Extending Heuer's Analysis of Competing Hypotheses Method to Support Complex Decision Analysis

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We implemented a software program to translate analytic problems represented as ACH matrices into Bayesian networks and compare the result with that using the ACH method. We propose an approach for acquiring analytic models that interpret situations and for evaluating hypotheses, thereby combining the strengths of ACH and Bayesian networks. For additional details and references, see http://www.cse.sc.edu/~mgv/reports/IA-05.pdf.

One way that some analysts go about their business is via a satisficing strategy, whose principal weakness is the failure to recognize that most of the evidence for the single hypothesis chosen might also be consistent with other alternatives not been refuted. Simultaneous evaluation of competing hypotheses is difficult to carry out for most people. Fortunately, with the help of ACH, that task is accomplished much more easily (Heuer 1999). The following description outlines the steps taken in ACH.

1. Identify the possible hypotheses to be considered. Make a list of significant evidence and arguments for and against each hypothesis.
2. Build a matrix with hypotheses across the top and the evidence down the side, and analyze the diagnostic value of each piece of evidence with respect to each hypothesis. Refine the matrix and repeat as necessary.
3. Draw tentative conclusions about the relative likelihood of each hypothesis by trying to disprove the hypotheses instead of proving them.
4. Analyze the sensitivity of each conclusion in step 3 to a few critical items of evidence, then report final conclusions by discussing the relative likelihood of all hypotheses rather than the most likely one, and identify milestones for future observation that may indicate events are taking a different course than expected.

To illustrate these concepts, we use a fictitious example. We imagine that an analyst who is a specialist on terrorist activities related to the oil infrastructure of Iraq and Iran has to evaluate hypotheses in the Abadan region of Iran. The interest in evaluating the hypotheses is high, because of the recent interception of a message between terrorists. We emphasize that this is a fictitious example, devised to illustrate our techniques.

Question: Will terrorists try to create conflict in Iran by attacking the oil infrastructures in Abadan region?

Hypotheses:

H1: Terrorists will bomb the oil refineries in Abadan.
H2: Terrorists will bomb the oil pipelines in Abadan.
H3: Terrorists will bomb the oil wells in Abadan.
H4: Terrorists will bomb the oil facilities in Shiraz.
H5: Terrorists will not launch an attack.

Evidence (fictitious for this example):

E1: A phone wiretap on a suspected terrorist cell in Beirut records a discussion about crippling the Iranian economy by destroying oil production facilities within the Abadan region.

E2: The oil refinery in Abadan can produce 0.37 million barrel per day. Oil is transported through pipeline.

E3: the oil refinery in Shiraz can produce 0.04 million barrel per day.

E4: There is an oil pipeline from Abadan to Basra, which crosses the border. The capacity of this pipeline is over 0.2 million barrel per day.

E5: Historical analysis allows us to conclude that the affected oil industry will cripple the Iranian economy, which will lead to conflict with its neighbors.

E6: The area near a border is easier for terrorist to infiltrate.

E7: Terrorists prefer a target that is near a road.

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The preceding question, hypotheses, and items of evidence lead to the ACH matrix presented in the following table.

Table 1: An ACH Matrix

	H1	H2	H3	H4	H5
E1	+	+	+	-	-
E2	+	+	+	-	-
E3	-	-	-	+	-
E4	+	+	-	-	-
E5	+	+	-	-	-
E6	-	+	-	-	-
E7	-	-	-	-	-

We now show that the ACH table of Table 1 can be represented as a bipartite graph, where the nodes are divided into two exhaustive and mutually exclusive sets, corresponding to hypotheses (columns in the ACH matrix) and items of evidence (the rows in the ACH matrix, also called findings). Figure 2 below shows the resulting Bayesian network structure.

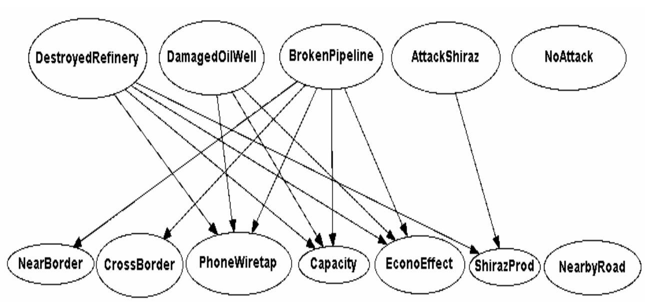

Figure 2: Bayesian network corresponding to the ACH matrix in Table 1

Heuer suggests using a simple linear, additive scoring mechanism to assess the probability of a hypothesis. However, as Heuer himself notes, it is sometimes preferable to use probabilities rather than a plus and minus notation. In particular, we observe that it is also possible and preferable to represent the sensitivity and specificity (or "diagnosticity," to use Heuer's term) of items of evidence for hypotheses directly in conditional probability tables. For example, we can represent a situation for which E4 ("CrossBorder") is a moderately sensitive but very specific item of evidence for the hypothesis H2 ("BrokenPipeline") as in the table below.

P(CrossBorder| BrokenPipeline)	BrokenPipeline = yes	BrokenPipeline = no
CrossBorder=yes	0.7	0.01
CrossBorder=no	0.3	0.99

In his book, Heuer makes it clear that it is very important to specify prior beliefs in order to obtain correct posterior beliefs. The translation of ACH matrices to Bayesian networks ensures that prior probabilities of hypotheses are assessed.

Bipartite Bayesian networks are a special case of Bayesian networks. There are limitations to the expressiveness of bipartite Bayesian networks. First, it is impossible to represent dependency among hypotheses that is not mediated by items of evidence. In other words, in the absence of evidence, one's belief in a hypothesis cannot affect the belief in another hypothesis. This is clearly inappropriate in situations in which a model exists of how hypotheses affect each other. Second, it is impossible to represent dependencies among items of evidence that are present even when the hypotheses are known. Such dependencies would be modeled by introducing intermediate variables between hypotheses and items of evidence. We note that this is a particularly serious issue when trying to model rumors and deception. Third, it is impossible to model context for hypotheses. As an illustration, we develop a more complex model for our motivating example, as shown in Figure 3, to overcome all these limitations:

1. We model a conflict situation, in which context is represented by the two related variables Conflict and AffectedOilProduction.
2. We introduce the intermediate nodes such as TerroristAction and ThreatLevel to represent the dependencies among items of evidence in Bayesian Network.
3. We represent the argument, the assumption the analyst made in ACH, as the structure of the BN fragment, instead of nodes in bipartite graph model.
4. In our model, the hypotheses are related through the context, even in the absence of evidence.

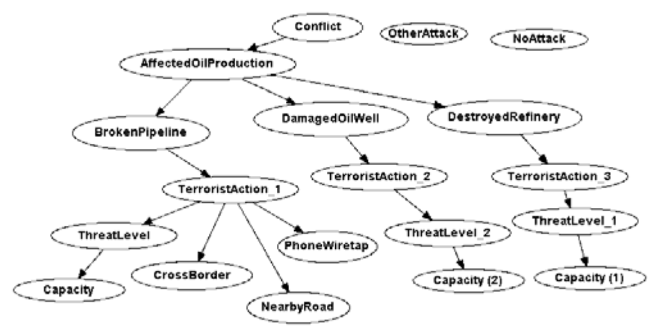

Figure 3: A more complex model for the oil facility example of Table 1 and Figure 2

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