b)) as a second tool and we explain to him that the interval widths for each state are 0,2 ; for example: the value "High" is associated with the interval $[0,6-0,8]$, etc.

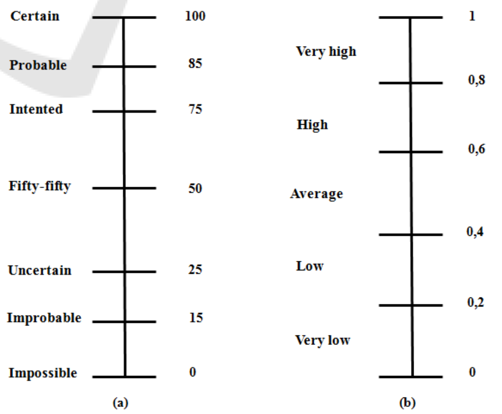

Figure 5: (a) Probability Scale given to the expert to determine the conditional probabilities of the compatible parental configurations (b) Weights Scale which was given to the expert to determine the relative weight for each parent nodes.

Then, he will complete the $2 \times (3-1)$ probability of each compatible parental configurations {Comp(2

= x)}, {Comp(3 = x)}, {Comp(4 = x)} and {Comp(5 = x)} while:

$$\sum_{y=L}^{I} P(8 = m|\{Comp(X = x)\}) = 1 \qquad (7)$$

where y present one state of the cavitation node (Low, Average, Important), $X = 2, 3, 4, 5$ and x present one state of the node used (Yes, No).

To facilitate the task of elicitation to the expert, we provided him a scale of probabilities (Figure 5 (a)), as the third tool, to give the conditional probabilities corresponding to the compatible parental configurations for every parental State. The following Tables 5 illustrate probability distribution of cavitation node obtained from the expert related to compatibility states $Comp(2)$.

Table 5: Distribution of cavitation node related to compatible parental configuration of node 2.

Probability Distribution over CAVITATION	Yes	No
$P(8 = Low\|\{Comp(2)\})$	0,05	0,8
$P(8 = Average\|\{Comp(2)\})$	0,35	0,15
$P(8 = Important\|\{Comp(2)\})$	0,6	0,05

Taking these distributions and the weights as input, the WSA would be able to calculate all the $(3-1)\prod_{i=1}^{4} n_i = 32$ distributions required to build the CPT of cavitation node.

Now, we ask the expert to fill us the CPT of node 7 which has, after applying the node divorcing method, tree parent nodes instead of six. In this case, he will elicit just $(2-1)\prod_{i=1}^{3} n_i = 12$ probabilities.

Then, we summarize in Table 6 the elicitation information needed for different methods.

Table 6: Elicitation information needed for different methods.

Method	NI To elicit	Percentage of information reduced
Raw	64	
WSA	30	53,12 %
Cluster-WSA	40	37,5%

We note that the rate of reduction number of information to elicit is not very important when we use our method. However, if we take more complicated example with several possible states, the gap will be important. To better understand and see the results, we made two curves showing the three methods by varying cluster size k'.

For the first curve (see Figure 6), it's our case study with $m' = 3$. We observe that as the size cluster increases, the number of information with Cluster-WSA decreases between 2 and 4 until it reaches 40 as a minimum value of information needed. Beyond

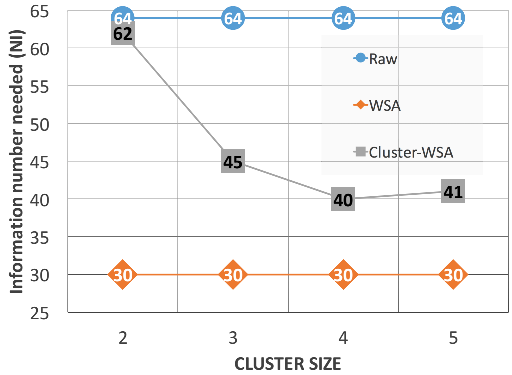

Figure 6: Elicitation information needed according to cluster size with **3 states** of intermediate node.

that it increases. We concluded that our method is better than the Raw method whereas it is less good with WSA concerning the number of information to elicit.

For the second curve (see Figure 7), we choose $m' = 2$ the minimum number of possible states which can be given for the intermediate node. This time,

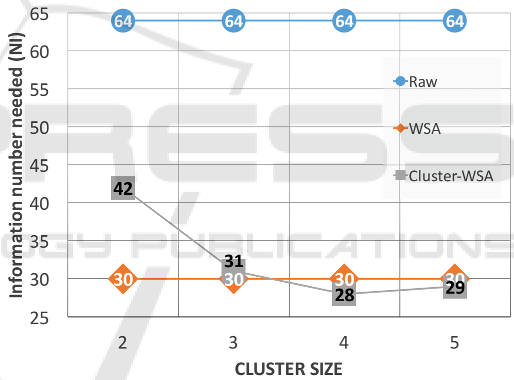

Figure 7: Elicitation information needed according to cluster size with **2 states** of intermediate node.

we notice that the number of information needed with cluster-WSA has decreased more than with the WSA method where $k' = [4, 5]$. In this case, our cluster-approach is better than the two other methods.

To summarize, it is true that cluster-WSA does not always give information in some cases compared to WSA. However, through the use of our method, we have remedied the scientific issue encountered.

6 CONCLUSION

Eliciting probability parameters for CPT is one of the important problems for BN. There are many methods of elicitation in the literature that facilitate and reduce the task of elicitation. The most generic is the WSA which was developed in this paper. This method is easy to apply and it makes the number of CPT's assessments linear instead of exponential. However, it presents two major issues when the expert must give the compatible parental configuration. The first is where the expert cannot select a single compatible parental configuration for a given state. This issue was solved in the literature. By contrast, the second isn't. The problem is when expert still unable to give compatible parental configuration for each state with other states of other parents. As a solution for this issue, we proposed, in this paper, a cluster approach by including a intermediate node. We applied the WSA on a generated cluster and we used Raw method of elicitation for the rest of nodes. Then, we applied our method on a part of BN of our case study. To facilitate the application of WSA, we have combine various different concepts. Among which we elaborate a table for compatible parental configurations which is easy to complete by the expert. In addition, we use a scale of probabilities and a scale of weights to facilitate the task of elicitation to him. In addition, we developed two practices equations to calculate the number of information needed from expert one for the WSA and the other for our method. After that, we compared information number needed obtained from our method with WSA and the Raw method by varying the cluster size and states number of intermediate node. Through using our method, the information number to elicit is less important than that obtained by the Raw method. But this is not always the case compared with the WSA. This comparison allows us to admit that our clustering method is better than the Raw method but it's still not good sometimes compared to WSA knowing that it has remedied the scientific issue encountered.

It is true that our clustering approach reduces the number of information to be elicited in order to develop our CPT and remedied the scientific issue encountered with WSA, nevertheless like other methods, it has some limits. In our next research, we will try to find them and to compare our method with other existing methods. Moreover, in this paper, we present our method to remedy the problem of compatible parental configuration and we have treated a single cluster. As a prospect, we may wonder what will become our method and results if we have several clusters.

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