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Title: **Dynamic Influence Nets: An Extension of Timed Influence Nets for Modeling Dynamic Uncertain Situations***

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Student Paper

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Dynamic Influence Nets: An Extension of Timed Influence Nets for Modeling Dynamic Uncertain Situation*

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Abstract

This paper proposes structural and parametric enhancements in the Timed Influence Nets (TINs) based framework for modeling Effects-Based Operations (EBO). The existing TIN framework does not have the capability to model the impact of different sequences of actions. Thus, no matter what the sequence of action is, the final outcome remains the same. Furthermore, it is assumed that the influence of an event on another event is stationary, i.e., the influence remains the same throughout the campaign. Both of these constraints may turn out to be unrealistic in many real world situations. The enhancements proposed in this paper would overcome the above two limitations. The proposed structural enhancement would enable a system modeler to model the impacts of different sequences of actions on the desired effect; while the parametric enhancements would aid the mathematical modeling of time-varying influences. Together these enhancements make it possible to model the impact of repetitive actions in a dynamic uncertain situation.

1. Introduction

Decision making in uncertain complex situations has always been a very difficult task. Access to a large amount of information has further magnified the complexity of this problem. For an *organization*, it has become an unmanageable task to analyze enormous amounts of information in a timely manner. Several efforts have been made to model this problem using the framework of probabilistic reasoning and inferencing, commonly referred to as Bayesian Networks [Pearl, 1987]. Timed Influence Nets (TINs), one of the instances of this framework, have been used experimentally in the area of Effects-Based Operations (EBOs). [Wagenhals and Levis, 2002;Wagenhals et al., 2003;Wagenhals and Wentz, 2003] A TIN models the uncertainties and temporal constraints present in a stochastic domain from a Discrete Event System (DES) perspective. The purpose of building a TIN is to form a coherent model of the situation at hand by combining the knowledge of several subject matter experts. The resultant model is then used as an aid to decision makers to help them reach a final *decision* in a rational manner.

Despite their acceptance as a modeling tool, the assumptions made by TINs limit the capabilities of a system modeler in terms of expressing real world situations. For instance, TINs do not model the impact of the sequence in which actions are taken. Thus, no matter what the

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sequence of the actions is, the final probability of achieving the desired *effect(s)* remains same. This behavior is because of the underlying assumption in TINs that events are *memoryless*, i.e. the probability of occurrence of an event at a particular time instant does not depend upon its own probabilities of occurrence during the previous time instants. As a consequence, the probability of an event depends only upon the actions executed so far and not on the sequence in which these actions are executed. This paper is an attempt to overcome this limitation of TIN.

Moreover, the assumption made by TINs that the influence of a cause remains the same once the cause has occurred is found to be unrealistic. In reality, events happen and they influence other relevant events. In many cases, the intensity of their influences decays over time. Thus, an event having a very strong influence at the time of its occurrence on another event might have an insignificant influence after a certain period of time. For example, a resolution passed by the United Nations has a very strong impact on the concerned parties at the time of its approval. As the days pass, the resolution starts loosing its affect and after a couple of months it completely looses its importance unless the problem is solved or it is backed up by another resolution on the same subject. That is, the influence of an event is *time-varying*. Currently, TIN lacks the ability to model such cases. It assumes that the causal strength of the influences does not change over time. This paper extends the capabilities of TIN by proposing a way for modeling time-varying influences.

The rest of the paper is organized as follows. Sections 2 and 3 describe Influence Nets and Timed Influence Nets, respectively. Sections 4 and 5 describe the limitations of TINs and the proposed enhancement. Finally, Section 6 concludes the paper and points towards the future research direction.

2. Influence Nets

Influence Nets (INs), an instance of the Bayesian framework, were proposed a decade ago to overcome the intractability issues present in BNs. They employ an approximation inference algorithm, termed as loopy belief propagation [Kschischang and Frey, 1998;McEliece et al., 1998;Murphy et al., 1999], and non-probabilistic knowledge acquisition interface, termed as the CAST logic [Chang et al., 1994;Rosen and Smith, 1996].

The modeling of the causal relationships using an IN is accomplished by connecting a set of actionable events and a set of desired effects through chains of cause and effect relationships. The strength of such relationships is specified using the CAST logic parameters (a brief overview of the logic is presented later in this section) instead of the probabilities. The required probabilities are internally generated by the CAST logic with the help of user-defined parameters. The Influence Nets are therefore appropriate for the following situations: i) for modeling situations in which it is difficult to fully specify all conditional probability values ii) and/or the estimates of conditional probabilities are subjective, and iii) estimates for the conditional probabilities cannot be obtained from empirical data, e.g., when modeling potential human reactions and beliefs.

The actionable events in an IN are drawn as root nodes (nodes without incoming edges). A desired effect, or an objective the decision maker is interested in, is modeled as a leaf node (node without outgoing edges). Typically, the root nodes are drawn as rectangles, while the non-root nodes are drawn as rounded rectangles. Consider the IN of Figure 1. The text associated with the non-root nodes represents the corresponding conditional probability values obtained from the CAST logic parameters (not shown in the figure) while the text associated with the root nodes represents the prior probabilities. The texts associated with arcs are time delays and are explained in Section 3. The belief propagation scheme used in INs is based on independence of parents assumptions. Thus, the marginal probability of a non-root node is computed with the help of its Conditional Probability Table (CPT) and the prior probabilities of its parents. For instance, the marginal probability of variable A is computed as

$$\begin{aligned} P(A) &= P(A \mid \neg B, \neg E)P(\neg B)P(\neg E) + P(A \mid \neg B, E)P(\neg B)P(E) + P(A \mid B, \neg E)P(B)P(\neg E) \\ &\quad + P(A \mid B, E)P(B)P(E) \\ &= 0.005 \times 0.95 \times 0.99 + 0.95 \times 0.95 \times 0.01 + 0.95 \times 0.05 \times 0.99 + 0.99 \times 0.05 \times 0.01 \\ &= 0.06 \end{aligned}$$

The probability of D is then computed by using its CPT and the marginal probabilities of A (computed above) and E. Thus

$$\begin{aligned} P(D) &= P(D \mid \neg E, \neg A)P(\neg E)P(\neg A) + P(D \mid \neg E, A)P(\neg E)P(A) + P(D \mid E, \neg A)P(E)P(\neg A) \\ &\quad + P(D \mid E, A)P(E)P(A) \\ &= 0.05 \times 0.99 \times 0.94 + 0.95 \times 0.99 \times 0.06 + 0.001 \times 0.01 \times 0.94 + 0.05 \times 0.01 \times 0.06 \\ &= 0.11 \end{aligned}$$

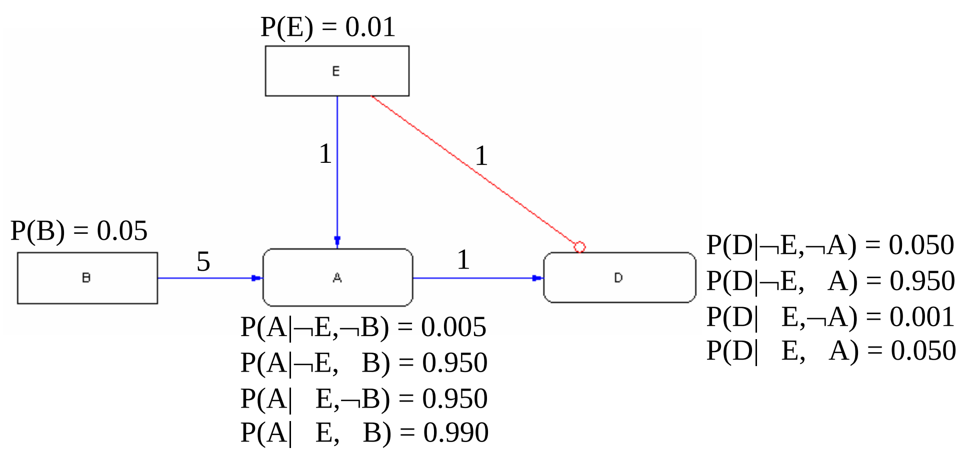


Figure 1: A Sample Influence Net

Formally, Influence Nets are Directed Acyclic Graphs (DAGs) where nodes in the graph represent random variables, while the edges between pairs of variables represent causal relationships. The following items characterize an IN:

1. A set of random variables that makes up the nodes of an IN. All the variables in the IN have binary states.
2. A set of directed links that connect pairs of nodes.
3. Each link has associated with it a pair of CAST Logic parameters that shows the causal strength of the link (usually denoted as g and h values).
4. Each non-root node has an associated CAST Logic parameter (denoted as the baseline probability), while a prior probability is associated with each root node.

Definition 1
An *Influence Net* is a tuple (**V, E, C, B**) where
V: set of Nodes,
E: set of Edges,
C represents causal strengths:
E → { (**h**, **g**) such that $-1 < \mathbf{h}, \mathbf{g} < 1$ },
B represents a Baseline or Prior probability:
V → [0,1]

2.1 CAST Logic

Chang et al. [Chang et al., 1994] developed a formalism, at George Mason University, called CAusal STrength (CAST) logic as an intuitive and approximate language to elicit the large number of conditional probabilities from a small set of user-defined parameters. The logic has its roots in Noisy-OR approach [Agosta, 1991;Drudzel and Henrion, 1993]. In fact, it can be shown that the Noisy-OR approach is a special case of the CAST logic. The logic requires only a pair of parameter values for each dependency relationship between any two random variables. The logic is briefly explained with the help of an example shown in Figure 2. Readers interested in a detailed description of the CAST logic should refer to [Chang et al., 1994;Rosen and Smith, 1996].

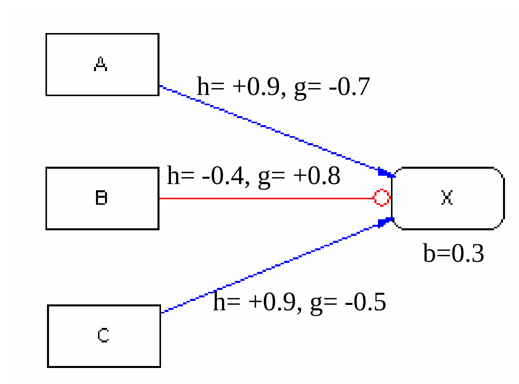


Figure 2: An Influence Network with CAST Logic Parameters

Figure 2 contains four nodes A, B, C and X. On each arc, two causal strengths are specified. These numbers represent the probability that a specified state of a parent node will cause a certain state in the child node. Positive values on arcs are causal influences that cause a node to occur with some probability, while negative values are influences that cause the negation of a node to occur with some probability. For instance, the arc between B and X has values –0.4 and 0.8. The first value, referred to as h, states that if B is true, then this will cause X to be false with probability 0.4, while the second value, referred to as g, states that if B is false, then this will cause X to be true with probability 0.8. Both h and g can take values in the interval (-1, 1). All non-root nodes are assigned a baseline probability, which is similar to the “leak” probability in the Noisy-OR approach. This probability is the user-assigned assessment that the event would occur independently of the modeled influences in a net.

There are four major steps in the CAST logic algorithm that converts the user-defined parameters into conditional probabilities:

a) Aggregate positive causal strengths
b) Aggregate negative causal strengths
c) Combine the positive and negative causal strengths, and
d) Derive conditional probabilities

In Figure 2, there are eight conditional probabilities that need to be computed to obtain the marginal probability of X. The marginal probability of X is computed as:

$$\begin{aligned} P(X) = {} & P(X \mid \neg A, \neg B, \neg C)\, P(\neg A, \neg B, \neg C) + P(X \mid \neg A, \neg B, C)\, P(\neg A, \neg B, C) \\ & + P(X \mid \neg A, B, \neg C)\, P(\neg A, B, \neg C) + P(X \mid \neg A, B, C)\, P(\neg A, B, C) \\ & + P(X \mid A, \neg B, \neg C)\, P(A, \neg B, \neg C) + P(X \mid A, \neg B, C)\, P(\neg A, \neg B, C) \\ & + P(X \mid A, B, \neg C)\, P(A, B, \neg C) + P(X \mid A, B, C)\, P(A, B, C) \end{aligned} \tag{1}$$

The four steps, described above, are used to calculate each of these eight conditional probabilities. For instance, to calculate the probability $P(X \mid A, B, \neg C)$, the h values on the arcs connecting A and B to X and the g value on the arc connecting C to X are considered. Hence, the set of causal strengths is {0.9, -0.4, -0.5}.

<u>Aggregate the Positive Causal Strengths:</u> In this step, the set of causal strengths with positive influence are combined. They are aggregated using the equation

$$PI = 1 - \prod_i (1 - C_i) \qquad \forall C_i > 0$$

where C_i is the corresponding g or h value having positive influence and PI is the combined positive causal strength. For our example

$$PI = 1 - (1 - 0.9) = 0.9$$

<u>Aggregate the Negative Causal Strengths:</u> In this step, the causal strengths with negative values are combined. The equation used for aggregation is

$$NI = 1 - \prod_i (1 - C_i) \qquad \forall C_i < 0$$

where C_i is the corresponding g or h value having negative influence and NI is the combined negative causal strength. Using the above equation, the aggregate negative influence is found to be:

$$NI = 1 - (1 - 0.4)(1 - 0.5) = 0.7$$

<u>Combine Positive and Negative Causal Strengths:</u> In this step, aggregated positive and negative influences are combined to obtain an overall net influence. The difference of these aggregated influences is taken. The overall influence is obtained by taking the ratio of this difference and the corresponding promoting or inhibiting influence. Mathematically,

If PI > NI

$$AI = \frac{PI - NI}{1 - NI}$$

If NI > PI

$$AI = \frac{NI - PI}{1 - PI}$$

Thus, the overall influence for the current example is

$$AI = (0.9 – 0.7) / (1 – 0.7) = .66$$

<u>Derive Conditional Probabilities:</u> In the final step, the overall influence is used to compute the conditional probability value of a child for the given combination of parents.

$$P(child \mid jth\ state\ of\ parent\ states) = baseline + (1 – baseline) \times AI \quad when\ PI > NI$$
$$= baseline – baseline \times AI \quad when\ PI < NI$$

Using the above equation, $P (X \mid A, B, \neg C)$ is obtained as:

$$P (X \mid A, B, \neg C) = 0.5 + 0.5 * 0.66 = .863$$

The steps explained above are repeated for the remaining seven conditional probabilities in Equation 1. If the experts had sufficient time and knowledge of the influences, then the probability matrix for each node can be used instead of g and h values. Also, after estimating the conditional probability matrix, if some entries do not satisfy the expert, then those entries can be modified and then used for computing the marginal probability of a node.

3 Timed Influence Nets

Influence Nets are designed to capture *static* interdependencies among variables in a system. However, a situation where the impact of a variable takes some time to reach the affected variable(s) cannot be modeled by either of the two approaches. Wagenhals et al. [1998] have added a special set of temporal constructs to the basic formalism of Influence Nets. The Influence Nets with these additional temporal constructs are called Timed Influence Nets (TINs) [Haider and Levis, 2004;Haider and Zaidi, 2004]. The temporal constructs allow a system modeler to specify delays associated with nodes and arcs. These delays may represent the information processing and communication delays present in a given situation. For example, in Figure 1, the inscription associated with each arc shows the corresponding time delay it takes for a parent node to influence a child node. For instance, event B influences the occurrence of event A in 5 time units.

(a) B at time 1 and E at time 6

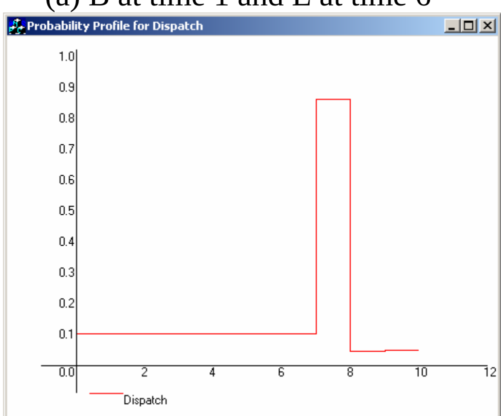


Figure 3: Probability Profiles of Event D

TINs have been experimentally used in the area of Effects Based Operations (EBOs) for evaluating alternate courses of actions and their effectiveness to mission objectives. [Wagenhals and Levis, 2000; Wagenhals and Levis, 2001; Wagenhals et al., 2003] The purpose of building a TIN is to evaluate and compare the performance of alternative courses of action. The impact of a selected course of action on the desired effect is analyzed with the help of a *probability profile*. Consider the net shown in Figure 1. Suppose it is decided that actions B and E are taken at time 1 and 7, respectively. Because of the propagation delay associated with each arc, the influences of these actions impact event D over a period of time. As a result, the probability of D changes at a different time instants. A probability profile draws these probabilities against the corresponding time line. The probability profile of event D is shown in Figure 3.

The following items characterize a TIN:

1. A set of random variables that makes up the nodes of a TIN. All the variables in the TIN have binary states.
2. A set of directed links that connect pairs of nodes.
3. Each link has associated with it a pair of parameters that shows the causal strength of the link (usually denoted as g and h values).
4. Each non-root node has an associated baseline probability, while a prior probability is associated with each root node.
5. Each link has a corresponding delay d (where $d \geq 0$) that represents the communication delay.
6. Each node has a corresponding delay e (where $e \geq 0$) that represents the information processing delay.
7. A pair (p, t) for each root node, where p is a list of real numbers representing probability values. For each probability value, a corresponding time interval is defined in t. In general, (p, t) is defined as

   $([p_1, p_2, \ldots, p_n], [[t_{11}, t_{12}], [t_{21}, t_{22}], \ldots, [t_{n1}, t_{n2}]])$,

   where $t_{i1} < t_{i2}$ and $t_{ij} > 0 \ \forall\ i = 1, 2, \ldots, n$ and $j = 1, 2$

The last item in the above list is referred to as an input scenario, or sometimes (informally) as a course of action. Formally, a TIN is described by the following definition.

Definition 2 Timed Influence Net (TIN)

A TIN is a tuple ($\mathbf{V, E, C, B, D_E, D_V, A}$) where

V: set of Nodes,

E: set of Edges,

C represents causal strengths:

$\mathbf{E} \rightarrow \{ (\mathbf{h}, \mathbf{g})$ such that $-1 < \mathbf{h}, \mathbf{g} < 1 \}$,

B represents Baseline / Prior probability: $\mathbf{V} \rightarrow [0,1]$,

$\mathbf{D_E}$ represents Delays on Edges: $\mathbf{E} \rightarrow \mathbf{Z^+}$, (where Z^+ represent the set of positive integers)

$\mathbf{D_V}$ represents Delays on Nodes: $\mathbf{V} \rightarrow \mathbf{Z^+}$, and

A (input scenario) represents the probabilities associated with the state of actions and the time associated with them.

A: $\mathbf{R} \rightarrow \{([p_1, p_2, \ldots, p_n],[[t_{11},t_{12}], [t_{21},t_{22}], \ldots,[t_{n1},t_{n2}]])$

such that $p_i = [0, 1]$, $t_{ij} \rightarrow \mathbf{Z^*}$ and $t_{i1} \leq t_{i2}$, $\forall\ i = 1, 2, \ldots, n$ and $j = 1, 2$ where $\mathbf{R} \subset \mathbf{V}$ }

(where Z^* represent the set of nonzero positive integers)

4. Limitations of TIN and the Proposed Enhancements

4.1 Modeling of Memory

The existing TINs are not capable of modeling the impact of different sequences of actions on the desired effect. This behavior is because of the underlying assumption in TINs that events are *memoryless*, i.e. the probability of occurrence of an event at a particular time instant does not depend upon its own probabilities of occurrence during the previous time instants. As a consequence, the probability of an event depends only upon the actions executed so far and not on the sequence in which these actions are executed. The proposed approach adds an optional *self-loop* to each node. The events having self-loops are no longer assumed to be memoryless. Like other arcs in a TIN, a self-loop is also specified using the CAST logic. A higher value (either positive or negative) of the parameters imitates strong memory while a lower value imitates weak memory. If both parameters (h and g) are set to zero then this is equivalent of having no self-loop. Thus, this class of TINs is a superset of the TINs that were defined in Definition 2. In the TIN of Figure 1, if events A and D depend upon their previous states, then this phenomenon is captured by adding a self-loop to each of them as shown in Figure 4.

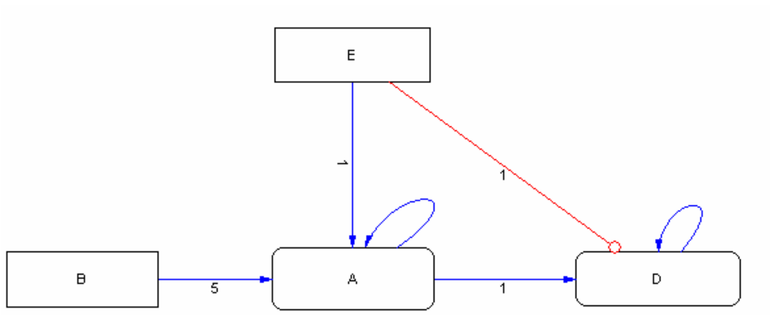


Figure 4: A Timed Influence Net with Self-loop

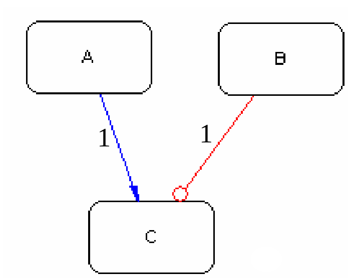
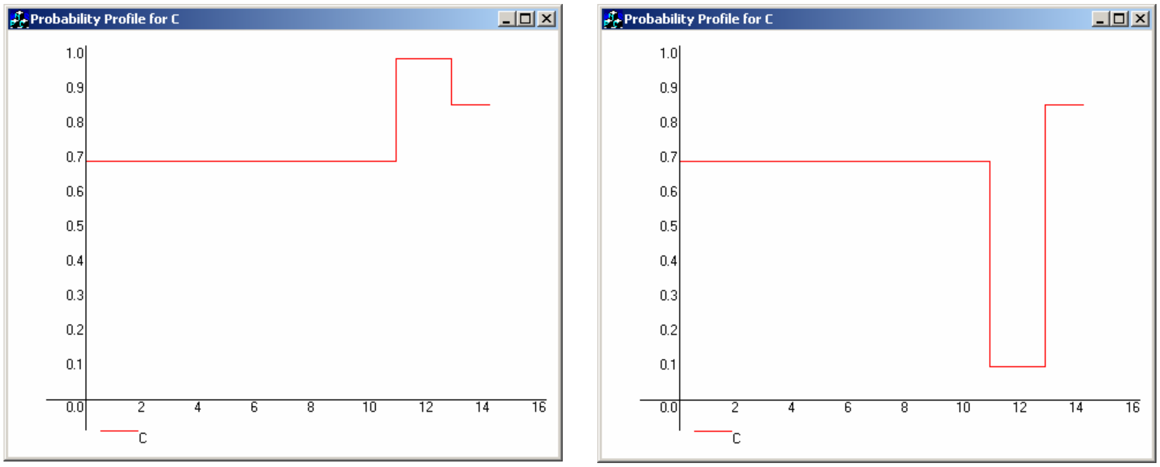


Figure 5: A TIN having 3 Nodes

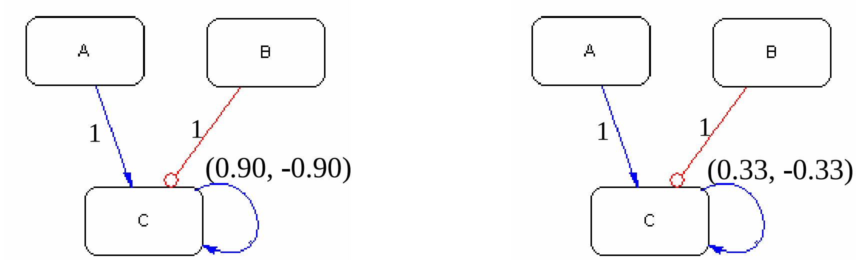
The addition of self-loop not only changes the final probability of the variable of interest, but it also has an affect on the trajectory of the probability profile. Consider the TIN shown in Figure 5. It has three variables A, B, and C. In the absence of a self-loop, the probability of event C depends only upon the probability of its parents, that is, A and B. Suppose two courses of action required to be evaluated for this model. In the first course of action (COA 1), actions A and B are taken at times 10 and 12, respectively while in the second course of action 2 (COA 2), A and B are taken at time 12 and 10, respectively. The respective probability profiles of C as a result of these courses of action are shown in Figure 6(a) and 6(b). Despite the fact that the trajectories shown in the two profiles differ significantly, the final probability of event C is same (0.85) in both profiles. This behavior is due to the fact that the underlying TIN model is memoryless. Thus, no matter what the sequence of actions A and B is, the likelihood of occurrence of C is same once both actions are taken.



(a) COA 1 **(b) COA 2**

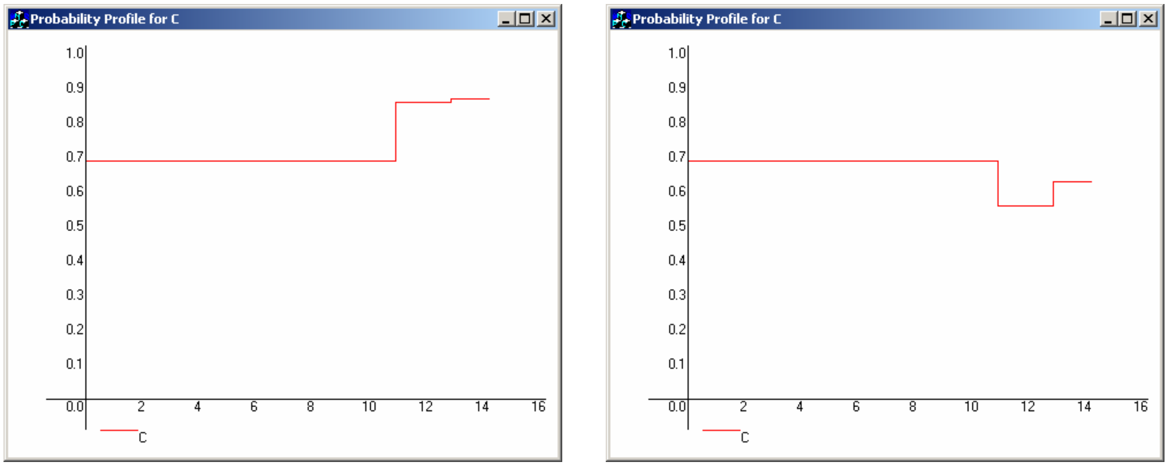
Figure 6: Probability Profiles of Event C in the TIN of Figure 5

In contrast to the given situation, suppose the likelihood of C at a particular time instance depends upon its own likelihood in the past. The proposed methodology attempts to model this situation by adding a self-loop to event C. The modified TIN is shown in Figure 7. The text associated with the self-loop shows the corresponding CAST logic parameters. In addition to their normal semantics, the parameters attached to a self-loop also represent the strength of the memory associated with the corresponding variable. For instance, high values of g and h strongly causes a node to remain in its previous state, while a lower values of g and h represents a weak memory and thus the previous state of a variable does not have a large influence on its current state. The two courses of action described earlier (COA 1 and COA 2) are executed for the model of Figure 7(a) and the respective profiles are shown in Figure 8.



(a) Strong Memory **(b) Weak Memory**

Figure 7: Different Levels of Memory Modeled Using Self-Loops



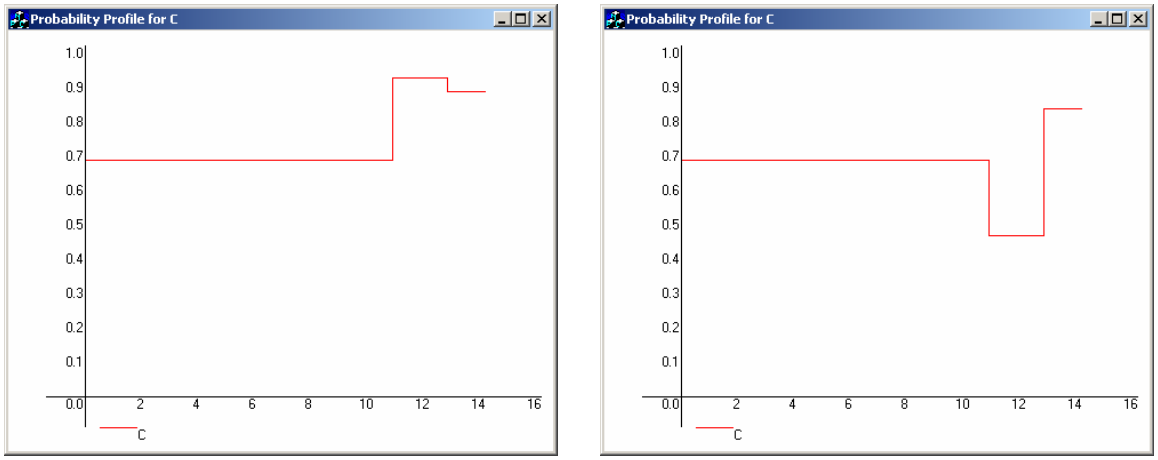
(a) COA 1 **(b) COA 2**

Figure 8: Probability Profiles of Event C in the TIN of Figure 7(a)

It can be seen from the profiles that the final probability of event C is different in the two profiles. This change in the behavior of the TIN occurs because of the fact that now the present likelihood of C depends upon its likelihood in the past along with the probabilities of its parents. For instance, in the profile of Figure 8(a), event A happens first which causes an increase in the probability of C (0.85) as the occurrence of A has a strong positive influence on the occurrence of C. B happens after A. Despite its negative influence, B fails to decrease the likelihood of C as C has a strong memory that causes it to remain in the previous state along with the fact that a strong positive influence from A counterbalances a moderate negative influence from B. Thus, the final probability of C is 0.87. In the second profile (Figure 8(b)), B happens first and due to its negative influence on C the probability of C is decreased to 0.56. A happens next and it slightly increases the probability of C to 0.63 but not as much as it is increased in COA 1 because of the dependency of C on its previous state. While computing the profiles of Figures 6 and 8, it can be noticed that the profiles have quite a different behavior in both courses of action.

As mentioned earlier, if the h and g values associated with a self-loop are low, then the loop represents a weak influence of the previous state of a node on its current state. Suppose in the model of Figure 7(a), the g and h values associated with the self-loop are revised and are as shown in Figure 7(b). The same two courses of action (COA 1 and COA 2) are executed in this situation and the resultant probability profiles are shown in Figure 9: a weak memory has resulted in the final probabilities very close to what is obtained in the profiles based on a memoryless TIN (Figure 6).

Up until now, it is assumed that a node's likelihood at a previous time stamp is used to update its current likelihood when a new piece of information arrives from one of its parents. A self-loop can also be used to update the probability of a node at a regular time interval. This time interval is specified as the delay associated with a self-loop. Thus a self-loop can be used to model *decay* in the belief of a node as the time passes and no new information from its parents influences it. Suppose in the model of Figure 7, the self-loop associated with node C has a delay of 1 time unit which means that the probability of C is updated after every 1 time unit regardless of whether there is new information coming from its parents or not. In the sequel, if the delay associated with a self-loop has a value of zero then it means that a previous value of a node is used to update its current likelihood only when there is new information coming from its parents. Positive values other than zero indicate that the update would occur at a regular time interval.

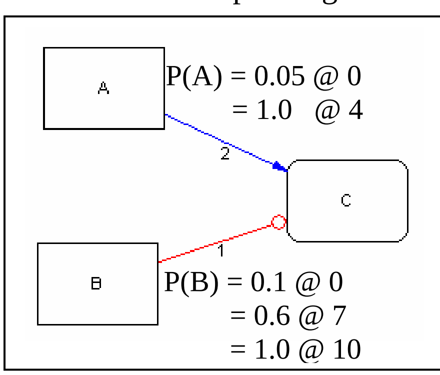


(a) COA 1 **(b) COA 2**

Figure 9: Probability Profiles of Event C in the TIN of Figure 7(b)

4.2 Modeling of Time Varying Influences

Events happen and they influence other relevant events. In many cases, the intensity of their influences decays over time. Thus, an event having a very strong influence at the time of its occurrence on another event might have an insignificant influence after a certain period of time. In other words, the influence of an event is *time-variant*. The *time-varying* property also holds true for the state of an action. An action may occur in two different states during two different time intervals. In TINs terminology, these two types of time-varying properties are referred to as *persistence*. The one related to the time dependent influence of an action is called *persistence of influence*, while the one related to the time-dependent state of an action is called *persistence of action*. Among these two types of persistence, a TIN currently models the latter one only. It assumes that the causal strength of the influences does not change over time, i.e., the underlying stochastic model is *stationary*. Thus, it lacks the ability to model persistence of influence. This paper attempts to overcome this limitation of TINs. The proposed approach enables a system modeler to model *non-stationary* influences. Instead of asking a modeler to specify single- valued influences, the proposed approach would allow the modeler to specify various strengths of influences and their corresponding window of effectiveness.



Influence of A on C when information at A is t time units old
Strong: $2 \leq t < 4$
Moderate: $4 \leq t \leq 6$
Low: $t > 6$
Influence of B on C when information at B is t time units old
Strong: $1 \leq t < 3$
Low: $t > 3$

Figure 10: A TIN Having Time-Variant Influences

Consider the TIN of Figure 10. The prior probability of nodes A and B at time 0 is 0.05 and 0.1, respectively. Action A is taken at time 4 while the probability of occurrence of B becomes 0.6 at time 7 and 1 at time 10. The CAST logic parameters associated with the arc are time-varying and are read in the following manner. A has a high positive influence on C, if the change occurred at A is 2 to 3 time units old, and its influence is moderate, if the change occurred at A is 4 to 5 time units, while its influence is low if the change occurred at A is more than 6 time units old. For simplicity "high influence" is assumed to mean that both h and g have the same values though with opposite signs (one is positive and the other is negative). Similarly, B has a strong negative influence on C when the change that occurred at B is 1 to 2 time units old, while it has a low influence when the change occurred at B is more than 2 time units old. Due to the provided input scenario, the probability of C is updated at time 6, 8, and 11 as the time delays between A and C and B and C are 2 and 1, respectively. C is updated at time 6 because action A is taken at time stamp 4. The last change that occurred at B is at time 0. Thus, the probability of B used in computing the marginal probability of C is 0.1. Since this value is 6 time units old, while computing the CPT values for node C a low negative influence of B on C is considered. The TIN with a particular instance of the CAST logic parameters along with the prior probabilities is shown in Figure 11. The Conditional Probability Table (CPT) values computed under this situation are also shown beside node C. Based on the parameters shown in the figure, the marginal probability of C at time 6 is computed as given below.

$$P(C) = P(C|\neg A,\neg B) \times P(\neg A) \times P(\neg B) + P(C|\neg A,\ B) \times P(A) \times P(B)$$
$$+ P(C|\neg A,\ B) \times P(\neg A) \times P(\ B) + P(C|\ A,\ B) \times P(A) \times P(B)$$

$$= 0.07 \times 0 \times 0.9 + 0.03 \times 0 \times 0.9 + 0.97 \times 1 \times 0.1 + 0.93 \times 1 \times 0.9$$
$$= 0.93$$

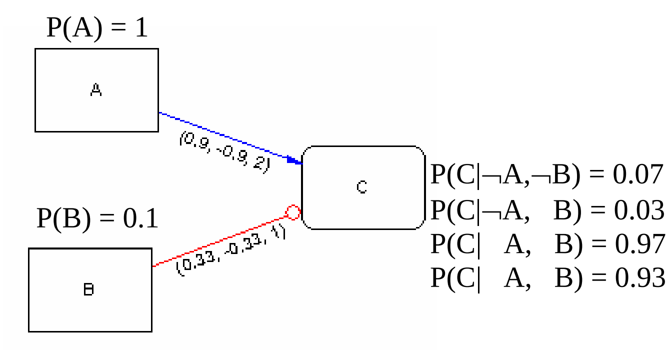


Figure 11: An Instance of the TIN of Figure 10

The next update of P(C) occurs at time 8. At this time instance, the marginal probability of A is 4 time units old; thus a moderate positive influence of A on C is considered while computing the CPT values. The probability of B is only 2 time units old and has a strong negative influence on C. The resultant parameters, along with the CPT values, are shown in Figure 12. The probability of C at time 8 is computed as shown below.

$$P(C) = P(C|\neg A,\neg B) \times P(\neg A) \times P(\neg B) + P(C|\neg A,\ B) \times P(A) \times P(B)$$
$$+ P(C|\neg A,\ B) \times P(\neg A) \times P(\ B) + P(C|\ A,\ B) \times P(A) \times P(B)$$

$$= 0.85 \times 0 \times 0.4 + 0.02 \times 0 \times 0.6 + 0.98 \times 1 \times 0.4 + 0.15 \times 1 \times 0.6$$
$$= 0.48$$

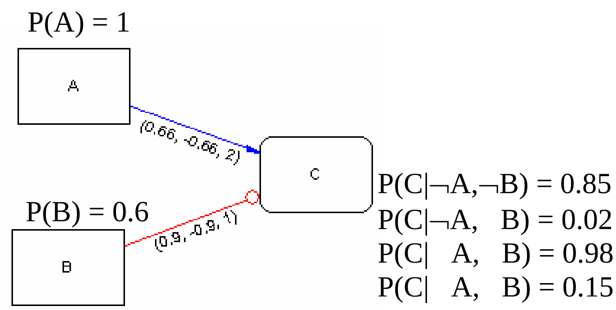


Figure 12: Another Instance of the TIN of Figure 10

The last update of P(C) occurs at time 11. The marginal probability of A is 7 time units old, while B's is 2 time units old. Thus, a low positive influence from A and a strong negative influence from B are considered. The updated probability of C is found to be 0.07. The above analysis demonstrated how non-stationary CAST logic parameters have resulted in non-stationary CPT values that are used in computing the probability of C at various time stamps. Thus, despite the fact that an action is still in effect, it may loose its significance as time passes by. The non-stationary CPT values used in the above computations are compared in Table 1 along with the time of their computation.

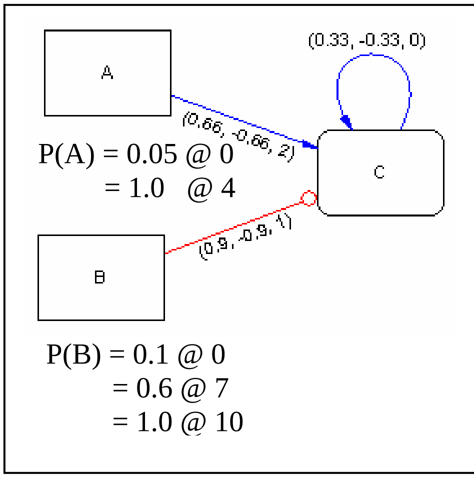
Table1: for Non-Stationary CPTs

		Time	
Parents Combination	6	8	11
P(C|¬A,¬B)	0.07	0.85	0.93
P(C|¬A, B)	0.03	0.02	0.03
P(C| A,¬B)	0.97	0.98	0.97
P(C| A, B)	0.93	0.15	0.07

5. DYNAMIC INFLUENCE NETS

The incorporation of the proposed structural and parametric changes in TINs, as described in the previous sections, would enable a system modeler to observe the impact of repeated actions. For instance, an air-strike on a bridge makes it inoperable for several days. The current implementation of TINs would assume that the influence of the air-strike remains the same throughout the campaign. It is obvious that the assumption is unrealistic. Furthermore, in the event of a new air-strike, a TIN would discard the impact of the previous air-strike as the events in a TIN are assumed to be memory-less. The proposed approach, which allows time-varying influences and incorporation of memory through self-loops, models this situation in a more intuitive manner. Like other arcs in a TIN, a self-loop also represents influence – from the previous state of a node to its current state. Thus, time-varying parameters can be associated with a self-loop too. For the air-strike example, the presence of self-loop would combine the influences of both (or many) air-strikes while the strength of the self-loop accounts for the time delay between the two air-strikes. If the timing of two air-strikes is far apart, then there is almost no influence of the first strike on the operability of the bridge (provided that the bridge has been rebuilt), but if the two strikes occurred very close in time then their impact would be more destructive. In other words the impact of two actions on the effect convolves. The issue is further explained with the help of the following example. Suppose the variables in the model of Figure 10 have the following descriptions:

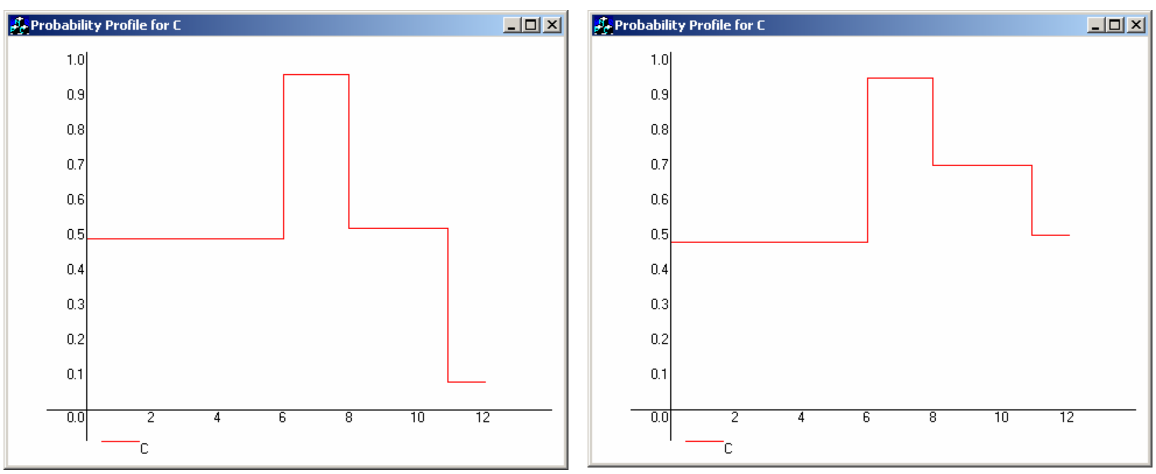
A - Regional Countries Opposes Sanctions against Country R
B – Country G Threatens to Take Unilateral Actions against Country R
C – Leader of Country R Decides to Accept UN Demands



Influence of A on C when information at A is t time units old
Strong: $2 \leq t < 4$
Moderate: $4 \leq t \leq 6$
Low: $t > 6$

Influence of B on C when information at B is t time units old
Strong: $1 \leq t < 3$
Low: $t > 3$

Figure 13: A TIN with Self-Loop and Time-Varying Influences



(a) Profile of event C in a DIN **(b) Profile of event C in a TIN**

Figure 14: Comparison of Profiles Generated by a TIN and a DIN

Further assume that the belief of event C at a particular time depends upon its own belief at a previous time instance though not very strongly. This behavior is modeled by adding a self-loop having a low influence on event C. The resultant model is shown in Figure 13. The probabilities of actionable events A and B are changed at various time stamps, as described earlier and shown in the figure. The resultant probability profile of C is shown in Figure 14(a). If the same situation is modeled using an existing TIN, that is, without the self-loop and time-invariants CAST logic parameters, then the resultant profile of C is as shown in Figure 14(b).

Currently, there is no validation technique that helps us in identifying which profile is a better representation of the situation at hand, but it can be said that the profile shown in Figure 14(a) is more in agreement with intuition than the profile of Figure 14(b). The impact of B is more dominating in the profile of Figure 14(a) as event A happened 6 time units earlier and has lost its significance. Furthermore, the previous state of event C also has an impact on its current state. Thus, a different sequence of actions would have resulted in a completely different outcome. Profile of Figure 14(b) fails to capture these characteristics.

The incorporation of the new constructs (self-loop and time-varying parameters) in the framework of TIN based modeling and reasoning enhances the capabilities of this modeling paradigm in terms of capturing dynamic uncertain scenarios. A TIN with these additional constructs has been defined as a Dynamic Influence Net (DIN). The following items characterize a DIN while a formal definition is given in Definition 3.

1. The nodes of a DIN are set of random variables. All the variables in the DIN have binary states.
2. A set of directed links that connect pairs of nodes. A node can also have an optional self-loop.
3. A pair (c, t) for each link, where c is a list of tuples representing the CAST logic parameters. For each element in c, a corresponding time interval is defined in t. This interval represents the time during which the corresponding element in c is in effect. In general, (c, t) is defined as

   $([(h_1, g_1)\ (h_2, g_2), \ldots, (h_n, g_n)], [(t_{11}, t_{12}), (t_{21}, t_{22}), \ldots, (t_{n1}, t_{n2})]$

   where $t_{i1} < t_{i2}$ and $t_{ij} > 0\ \forall\ i = 1, 2, \ldots, n$ and $j = 1, 2$
4. Each non-root node has an associated baseline probability, while a prior probability is associated with each root node.
5. Each link has a corresponding delay d (where $d \geq 0$) that represents the communication delay.
6. Each node has a corresponding delay e (where $e \geq 0$) that represents the information processing delay.
7. A pair (p, t) for each root node, where p is a list of real numbers representing probability values. For each probability value, a corresponding time interval is defined in t. In general, (p, t) is defined as

   $([p_1, p_2, \ldots, p_n], [[t_{11}, t_{12}], [t_{21}, t_{22}], \ldots, [t_{n1}, t_{n2}]]$

   where $t_{i1} < t_{i2}$ and $t_{ij} > 0\ \forall\ i = 1, 2, \ldots, n$ and $j = 1, 2$

Definition 3

A *Dynamic Influence Net* is a tuple (**V, E, C, B, $\mathbf{D_E}$, $\mathbf{D_V}$, A**) where

V: set of Nodes,

E: set of Edges,

C represents causal strengths:

$\mathbf{E} \rightarrow \{([(h_1, g_1)\ (h_2, g_2), \ldots, (h_n, g_n)], [(t_{11}, t_{12}), (t_{21}, t_{22}), \ldots, (t_{n1}, t_{n2})])$

such that $-1 < \mathbf{h_i}, \mathbf{g_i} < 1$ }, $t_{ij} \rightarrow \mathbf{Z}^+$ and $t_{i1} \leq t_{i2}$, $\forall\ i = 1, 2, \ldots, n$ and $j = 1, 2$ }

B represents Baseline / Prior probability: **V** → [0,1],

$\mathbf{D_E}$ represents Delays on Edges: **E** → $\mathbf{Z}^+$,

$\mathbf{D_V}$ represents Delays on Nodes: **V** → $\mathbf{Z}^+$, and

A (input scenario) represents the probabilities associated with the set of actions and the time associated with them.

$\mathbf{A}: \mathbf{R} \rightarrow \{([p_1, p_2, \ldots, p_n], [[t_{11}, t_{12}], [t_{21}, t_{22}], \ldots, [t_{n1}, t_{n2}]])$
such that $p_i = [0, 1]$, $t_{ij} \rightarrow \mathbf{Z}^*$ and $t_{i1} \leq t_{i2}$, $\forall$ i = 1, 2, …., n and j = 1, 2 where $\mathbf{R} \subset \mathbf{V}$ }

Conclusions

The paper presents structural and parametric enhancements to Timed Influence Nets based modeling framework. Currently, nodes in a TIN are considered memoryless. This inability results in lack of modeling the impact of different sequences of actions on a desired effect. TINs also fail to capture time-varying influences. The proposed enhancements would allow a system modeler to specify such influences. Thus, the modeler would be able to specify both stationary and non-stationary influences. Furthermore, the dependency of an event on its previous state could also be modeled by adding a self-loop to the corresponding node. The incorporation of self-loop adds memory to the existing memory-less TIN. The addition of both self-loop and time-varying influences would enable a modeler to model impacts of repeated actions on an effect. Currently, in the event of repeated actions, a TIN only considers the latest impact on the effect while ignoring the previous attempts. The proposed DIN would convolve the impact of repeated actions on the desired effect and, thus, further enhance the capabilities of TINs based modeling paradigm.

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