On Extending Temporal Models in Timed Influence Networks

Abbas K. Zaidi
Alexander H. Levis
P. Papantoni-Kazakos

Presented by
Ashraf AbuSharekh

14th International Command and Control Research and Technology Symposium
June 2009

Outline

- Introduction to Timed Influence Networks
- Definition of a Class of Influence Functions
  - Additive
  - Multiplicative
- Temporal Extensions
  - Temporal Models for Affecting Events
  - Time-Varying Influences
  - Cyclic Influences
- Application

Influence Networks

Influence Nets (IN) are variants of Bayesian Networks

The Graph Representation

•A set of random variables that makes up the nodes of an IN. All the variables in the IN have binary states.

•Each directed link has associated with it a pair of parameters that shows the causal strength of the link.

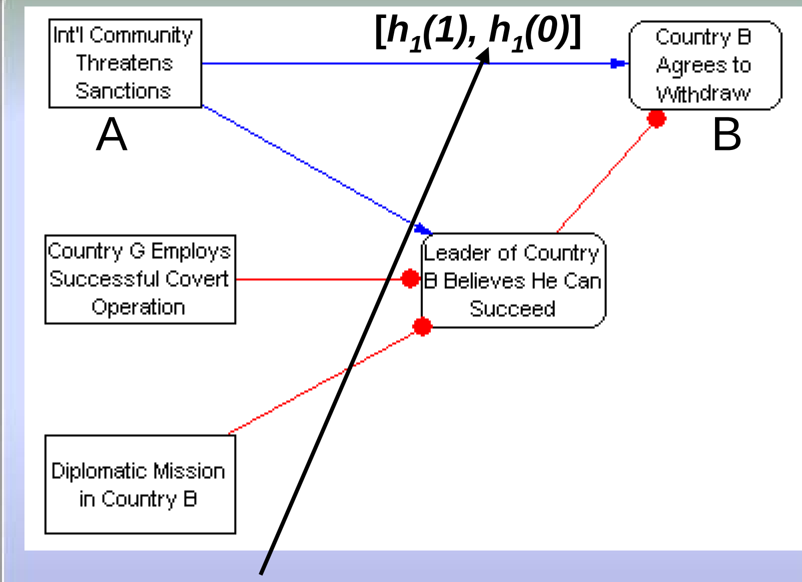
Situational and Behavioral Assessment Modeling

•Nodes with propositional statements representing PMESII* aspects of a domain

•Links represent causal influences from one (affecting) proposition to another (affected)

Analysis

•Given evidence (states) on some nodes, what is the effect of the evidence on other nodes?



h1(1) **is Influence of A on B**

h1(0) **is Influence of ¬A on B**

Positive Impact

Negative Impact

* PMESII: political, military, economic, social, infrastructure, and information

Influence Networks

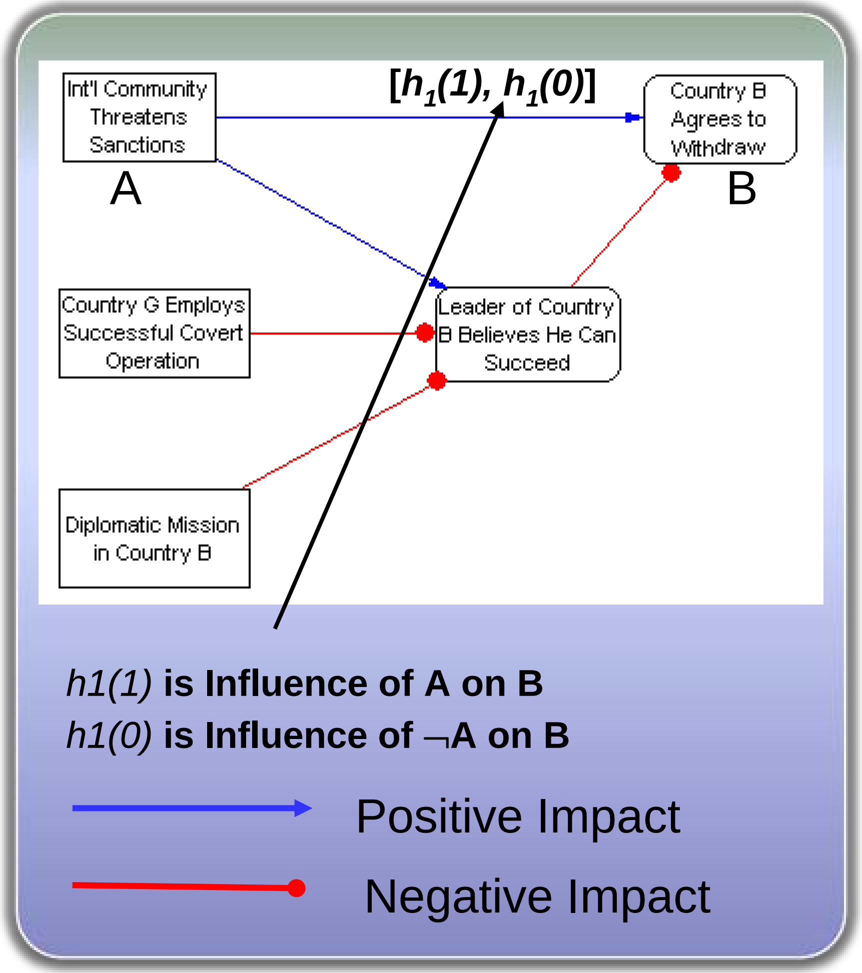
- **The combined effect of the input nodes is calculated as a n-dimensional influence function by aggregating the *h1s*.**

$$h_n(x_1^n) = f_n(\{h_1^{(i)}(x_i)\} \quad ; \quad 1 \le i \le n)$$

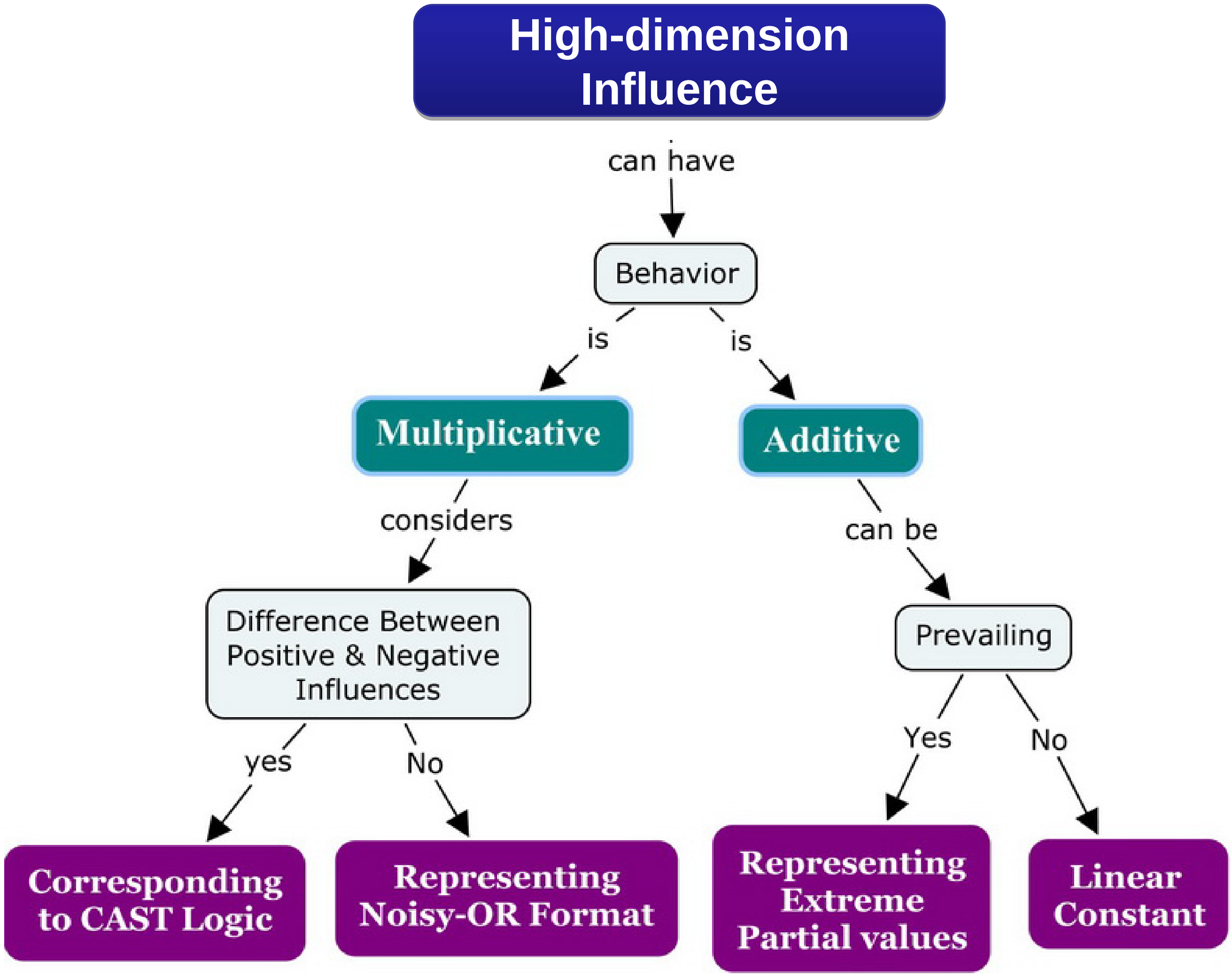
  - ***h_ns are static functions of h1s.***

- **The n-dimensional influence function is mapped to conditional probabilities.**

$$P(B \mid x_1^n) = \begin{cases} P(B) + h_n(x_1^n)[1 - P(B)]; \text{if } \; h_n(x_1^n) \in [0,1] \\ P(B) + h_n(x_1^n)P(B) \quad ; \text{if } h_n(x_1^n) \in [-1,0] \end{cases}$$



Aggregate Influences



Example Aggregations

Additive

The effects of events $\{A_i\}_{1\le i\le n}$ on event B are weighted by a known set $\{w_i\}_{1\le i\le n}$ of weights, such that $w_i \ge 0; \forall i$ and $\sum_{i=1}^{n} w_i = 1$. Given the constants $\{h_1^{(i)}(x_i)\}_{1\le i\le n}$, $\alpha : 0 \le \alpha < 1$:

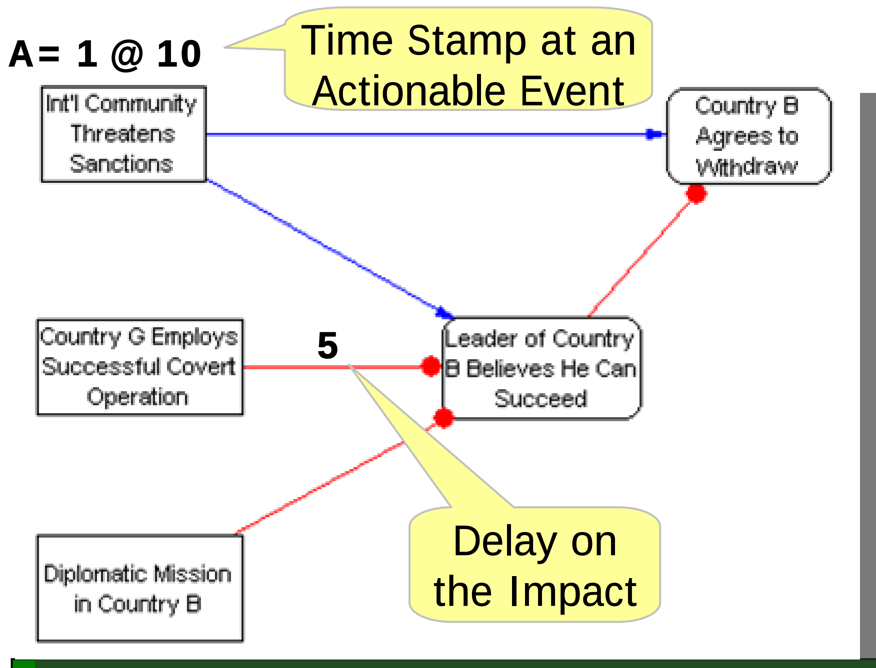
$$h_n(x_1^n) = \begin{cases} (1-\alpha)^{-1}\sum_{i=1}^{n} w_i h_1^{(i)}(x_i) & ; \quad \left|\sum_{i=1}^{n} w_i h_1^{(i)}(x_i)\right| \le 1-\alpha \\ 1 & ; \quad \sum_{i=1}^{n} w_i h_1^{(i)}(x_i) \ge 1-\alpha \\ -1 & ; \quad \sum_{i=1}^{n} w_i h_1^{(i)}(x_i) \le -(1-\alpha) \end{cases}$$

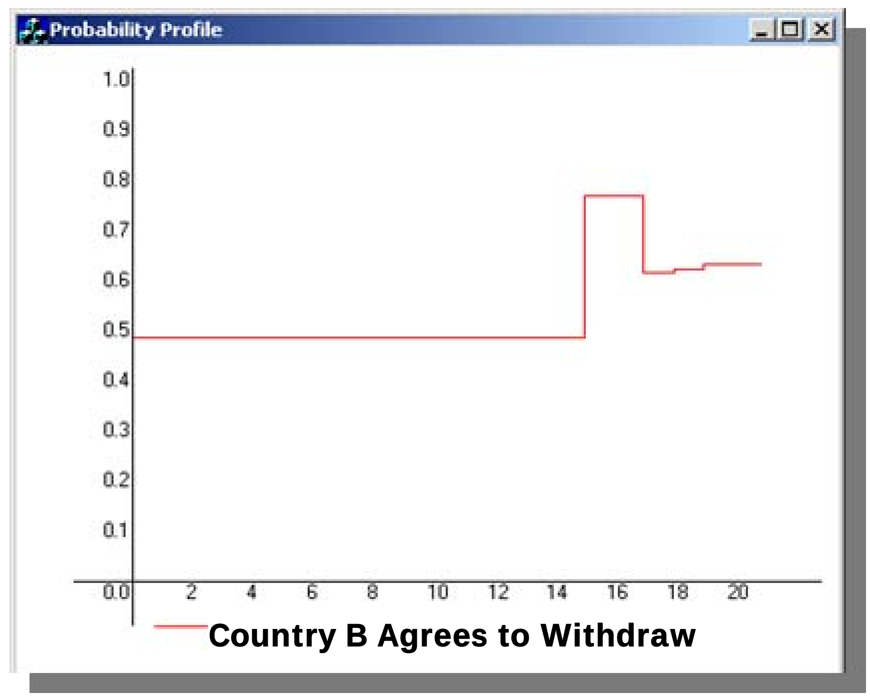
Multiplicative

$$h_n(x_1^n) = \left[\prod_{i:h_1(x_i)<0}\left(1-\left|h_1^{(i)}(x_i)\right|\right) - \prod_{i:h_1(x_i)>0}\left(1-\left|h_1^{(i)}(x_i)\right|\right)\right] \bullet \left[\max\left(\prod_{i:h_1(x_i)<0}\left(1-\left|h_1^{(i)}(x_i)\right|\right), \prod_{i:h_1(x_i)>0}\left(1-\left|h_1^{(i)}(x_i)\right|\right)\right)\right]^{-1}$$

Timed Influence Networks

- **Timed Influence Network (TIN) are variants of Dynamic Bayesian Networks with provisions of time stamps on nodes and time delays on arcs (influences).**
  - **The time stamp on an ‘input node’ represents time of evidence on (or change of state of) the node – Course of Actions**
  - **The delay on an arc represents time it takes for an influence to reach its target node.**





Timed Influence Networks

A Timed Influence Network (TIN) is a Bayesian Network mapping conditional probabilities $P(B \mid x_1^n)$ via the utilization of influence constants as in (3). Formally, TIN is a tuple (**V**, **E**, **C**, **D**, **A$_T$**, **B**) with **G** = (**V**, **E**) representing a *directed-acyclic* graph satisfying the Markov condition (as in BN), where

V: set of nodes representing binary random variables,
E: set of edges representing causal influences between nodes,
C: set of causal strengths: $E \rightarrow \left\{\left[h_1^{(i)}(x_i = 1), h_1^{(i)}(x_i = 0)\right] \text{such that } h_1\text{'s} \in [-1,1]\right\}$,

B: Probability distribution of the status vector X_1^n corresponding to the external affecting events $\{A_i\}_{1 \le i \le n}$.

D: set of temporal delays on edges: **E** $\rightarrow$ N,

A$_T$: a subset of **V** representing *external* affecting events $\{A_i\}_{1 \le i \le n}$ and a status of the corresponding vector X_1^n. The status of each external affecting event is *time tagged* representing the time of realization of its status. In the TIN literature, A_T is also referred to as a Course of Action (COA). A COA is, therefore, a time-sequenced collection of external affecting events and their status.

Timed Influence Networks

- **TINs are appropriate for the following situations:**

  1) **for modeling situations in which it is difficult to fully specify all conditional probability values, and/or**
  2) **the estimates of conditional probabilities are subjective and estimates for the conditional probabilities cannot be obtained from empirical data, e.g., when modeling potential human reactions and beliefs.**
  3) **for modeling situations where the impact of events (actions or effects) takes some time to reach and be processed by the affected events or conditions.**

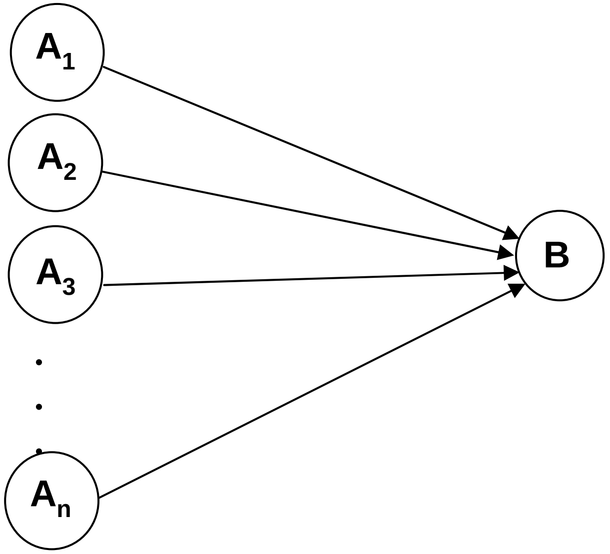
Temporal Extensions

- **Temporal Case I**

  When the existence of all the *affecting* events is known to an *affected* event; however the status of these events may unfold sequentially. At one point in time the status of only k *affecting* events may be influencing an *affected* event.

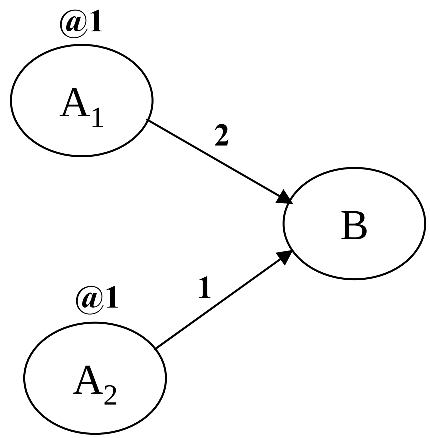
- **Temporal Case II**

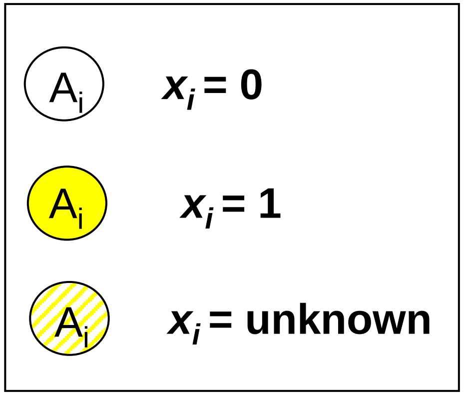
  When the existence as well as the status of *affecting* events are revealed sequentially. The value n is revised each time a new affecting event is known to an affected event.

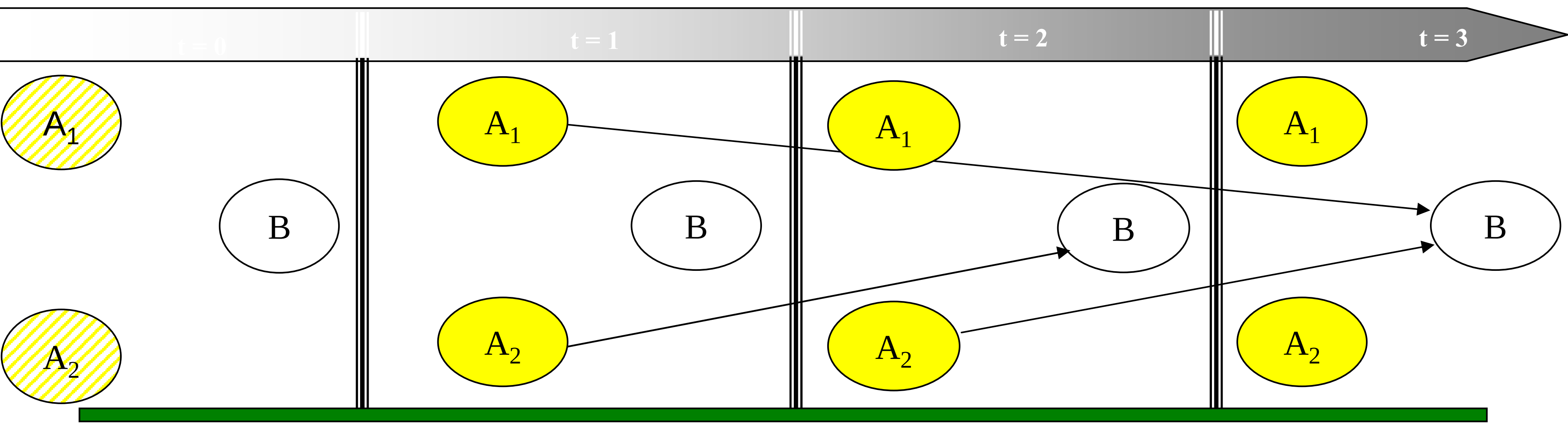


Example Illustration

- **Temporal Case I**

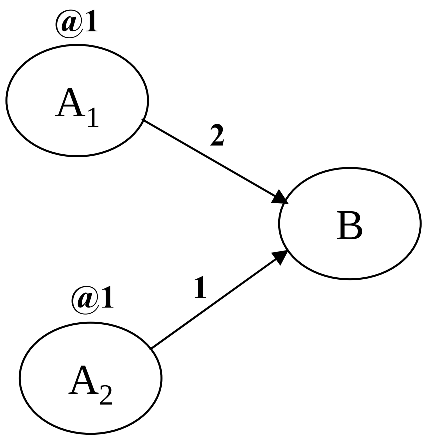


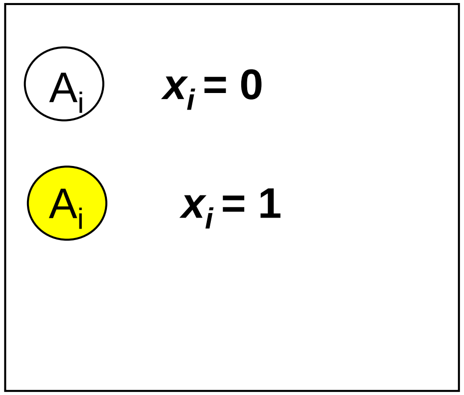


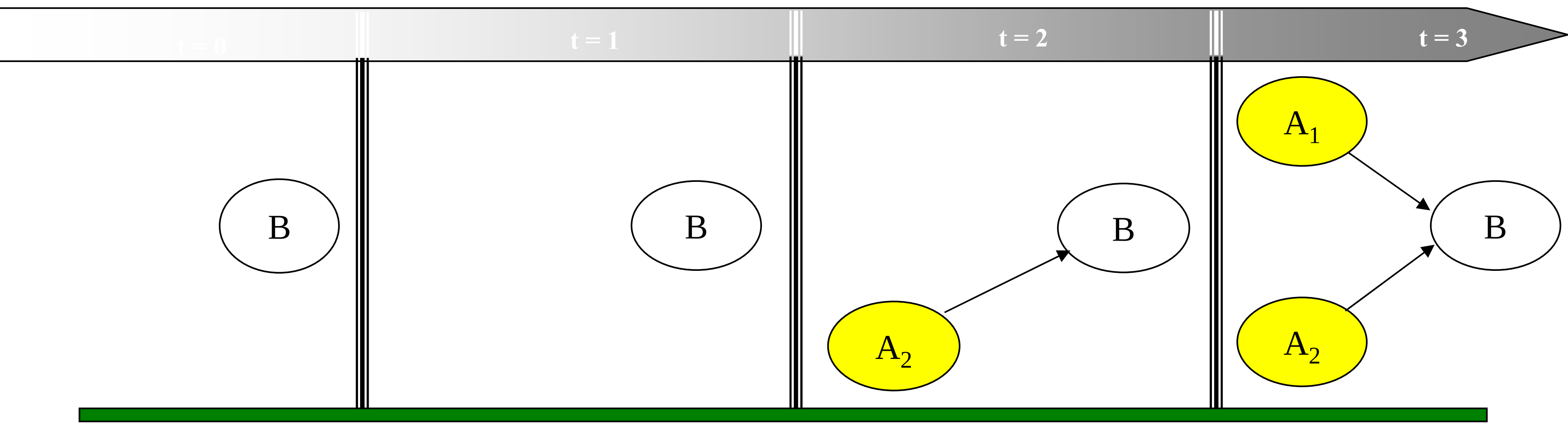


Example Illustration

- **Temporal Case II**





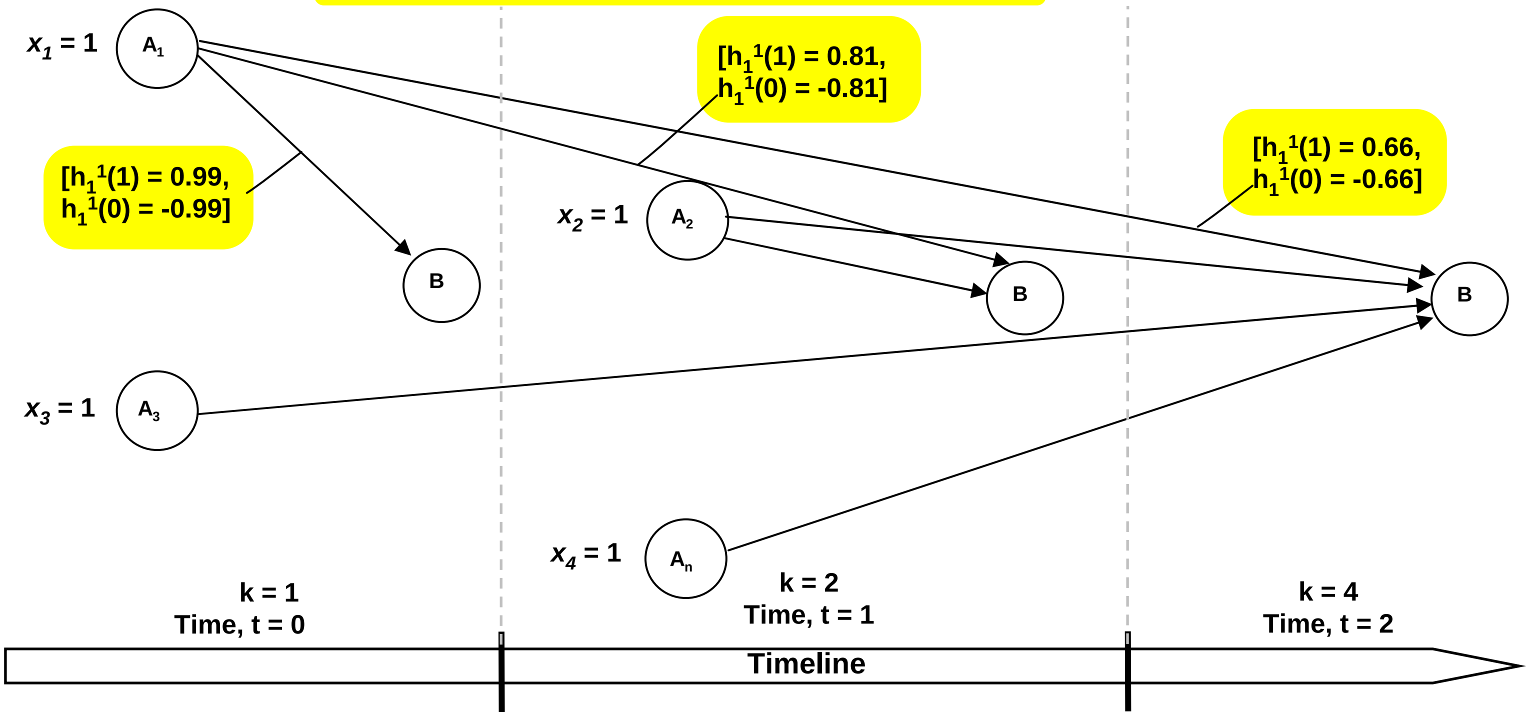


Time-Varying Influences

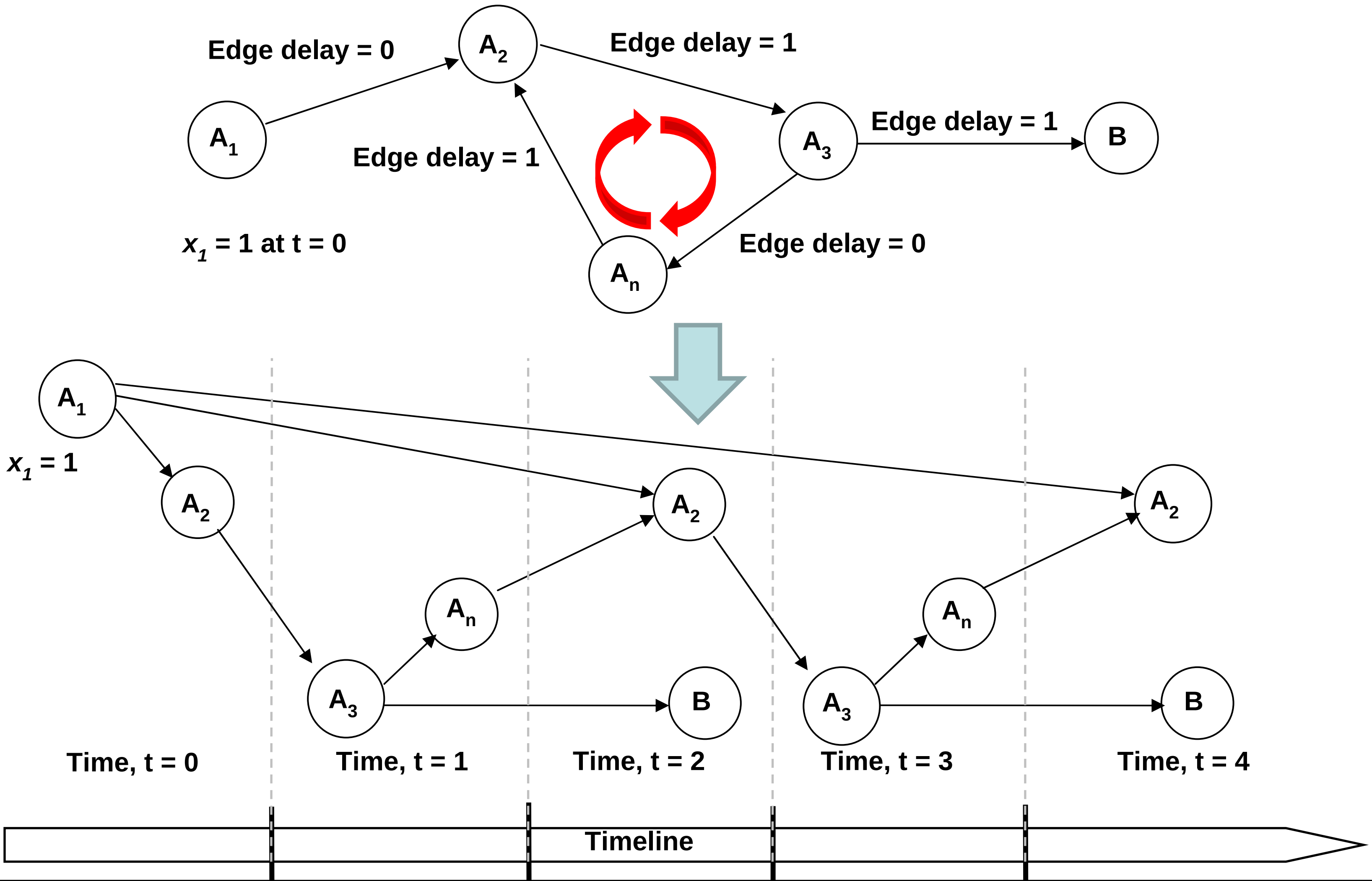
$$h_n(x_1^n) = f_n(\{h_1^{(i)}(x_i), t\} \;\; ; \;\; 1 \le i \le n)$$

- **Example:** **where $i = 1$, $\alpha = 0.2$**

$$f(h_1^{(i)}(x_i), t) \rightarrow 0.99 \;\; e^{-\alpha(t)}$$

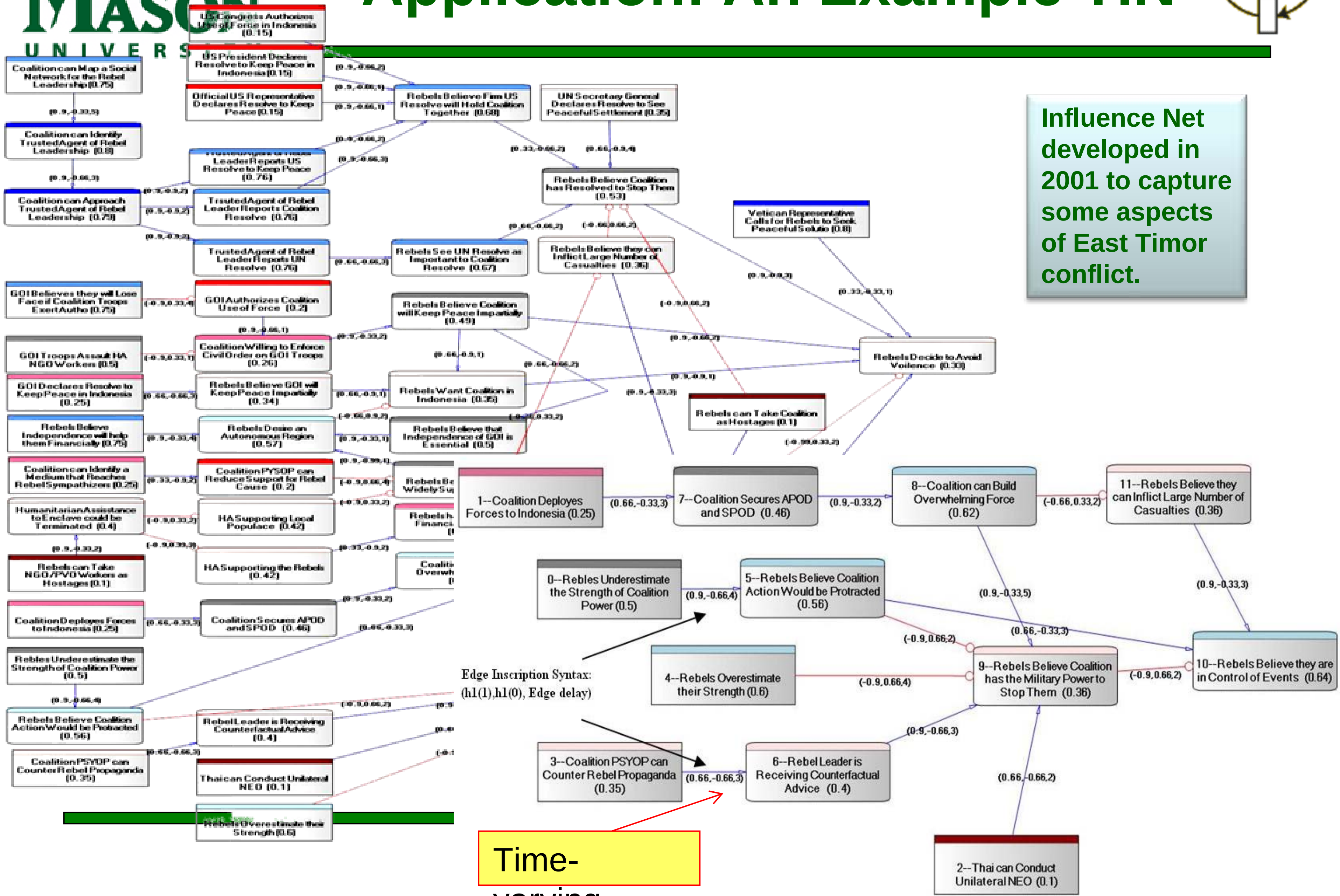


Cyclic Influences



Application: An Example TIN

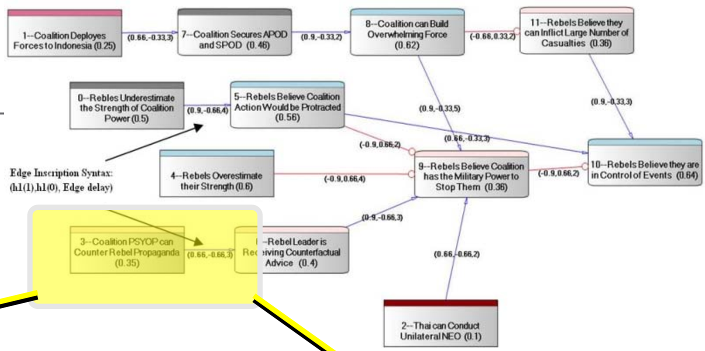
Influence Net developed in 2001 to capture some aspects of East Timor conflict.

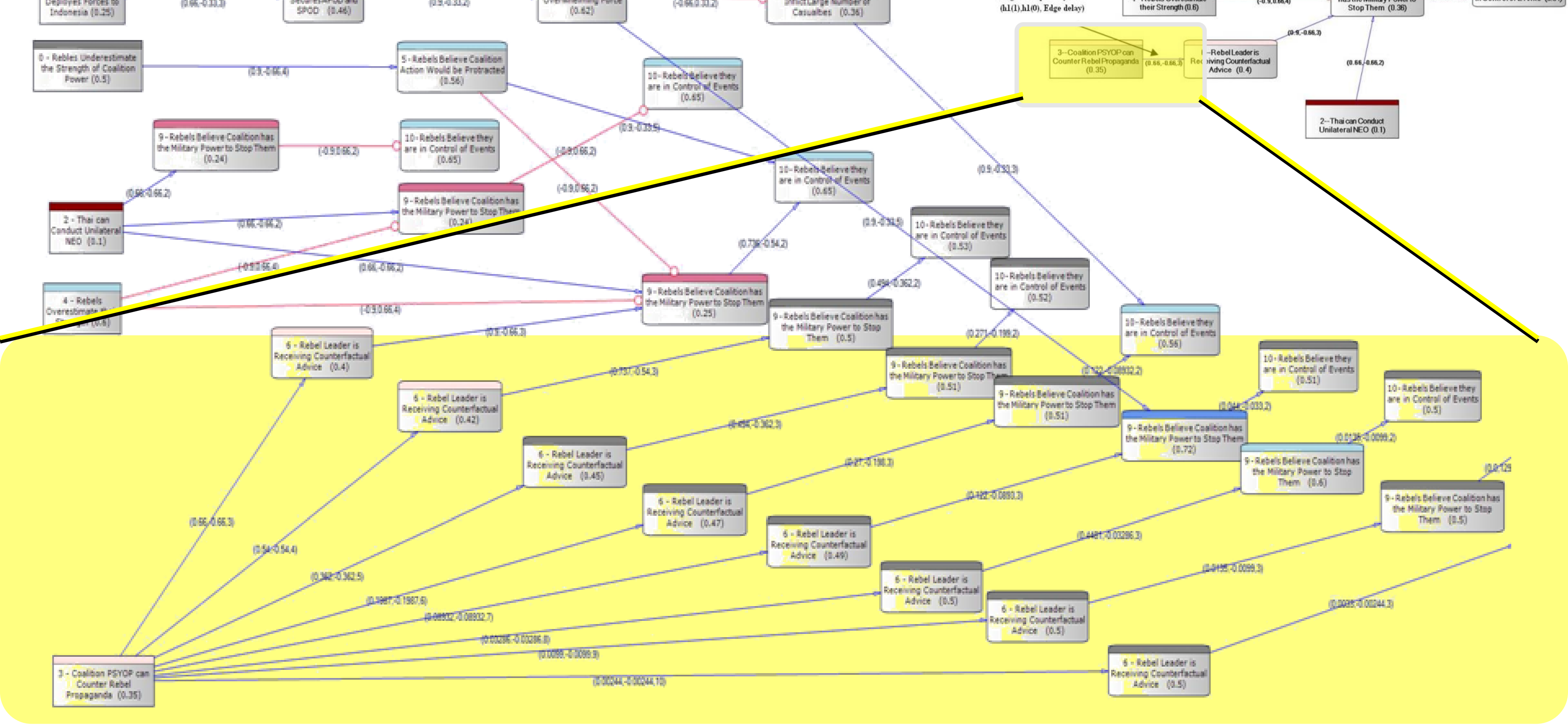


Time-varying

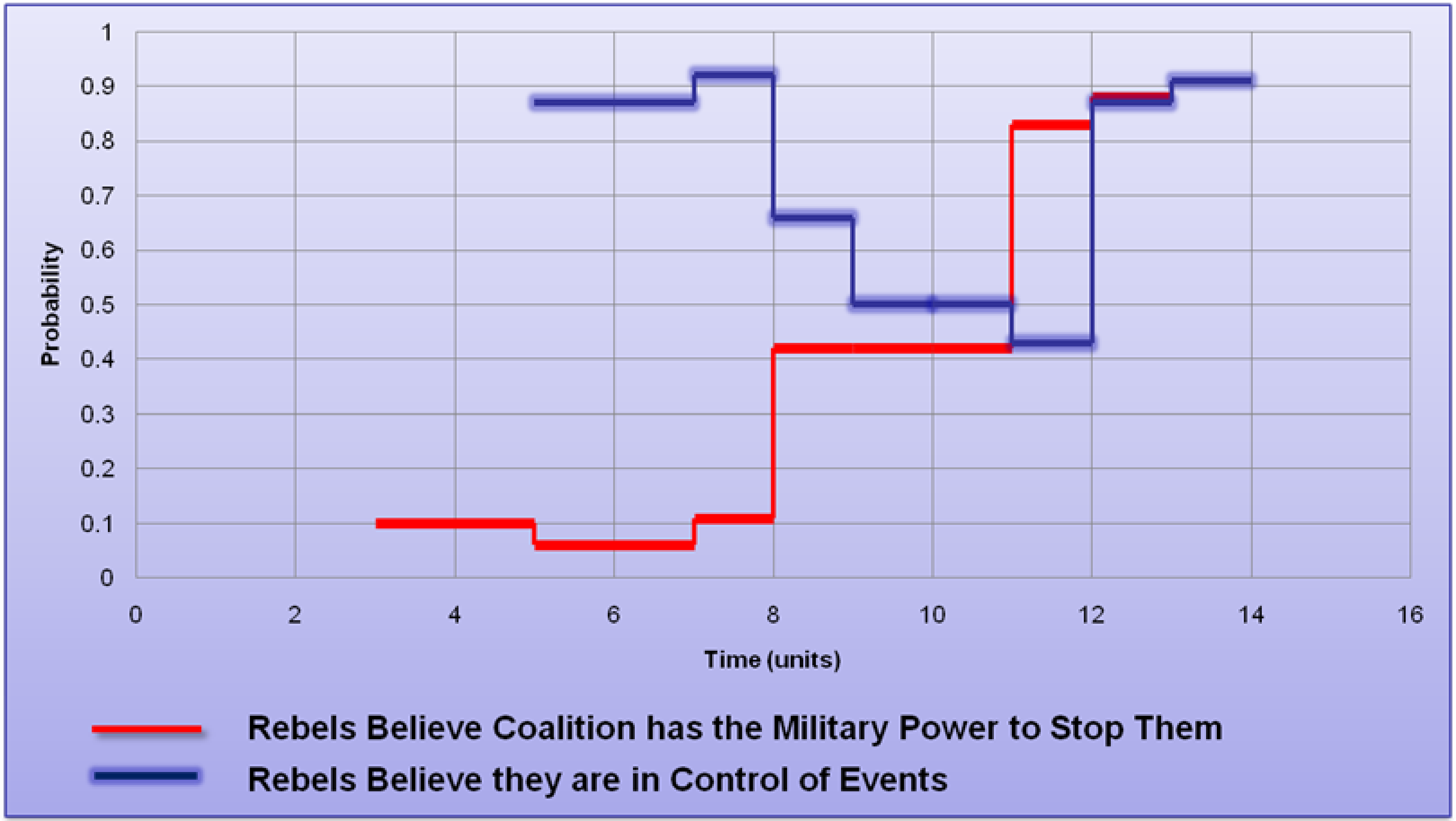
Illustration of Time-Varying Influences

COA1: *All external affecting events are taken simultaneously at time 1 and are mutually independent.*





Resulting Probability Profile



Conclusion

- Over the past 12 years, a great deal of progress has been made in developing Influence Nets tools and techniques suitable to provide analytical capability to the war-fighters to support effect-based operations.
- There has been some “experimentation” with these tools and a process within the context of war games with some success.
- They can provide an important method for reasoning about very complex situations and the impact of blending kinetic and non kinetic operations.
- The proposed *time-varying influence* functions allow modeling of influences whose strengths vary with time.
- A *cyclic influence*, on the other hand, provides a provision for self-promoting set of influences.
- The two extensions will allow for further modeling flexibility regarding the use of TINs in the representation of uncertain domains.