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Research Article

Modelling the Change in River Water Allocation Using Bayesian Networks: A Case Study of SYL Canal

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ABSTRACT

It is expected that a water conflicts could end up into an agreement or a bilateral. Hence, it is an important topic to study the change in allocation of river water share as an outcome of an agreement or bilateral, in both aspects, scientific study and policy making. The current study deals with the conflict over sharing of the Beas, Ravi and Sutlej river water. The conflict began in 1966 when the new state of Haryana was bifurcated out of Punjab and she demanded her share of water under the Punjab Reorganisation Act. Bayesian Networks, used in this study to model conflict, are data driven tools helping the policy makers them out to predict a most likely outcome before moving any step further. From the netwrok learnt it is almost a sure event that a challenger state would be complying with the agreement provided a target state is complying with the agreement reached by both states. There is quite a chance that if challenger state offers major concessions it is quite likely that the this will lead to change in status quo. Likewise, belief updates were performed over the network for the SYL river water sharing conflict. The consequences of updating the networks for the hard evidences, matched well with real life events and had already occurred events about SYL issue. Bayesian network models in this study proved to be good enough for predicting the complex event such that of change in status quo. Bayesian network approach is a growing field for modelling the resource conflicts and it can help policymakers for understanding the conflicts a better way.

Keywords: *Sutlej Yamuna Link Canal, Bayesian Network Model, Water allocation*

INTRODUCTION

Water has been a cause of conflict since ancient times. In India, water conflicts have now penetrated at all levels. Water conflict management, hence, is an important topic to study in both aspects, scientific study and policy making. Bayesian Networks, used in this study to model conflict, are data driven tools helping the policy makers them out to predict a most likely outcome before moving any step further.

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Machine learning has a huge library of sub-fields along with possible strategies. One such sub-field is Bayesian Networks. A successful implementation of Bayesian networks (BNs') have been seen in recent to assist problem solving in a good range of disciplines including engineering, information technology, medicine and more freshly ecology and biology. BNs' are a helpful tool for policy makers and decision makers in situation of when there is uncertainty about the data or events. In agricultural context it is very much sure that researcher has uncertainty about many factors that might be influencing his study and BNs are best at addressing it. BNs helps the planning process, allowing the development of complex systems from a multi-disciplinary perspective. Bayesian networks are rich frameworks. And furthermore, BNs present the crucial conclusions in a format such that it becomes easy to interpret and provides ease of communication. This finally results in reduced gap between a statistician and the subject expert.

The conflict over sharing of the Beas, Ravi and Sutlej waters began in 1966 when Haryana was bifurcated out of Punjab and the new state demanded a share under the Punjab Reorganisation Act. In 1976, the union government announced that both states would receive 3.5 million acre-feet (MAF) of water from the available annual flow of 15 MAF through the construction of the SYL. This would benefit farmers in southern Haryana who could then use it through lift irrigation schemes. The canal starts from the tail end of Anandpur Hydel canal near Nangal and goes up to the Western Yamuna Canal from where it collects waters of the Ravi and Beas. Haryana dug the canal of its part within two years of agreement whereas 121 km stretch on the side of Punjab came to a grinding halt in 1990 due to militancy and the killing of a senior officer and labourers. The state of Punjab argues that availability of water in the rivers is overestimated and share offered to Punjab is not at all fair. On the other hand, government of Haryana claims that Haryana is eligible of equal share of water from the above-mentioned rivers. Despite numerous interventions by the Supreme Court and the centre, the Sutlej Yamuna Link canal (SYL) remains incomplete and a general stalemate prevails (Khurana, 2006). BNs have been progressively applied to land use policy and management. For example, Ticehurst et al. (2007) used BNs for assessing the sustainability of social, economic and K Bayesian networks that could provide the generic framework to develop a DSS for agricultural system management. In addition, Bacon et al. (2002) had developed a two-stage model of land use change in his study. BNs' had been to applied to many real-world problems that range from biomedical to petro-physics (Wiegerinck et al., 2013).

In this study, BNs were used to model the river water conflicts to know if the allocation of water changed or not after two parties went for an agreement. ICOW datasets and then the hard evidence inference of Bayesian networks was drawn from the learnt networks.

MATERIALS AND METHODS

Bayesian Network

A graphical model is a set of multivariate joint distributions that exhibit certain conditional independencies. Each model is associated with a graph $G = (V, E)$, where the vertex set V indexes the variables and the edge set E encodes the conditional independence constraints. These constraints require variables X_v and X_w to be conditionally independent given $X_c \coloneqq (X_u : u \in C)$, denoted by $X_v \perp_p X_w | X_c$, if every path between nodes v and w in G is suitably blocked by the nodes in C (Nagarajan, Scutari, & Lèbre 2013).

BBNs are a generic modelling tool both for representing a correlation structure in a causal network and for decision analysis under uncertainty. Bayesian Networks (BBNs) are increasingly being used in ecological modelling, decision support in the provision and demand of ecosystem services, and environmental and resource management (Uusitalo 2007; Barton et al., 2012; & Landuyt et al., 2013). BN's are well demonstrated to be useful in modelling resource conflicts (Musella et al., 2016).

BBNs are directed acyclic graphs whose nodes represent variables (or correlates) and whose arcs encode conditional dependencies between the variables (Scutari, 2010; & Marcot et al., 2006). Both the conditional dependencies, which are expressed through conditional probability tables (CPTs), and the structure of the model can be "learned" using many algorithms that are implemented within a large selection of existing software packages or toolboxes. These variables can be quantitative or qualitative and a small number of classes are defined for each of them. Then probabilities, originating from data analysis or from consultation with experts, are attached to each class of each variable. When variables are linked, the resulting probabilities are calculated throughout the network using the Bayes' formula.

D-separation

If A, B, and C are three disjoint subsets of nodes in a DAG 'G', then C is said to d-separate A from B, denoted $A \perp_G B|C$, if along every sequence of arcs between a node in A and a node in B there is a node v satisfying one of the following two conditions:

1. v has converging arcs (i.e., there are two arcs pointing to v from the adjacent nodes in the path) and none of v or its descendants (i.e., the nodes that can be reached from v) are in C.
2. v is in C and does not have converging arcs.

The Markov property of Bayesian networks, which follows directly from d-separation, enables the representation of the joint probability distribution of the random variables in X (the global distribution) as a product of conditional probability distributions (the local distributions associated with each variable X_i). This is a direct application of the chain rule (Korb & Nicholson, 2010). In the case of discrete random variables, the factorization of the joint probability distribution P_X is given by

$$P_X\,(X) = \prod_{i=1}^{p} P_{X_i} \quad (X_i \,|\Pi_{X_i})$$

where Π_{X_i} is the set of the parents of X_i; The BN approach provides a framework for applying Bayes' rule (Fenton, N 2016) which allows users to evaluate the probability of a specific outcome based on causal relationships between a wider range of variables deemed important by users.

Score-Based Structure Learning Algorithms

Score-based structure learning algorithms (also known, a search-and-score algorithms) represent the application of general heuristic optimization techniques to the problem of learning the structure of a Bayesian network. Each candidate network is assigned a network score reflecting its goodness of fit, which the algorithm then attempts to maximize.

Greedy search algorithms such as hill-climbing with random restarts search. These algorithms explore the search space starting from a network structure (usually the empty graph) and adding, deleting, or reversing one arc at a time until the score can no longer be improved.

Hill Climb Algorithm

1. Choose a network structure G over V, usually (but not necessarily) empty.
2. Compute the score of G, denoted as $Score_G = Score(G)$.
3. Set $maxscore = ScoreG$.
4. Repeat the following steps as long as $maxscore$ increases:
a. for every possible arc addition, deletion or reversal not resulting in a cyclic network:
i. compute the score of the modified network $G*, Score_{G*} = Score(G*)$:
ii. if $Score_{G*} > Score_G$,set $G = G^*$ and $Score_{G*} = Score_G$
b. update $maxscore$ with the new value of $ScoreG$.
5. Return the directed acyclic graph G.

Probabilistic reasoning on Bayesian networks has its roots embedded in Bayesian statistics and focuses on the computation of posterior probabilities or densities. For example, suppose we have learned a Bayesian network

B with structure G and parameters Θ. Subsequently, we want to investigate the effects of a new piece of evidence E on the distribution of X using the knowledge encoded in B, that is, to investigate the posterior distribution $P(X|E,B) = P(X|E,G,\Theta)$. The approaches used for this kind of analysis vary depending on the nature of E and on the nature of information we are interested in. The two most common kinds of evidence are as follows:

- Hard evidence, an instantiation of one or more variables in the network. In other words,

$$\boldsymbol{E} = \{X_{i_1} = e_2, X_{i_2} = e_2, X_{i_3} = e_3, \ldots . X_{i_k} = e_k,\}, \quad i_{1,\ldots\ldots\ldots,}i_k \in (1,2,\ldots..n)$$

which ranges from the value of a single variable Xi to a complete specification for X. Such an instantiation may come, for instance, from a new (partial or complete) observation recorded after the Bayesian network was learned.

As far as queries are concerned, in this study the focus would be on conditional probability queries (CPQ) and maximum a posteriori (MAP) queries, also known as most probable explanation (MPE) queries. Conditional probability queries are concerned with the distribution of a subset of variables $Q = \{X_{j_1}, \ldots, X_{j_l}\}$ given some hard evidence **E** on another set $\{X_{j_1}, \ldots, X_{j_l}\}$ of variables in X. The two sets of variables are usually assumed to be disjoint. In discrete Bayesian networks, this distribution is computed as the posterior probability

$$CPQ(\boldsymbol{Q}|\boldsymbol{E},B) = P(\boldsymbol{Q}|\boldsymbol{E},G,\Theta) = P(X_{j_1}, \ldots, X_{j_l}|E,G,\Theta)$$

Maximum a posteriori (MAP) queries are concerned with finding the configuration q∗ of the variables in Q that has the highest posterior probability

$$MAP(Q|E,B) = q^* = argmax\, P(Q = q|E,G,\Theta)$$

Applications of this kind of query fall into two categories: imputing missing data from partially observed hard evidence, where the variables in Q are not observed and are to be imputed from the ones in E, or comparing q∗ with the observed values for the variables in Q for completely observed hard evidence Both conditional probability queries and maximum a posteriori queries can also be used with soft evidence, albeit with different interpretations.

Dataset

The Issue Correlates of War (ICOW) project is a research project that is collecting systematic data on contentious issues in world politics (Hensel & Mitchel, 2017). The ICOW project is currently collecting data on river, maritime, territorial and identity issues in all regions of the world since 1816, compiled into several related data files. The dataset provides a good coverage of the 20^{th} century world resource conflicts.

Datasets used was 'ICOWsettle'. Territorial and maritime claims were dropped from the data as the focus of the study is river water disputes. Out of 417 claims mentioned (including territorial and maritime claims) in ICOW data only 83 were considered for data. Description of variables used for the analysis is given below.

Challenger Compliance: The variable Challenger Compliance is a binary variable. If the challenger comply with the agreement that both sides reached to the variable takes values in yes or else no.

Challenger Target: It is binary factor and informs about if the target comply with the agreement that both sides reached to.

Claim End: It is binary factor. If an agreement ended the contention over claim it is valued as yes otherwise no.

Concessions in Agreement: Concessions in agreement variable tells about whether or not the agreement major, minor or even included concessions for target or challenger states.

Status Quo: It is a binary factor which is if agreement change the issue-related status quo. For the river claims it refers to a change in the allocation of water from the river.

RESULT AND DISCUSSION

3.1 Frequency and Probability Distributions

The frequencies and respective probabilities of the considered variables were observed and represented in Table 1. The frequency and probability distributions in Table 1 shows that there is a very high probability that the 'Target State' will comply with in the agreement a high probability of 78.57 per cent, and oppositely there is a very low likelihood of 'Target State' not to comply with the concurrence which is 21.43. Similarly, in the variable compliance 'Challenger State' as 27.59 per cent, the probability of not to comply with the agreement is 20.41 per cent.

Table 1: Probability and frequency distributions of the variable Compliance Target, Compliance Challenger, Claim End, Concessions in Agreement and Change in Status Quo

Factor	Level	Probability	Frequency
Compliance Target	No	21.43	21
	Yes	78.57	77
Compliance Challenger	No	20.41	20
	Yes	79.59	78
Claim End	No	65.31	64
	Yes	34.69	34
Concessions in Agreement	Major Challenger Concessions	4.08	4
	Minor Challenger Concessions	5.20	5
	Roughly Even Concessions	41.84	41
	Minor Target Concessions	40.82	40
	Major Target Concessions	8.16	8
Change in Status Quo	No	16.33	16
	Yes	83.67	82

The variable 'Claim End' which is dependent on the variable 'Compliance of Challenger State'. The variable 'Compliance of Challenger State' is the parent node 'Compliance of Target State' show that there is 65.31 per cent chance that a claim will be ended where is there is only a 34.69 percentage chance that the allegation will not end with the agreement.

The variable 'Concessions In Agreement' exposed that there is a very rare probability that an agreement involves major concessions by 'Challenger State' without comparable concessions by 'Target State' with a low probability of 4.08. Whereas, the two most probable consequences were roughly even concessions for both states which mean the agreement involves concessions by both sides in the claim are there some concessions by 'Target State', although these concessions are not major, with the probabilities 41.84 and 40.82 respectively. The other data points include, minor 'Challenger State' concessions and major 'Target State' concessions, also show a very rare probability of occurring with the probabilities of 5.20 and 8.16 respectively.

The variable change in 'Status Quo' shows that most probably in the agreement and end of a claim leads to change in location of river waters. The 'Status Quo' is being changed and updated fit a probability of 83.67 where is a low probability of 16.33 is also there that there is no change in 'Status Quo' quo even after any agreement and claim being ended.

However, as it could be seen that just learning the probabilities of these different variables do not help a lot in understanding a new conflict. This lead to go for learning of Bayesian Belief Networks which are based on conditional probabilities of the variables and each variable act as a node of the network. In the next section, a complete discussion of the results of the observed networks is provided.

3.2 Bayesian Network for Change in Status Quo

The Figure 1 shows the interdependencies of the variables change in 'Status Quo', compliance with the agreement of the 'Target State' and 'Challenger State', 'Claim End' and 'Concessions in Agreement' as a Bayesian network derived from the ICOW data set ICOWsettle.

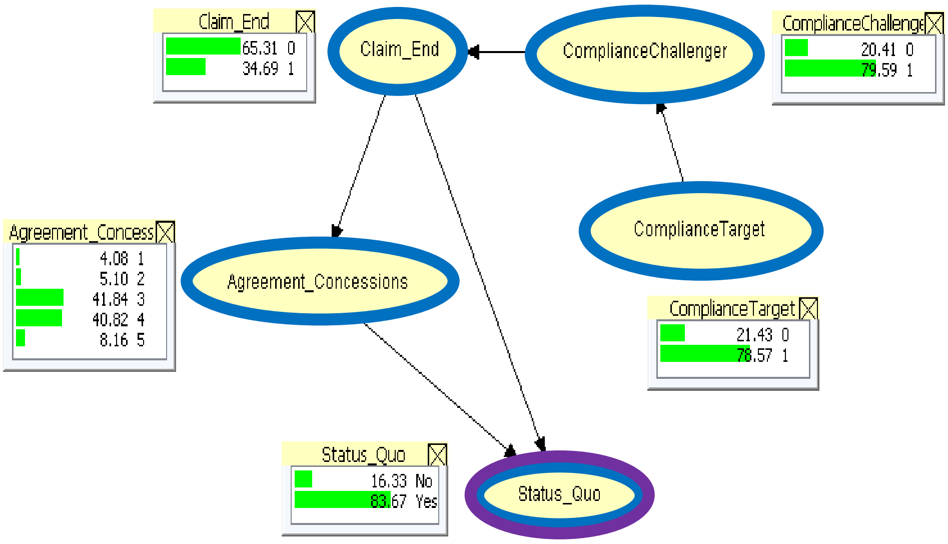

Fig. 1: DAG for the Bayesian network

Model String

P(Compliance Target) P(Compliance Challenger | Compliance Target)
P(Claim End | Compliance Challenger) P(Concession in Agreement | Claim End)
P(Status Quo | Concession in Agreement , Claim End)

The above-mentioned model has a log-likelihood, AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) scores of -266.915, -289.915 and -319.643 respectively.

Bayesian Network learned from the data shows that the compliance of 'Target State' with the agreement is the root note having children note compliance off 'Challenger State' which again is having children note 'Claim End'. So, it can be determined that the variable 'Claim End' is dependent on both the variables compliance of 'Challenger State' and the 'Target State'.

The variable 'Status Quo' quo had parent nodes 'Claim End' as well as 'Concessions in the Agreement' whereas 'Concessions in Agreement' node had the 'Claim End' node as a parent node.

The Markov blanket of the node 'Status Quo' consisted of the nodes 'Claim End' and 'Concessions in Agreement' node both being the parent nodes. The node does not have any other children node. The node 'Claim End', was present as d-separate between Status Quo' node and 'Compliance Challenger' node, hence helping to conclude that the node is not independent of any the nodes in the network. Because the node 'Compliance Target' is nothing but the parent node to the node 'Compliance Challenger'. The Local Markov Property is satisfied by the network.

Table 2: The probability distribution of the variable Compliance Target which is root node in Figure 1

P (Compliance Target)	
No	0.214286
Yes	0.785714

The 'Compliance Target' being a root node in the network only independent probabilities of it were studied at the levels 'Yes' and 'No'. The figures recorded in Table 2 reported that it was 0.2143 probability that a 'Target State' will not comply with an agreement and otherwise oppositely one can say that there was a high probability (i.e. 0.7857) that for the River conflict or claim related issues.

Table 3: The conditional probability distribution of the variable Compliance Challenger given Compliance Target which is P(Compliance Challenger | Compliance Target)

P (Compliance Challenger | Compliance Target)		
Compliance Challenger	**Compliance Target**	
	No	**Yes**
No	0.761905	0.0519481
Yes	0.238095	0.948052

The conditional probability Table 3 represented the conditional probabilities of the variable 'Compliance Challenger' given the variable 'Compliance Target' at the levels 'Yes' and 'No'. It was noticed from the table that when the variable 'Compliance Target' is at the level 'No' the event of 'No' for the variable 'Compliance Challenger' showed a mild decrease in probability which was 0.7619 a slightly lower value as compared to the unconditional probability value of 0.7959 (as in Table 1). Harmoniously, it was noticed that at the level 'Yes', for which the conditional probability value for the event 'Yes' shown a great dip from the unconditional probability 0.2041 to the conditional probability value of 0.0519.

The above reported can be seen as if a 'Target State' is complying with the agreement reached by both states is found, it is almost a sure event that a 'Challenger State' would be complying with the agreement. As well, 'Target State' is not complying with the agreement, there is good chance that the challenger State' will also not be complying with the agreement.

Table 4: The conditional probability distribution of the variable Claim End given Compliance Challenger which is P (Claim End | Compliance Challenger)

P(Claim End | Compliance Challenger)		
Claim End	**Compliance Challenger**	
	No	**Yes**
No	1.000000	0.564103
Yes	0.000000	0.435897

The conditional probability Table. 4 represented the conditional probabilities of the variable 'Claim End' given the variable 'Compliance Challenger' at the levels 'Yes' and 'No'. It was noticed from the table that when the variable 'Compliance Challenger' is at the level 'No' the event of 'No' for the variable 'Claim End' reached one in probability which was 0.6531 as its unconditional probability. An opposite pattern was noticed at the levels 'Yes', for which the probability value for the event 'Yes' shown a rise from the unconditional probability 0.3469 to the probability value 0.4359.

The facts in Table 4 can be interpreted as if a ‘Challenger State’ fails to comply with the agreement certain evidence of the occurrence of a claim not to end is found which is very much clear from the definition of the variable. Nevertheless, ifin its place the ‘Challenger State’ comply with the treaty, there is fifty-fifty chance that a claim will be ended.

Table 5: The conditional probability distribution of the variable ‘Concessions in Agreement’ given Claim End which is P (Concessions in Agreement | Claim End)

P (Concessions in Agreement | Claim End)		
Concessions in Agreement	**Claim End**	
	No	**Yes**
Major Challenger Concessions	0.015625	0.088235
Minor Challenger Concessions	0.031250	0.088235
Roughly Even Concessions	0.546875	0.176471
Minor Target Concessions	0.375000	0.470588
Major Target Concessions	0.031250	0.176471

The conditional probability Table. 5. signified the conditional probabilities of the variable ‘Concessions in Agreement’ given the variable ‘Claim End’ at the levels ‘Yes’ and ‘No’. It was perceived from the table that when the variable ‘Claim End’ is at the level ‘No’ the events of ‘Roughly Even Concessions’ and ‘Minor Target Concessions’ for the variable ‘Concessions in Agreement’ shown higher probabilities, 0.5469 and 0.3750 respectively, among all other events. Moreover, rest of the three events ‘Major Challenger Concessions’, ‘Minor Challenger Concessions’, ‘Major Target Concessions’ shown very low probabilities which were 0.0156, 0.0312 and 0.0313 respectively. At the level ‘Yes’ ‘Minor Target Concessions’ was only an event indicating a high probability of 0.4706. The events ‘Major Challenger Concessions’ and ‘Minor Challenger Concessions’ were equally probable with values, 0.0882. Also, the events ‘Roughly Even Concessions’ and ‘Major Target Concessions’ were equally probable with probabilities of 0.1765 both.

The statistics in Table 5 can be interpreted as if at least one of ‘Challenger State’ or ‘Target State’ fails to comply with the agreement there is a good chance that a claim wouldhave Roughly Even Concessions for both states or Minor Target Concessions (i.e. the agreement involves some concessions by the challenger, although these concessions are not major or if they are substantial, the target state also makes partially offsetting concessions of its own). On the other hand, if in its place the ‘Challenger State’ comply with the agreement then it is most likely that conflict would be of type Minor Target Concessions.

The Table 6 offers the conditional probabilities of the variable ‘Change in Status Quo’ given the variables ‘Concessions in Agreement’ and ‘Claim End’ at the levels of both the variables. It was perceived from the table that when the variable ‘Claim End’ was at the level ‘No’ and ‘Minor Target Concessions’ for the variable ‘Concessions in Agreement’, the events of ‘No’ for change in Status Quo shows zero probability.

Same was observed at ‘Yes’ level of ‘Claim End’ variable at same levels of concessions. At ‘Minor Challenger Concessions’, when ‘Claim End’ variable is at level ‘No’ probability one for change in status quo whereas at level ‘Yes’ claim end probabilities of 0.6667 and 0.3333 were observed in favour and against of changing of status quo. Moreover, at the level ‘Roughly Even Concessions’ when ‘Claim End’ variable is at level ‘No’ probability one for change in status quo whereas at level ‘Yes’ claim end probabilities of 0.3333 and 0.6667 were observed in favour and against of changing of status quo respectively. Given ‘Minor Target Concessions’ at levels ‘No’ and ‘Yes’ of ‘Claim End’ shown very high probabilities which for change in ‘Status Quo’ 0.8750 and 0.8125.

Table 6: The conditional probability distribution of the variable Status Quo given Claim End, 'Concessions in Agreement' which is P (Status Quo | Concessions in Agreement, Claim End)

P (Status Quo | Concessions in Agreement, Claim End)		
Concessions in Agreement		
	Major Challenger Concessions	
	Claim End	
Status Quo	**No**	**Yes**
No	0.000000	0.000000
Yes	1.000000	1.000000
	Minor Challenger Concessions	
	Claim End	
Status Quo	No	Yes
No	0.000000	0.333333
Yes	1.000000	0.666667
	Roughly Even Concessions	
	Claim End	
Status Quo	**No**	**Yes**
No	0.000000	0.666667
Yes	1.000000	0.333333
	Minor Target Concessions	
	Claim End	
Status Quo	**No**	**Yes**
No	0.125000	0.187500
Yes	0.875000	0.812500
	Major Target Concessions	
	Claim End	
Status Quo	**No**	**Yes**
No	0.000000	0.833333
Yes	1.000000	0.166667

At the level 'Yes' 'Minor Target Concessions' was only an event showing a high probability of 0.4706. The events 'Major Challenger Concessions' and 'Minor Challenger Concessions' were equally probable with values, 0.0882. Furthermore, at the level 'Major Challenger Concessions' when 'Claim End' variable is at level 'No' probability was one for change in status quo whereas at level 'Yes' claim end probabilities of 0.1667 and 0.8333 were observed in favour and against of changing of status quo respectively.

It could be understood that if Major Challenger Concessions are given there is sure chance of changing in status quo independent of change in claim end variable. If even concessions are given to both states and claim is ended it is less likely that status quo will change. In addition to this, if challenger offers minor or major concessions there are sure chances of changing of status quo. Also, if target offers minor concessions there is a good chance of changing of status quo, but if major concessions were provided by target state, it is very much likely that status quo will not change.

Study of all above, earth out the behaviour of the type of resolution and the change of allocation of water in a river water-related conflict in relation with the different variables as suggested by Bayesian Networks.

It is important to study the scenario of water conflict in Punjab i.e. Sutlej-Yamuna Link Canal water allocation by updating the beliefs for Bayesian networks wherever the Hard evidence wasfound for a particular variable.

5.3. Updating Beliefs for the Scenario of SYL

For extracting the information from BN's beliefs for the different nodes in network were updated (Marcot et al., 2006). The Bayesian network in figure 1 was learnt from dataset to predict the change in status quo and the belief update was hence done.

When the belief for the node 'Compliance Target' was updated for the event 'No', the chances for the event 'No' under the node 'Claim End' increased to 0.8962. An increase in probability was realised for roughly even concessions under the nod agreement concessions. Although, it was perceived that it leads to increase in the occurrence of a change in Status quo.

It can be interpreted as the state of Punjab then didn't comply with the agreement decrease to the chances of claim to get ended which is also true by the definition of the variable claim end (Hensel & Mitchell, 2015). As the state of Punjab had not done with digging the canal on its side, it is also known that the state of Haryana had finished the digging of the canal on its side this shows that the Challenger complied with the agreement (Swami, 2003).

Hence, the updated belief for the node 'Compliance Challenger' has been seen. It led to increase in probability for a claim to end whereas only a small change for the node 'Agreement Concession' was viewed. Likewise, the shift in status quo node showed a slight decrease in favour of a change of status quo from 0.8367 to 0.8069. The belief is updated such that the claim is not ended till to the date of study. It resulted in a surge in probability for the node change in status quo for the event 'Yes' from 0.8367 to 0.9531.

The above can be interpreted as even if the claim does not end there is a good chance that the allocation of river waters will change that is the change in status quo. As the conflict of interest of study shows some minor target concessions as the state of Punjab is already allowing 1.62 MAF Water to the state of Haryana can be considered as a small concession from the 'Target State'. So, a belief update was done for 'Agreement Concession' node, and the value given was 'Minor Target Concessions'. It was realised that it did not and impacted too much on the outcome node only a slight variation was observed in probabilities of events 'Yes' and 'No' under the node status quo.

Table 6: Value of Information Analysis of variable Status Quo with all other variables

X	Y	VOI
Status Quo	Claim End	0.166
Status Quo	Compliance Target	0.016
Status Quo	Compliance Challenger	0.033
Status Quo	Concessions in Agreement	0.071

In a similar way, high VOI value of 0.166 (as in Table 6) was observed for the variable claim end. It is signing in the direction that the improvement in knowledge for the variable Status quo can be made by taking more observation over the variable claim end(Bromley et al., 2005; & Barton et al., 2016).

CONCLUSION

The study gives an understanding that Bayesian Networks can be used to model such a skirmish process of conflicts for the prediction of the events of the type of resolution a conflict will lead to or if the status quo held during a conflict will change or not. There are good chances of changing in status quo if both parties are given roughly even concessions or the target state gives some minor concessions for the challenging party. The factor 'Claim end' was found to cause quite a change in levels of factor 'Status quo'. The conflict if is going to end there is a good chance that the allocation of the water of the rivers may change. Such an allocation of water is needed to be ensured so that farmers of both the states may properly utilize the water.

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