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Temporal Bayesian Network of Events for Diagnosis and Prediction in Dynamic Domains

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Abstract. In some domains like industry, medicine, communications, speech recognition, planning, tutoring systems, and forecasting; the timing of observations (symptoms, measures, test, events, as well as faults) play a major role in diagnosis and prediction. This paper introduces a new formalism to deal with uncertainty and time using Bayesian networks called Temporal Bayesian Network of Events (TBNE). In a TBNE each node represents an event or state change of a variable, and an arc corresponds to a causal-temporal relationship. A temporal node represents the time that a variable changes state, including an option of no-change. The temporal intervals can differ in number and size for each temporal node, so this allows multiple granularity. Our approach is contrasted with a Dynamic Bayesian network for a simple medical example. An empirical evaluation is presented for a subsystem of a thermal power plant, in which this approach is used for fault diagnosis and event prediction with good results. The TBNE model can be used for the diagnosis of a cascade of anomalies arising with certain delays; this situation is typical in the diagnosis of medical and industrial processes.

Keywords: bayesian networks, temporal uncertainty, diagnosis, prediction, industrial applications

1. Introduction

Artificial intelligence techniques are entering real world domains, such as medicine, industrial diagnosis, communications, planning, financial forecasting and scheduling. These applications have revealed a great need for powerful methods for knowledge representation. In particular, the evolutionary nature of these domains requires a representation that takes into account temporal information. The exact timing information for things like lab-test results, occurrence of symptoms, observations, measures, as well as faults, can be crucial in these kind of applications.

For example, in medicine, representing and reasoning about time is crucial for many tasks like prevention, diagnosis, therapeutic management, prognosis and discovery [1–4]. In industrial diagnosis, the timing observations play a major role in diagnosis and prediction of events and disturbances [5].

To model temporal relations is a complex task. Temporal models are more complex than atemporal ones [6, 7]. Even when they involve a few variables, in a temporal model each variable and its relationships with other variables must be examined over multiple points of time. These tasks often entail an inordinate amount of computation, due to the size and the complexity of the resulting model. In the context of intelligent systems, a temporal model must be capable of reasoning about the present, past and future state of the domain.

Aside from temporal considerations, real world information is usually imprecise, incomplete and noisy.

The temporal model must be able to deal with uncertainty. Among the formalism proposed for dealing with uncertainty, one of the most used techniques for the development of intelligent systems are Bayesian networks (BN) [8]. Although Bayesian networks were not designed to model temporal aspects explicitly, recently Bayesian networks have been applied to temporal reasoning under uncertainty [2, 9, 10]. The extension of Bayesian networks semantics to deal with temporal relationships can be complicated. The main problem is to represent each node with its dependence relationships over multiple points of time.

A way to apply Bayesian networks to dynamic domains consists in both discretizing time and creating an instance of each random variable for each point in time [10]. Initially a static model is built. Then a copy of this model is generated for each instant belonging to a certain temporal range of interest. Finally, links between nodes in adjacent static networks are established, assuming the process is Markovian. Although dynamic Bayesian networks are an alternative representation for these domains, they are too complex for realistic applications.

Based on the fact that in many cases there are few state changes in the temporal range of interest, in this paper we present an alternative representation called Temporal Bayesian Network of Events (TBNE), a network of probabilistic events (state changes) in discrete time. In a TBNE each node represents an event or state change of a variable, and an arc corresponds to a causal-temporal relationship. A temporal node represents the time that a variable changes state, including an option of no-change. Including more temporal nodes can represent more than one change for the same variable. The temporal intervals can differ in number and size for each temporal node, so this allows multiple granularity. Temporal information is relative, that is, there is not absolute temporal reference. We developed a mechanism for transforming the relative times to absolute, based on the timing of the observations. With this representation we can model complex real-world systems with a simple network, and use standard probability propagation techniques for diagnosis and prediction. The proposed approach is applied to the diagnosis and prediction of events and disturbances (events evolution) in power plants.

The rest of this paper is organized as follows. Section 2 introduces our approach, which is contrasted with a BN and DBN for a simple medical example. Section 3 presents a formal definition of the proposed model. Section 4 presents the inference mechanism for a TBNE. In Section 5 an empirical evaluation is presented for a subsystem of a fossil power plant. Section 6 presents a brief discussion of several extensions of BN's for time modeling. Finally, Section 7 presents the conclusions and future research.

2. A Medical Example

To illustrate the proposed temporal probabilistic model, we present the hypothetical example of the consequences of an automobile accident based on [11]. The example expresses the necessity for representing temporal relations for medical diagnosis.

Assume that at time $t = 0$ an automobile accident occurs. The driver is a healthy 45 years old man and contact with steering wheel is noted. This kind of accident can be classified as *severe*, *moderate* or *mild*. The immediate consequences in this sort of accident are injuries to the *head*, *abdominal cavity* and *internal organs*, *chest* and *extremities*. For demonstration purpose we only consider *head* and *chest* injuries. Injury of the head can bruise the brain, which will cause it to begin swelling. Chest injuries can include a fractured sternum, one or both punctured lungs, and bleeding in the chest cavity. These instantaneous state changes can initiate a set of internal changes that will generate subsequent changes. For example, brain trauma will cause the brain to begin swelling. This increase of the brain volume tends to increase intracranial pressure, which in turn eventually causes *dilated pupils*, *destabilized vital signs* (pulse and blood pressure) and loss of consciousness. Bleeding into the chest cavity decreases blood volume over time, which also tends to destabilize vital signs. Internal bleeding will also eventually increase pressure on the heart, decreasing its efficiency, further destabilizing vital signs. The collision itself can be modeled as an external event, which can immediately cause certain changes in the patient's state: trauma to the brain, broken sternum, punctured lung, and bleeding in the chest cavity. These changes cause internal changes, which are not immediate: dilated pupils, vital signs unstable, and loss of consciousness, and depend on the severity of the accident.

Suppose that we gathered the following statistics about the accidents that occurred in a specific zone of a city:

- 36.80% of the collisions (**C**) are severe, 39.20% are moderate and 24% are mild.

- If the accident is mild, then the probability that head injury occurs is 0.1 and the probability of an injury resulting in slight internal bleeding (**IB**) is 0.6 and gross internal bleeding is 0.05.
- If the accident is moderate, then the probability that head injury occurs is 0.4 and the probability of an injury resulting in slight internal bleeding is 0.15 and gross internal bleeding is 0.65.
- If the accident is severe, then the probability that head injury occurs is 0.9 and the probability of an injury resulting in slight internal bleeding is 0.4 and gross internal bleeding is 0.5.

This information indicates that there is a strong causal relationship between the severity of the accident and the immediate effect in the patient's state. Additionally, there is some important temporal information about the relations between the instantaneous consequences (head injury and internal bleeding) and the symptoms (pupils dilated and vitals signs unstable).

- If a head injury (**HI**) occurs, the brain will start to swell, and if left unchecked, the swelling will cause the pupils to dilate (**PD**) within 0 to 10 minutes.
- If internal bleeding (**IB**) begins, the blood volume will start to fall, which will tend to destabilize vital signs (**VS**). The time required to destabilize signs will depend on the severity of bleeding:
- If the bleeding is gross, it will take from 10 to 30 minutes.
- If the bleeding is slight, it will take between 30 to 60 minutes.
- A head injury (**HI**) also tends to destabilize vital signs, taking between 0 to 10 minutes to make them unstable.

Figure 1 shows the temporal occurrence of the symptoms in relation with the time of the immediate effects.

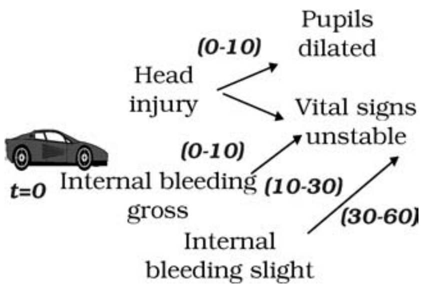

Figure 1. Temporal relations between immediate effects and symptoms.

Suppose that at time $t = 10$ minutes the patient is observed by paramedics. They observe a probable broken sternum, the patient is complaining of shortness of breath and dizziness, *vital signs* are *unstable*, but *pupils* are *not dilated*. From this symptoms the probable chest injury and unstable vital signs suggest internal bleeding, which will soon cause serious problems if left unattended. Intravenous fluids should probably be administered immediately to increase the blood volume, and if the transportation to the hospital is expected to take more than 20 minutes it might be best to insert a chest tube to drain blood from the chest cavity and reduce pressure on the heart. Finally, the collision and shortness of breath suggest a collapsed lung and decreased oxygen transfer, which should be treated immediately by administering oxygen.

2.1. *Probabilistic Models for Medical Example*

Static Bayesian Network. In this example there is an external event: the collision (**C**); that generates two immediate effects in the patient's state: head injury (**HI**) and internal bleeding (**IB**). These internal events produce certain posterior endogenous changes in the patient. These changes are not immediate and are manifest through two observations: pupils dilated (**PD**) and vital signs unstable (**VS**). The severity of the collision has a direct causal relation with the variables head injury and internal bleeding. Figure 2 shows a static Bayesian network for the collision event.

A Bayesian network can not represent the temporal information of the dynamic domain. That is, the temporal relationships between the occurrence of the immediate effects (HI and IB) and the symptoms (PD and VS). We can conclude the following: (i) the symptoms "vital signs unstable" and "pupils normal" do not consider the time in which they were observed, (ii) static

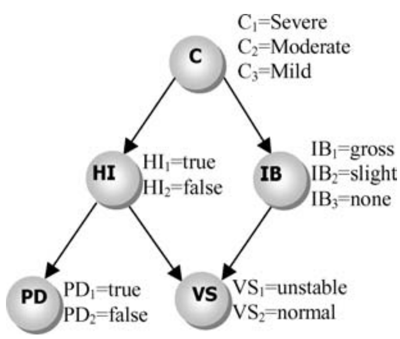

Figure 2. Static Bayesian network for the accident example.

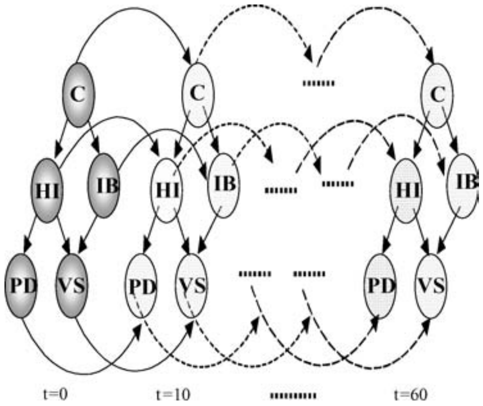

Figure 3. Dynamic Bayesian network for the "accident" example.

Bayesian network does not take into account the timing observations of the symptoms and the arrival time of the paramedics to the collision scene, and (iii) it seems that the information is not sufficient for an adequate diagnosis, the timing observations play a major role in diagnosis.

Dynamic Bayesian Network. The most common representation of dynamic relations are dynamic Bayesian networks [12, 10]. Figure 3 shows a simple DBN for the "accident" example, with a time slice each 10 minutes, the maximum common divisor of the time intervals. This is a simple DBN for the example, which considers the following assumptions: (i) a state depends only on the previous one (Markovian assumption), (ii) there are links only between the same variable at different slices. Even with these simplifications, it is a complex model in terms of storage requirements and computation time for probability propagation. If we consider a more complex model, relaxing the previous assumptions, it could become prohibitive for realistic applications. Also, the acquisition of the model (structure and parameters) could become a problem.

DBN's present the following problems for realistic applications [1, 2]: (1) A DBN is a model of high complexity, which increases according with the number of variables or time slices; (2) DBN's handle a predefined temporal range of interest, they do not allow to vary the temporal range as a model parameter; and (3) DBN's do not have an integrated temporal/causal semantics, the knowledge about time can not be exploited easily to prevent serious inconsistencies.

Temporal Bayesian Network of Events. We propose an alternative representation of temporal aspects in Bayesian networks. In many cases, there are few states changes (events) in the temporal interval of interest in the domain. The timing of these events is usually important for diagnosis and prediction task. For instance, in the medical example, the time when "vital signs unstable" and "pupils dilated" occur is crucial for the accident diagnosis.

To model these changes, we require a representation of events. We propose a temporal representation based on events and its time interval of occurrence, called *Temporal Bayesian Networks of Events* (TBNE) [9]. A TBNE is a Bayesian network in which each node represents an event or state change of a variable, and an arc corresponds to a causal-temporal relation. A *temporal node* represents a possible state change of a variable and the time when it happens. Each value of a temporal node is defined by an ordered pair: the value of the variable to which it changes and the time interval of its occurrence. Time intervals represent relative times between the parent events and the corresponding state change. A temporal node has an initial or default state, so a value is associated to this state with a maximum time interval (*temporal range*) and it indicates the condition of no change. For example, for the temporal node *vitals signs* the relationships between its time intervals are represented in Fig. 4.

In the accident example, there are 3 instantaneous events: *collision*, *head injury* and *internal bleeding*; and two events that can be represented by nodes with temporal intervals: *pupils dilated* and *vital signs unstable*. ***PD*** has *normal* as initial state, and can change to *dilated* in 2 temporal intervals ([0, 3], [3, 5]); while ***VS*** has *normal* as initial state, and can change to *unstable* in 3 different time intervals ([0–10], [10–30], [30–60]). Both variables have the default state associated to the overall time interval, ([0–5] and [0–60]) which correspond to the no change condition. The time intervals

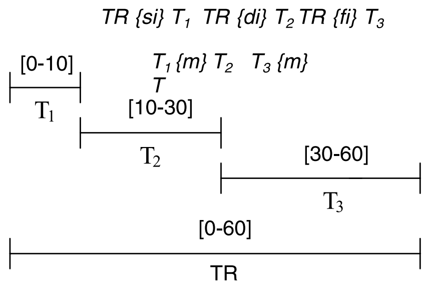

Figure 4. Temporal relationships between the time intervals of node vitals signs. The relation between the time intervals is shown based on Allen's temporal algebra (*si*-start, *di*-during, *fi*-finishes, *m*-meets).

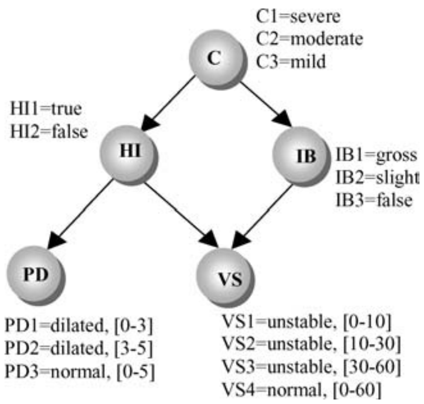

Figure 5. TBNE for the accident example.

were defined based on the temporal information of the accident example. Figure 5 shows a TBNE model for the "accident" example.

The TBNE model can be used, for example, to predict the consequences of an accident or to diagnose its severity. The resulting network is less complex than the corresponding DBN. The main difference with a DBN is that the representation is based on state changes at different times represent by temporal nodes instead of state values at different times, represent by state variables. A TBNE can be seen as natural extension of a Bayesian network and its properties are parallel. The temporal intervals can differ in number and size for each temporal node, so this allows multiple granularity. Temporal information is relative, that is, there is not an absolute temporal reference. We also developed a mechanism for transforming the relative times to absolute, based on the timing of the observations. A formal definition of a TBNE is presented in the next section.

3. Formal Definition of a TBNE

A TBNE is a Bayesian network of events in discrete time in which each node represents an event or state change of a variable, and an arc corresponds to a causal-temporal relation. This representation is based on the definition of a temporal node. A temporal node is defined by a set of states. Each state is defined by an ordered pair: the value of the variable (to which it corresponds) and a time interval associated to the change of value of the variable. A temporal node is defined as follows:

Definition 1. A temporal node (***TN***) is defined by a set of states, each defined by an ordered pair $(\boldsymbol{\sigma}, \boldsymbol{\tau})$, where $\boldsymbol{\sigma}$ is a value of a random variable and $\boldsymbol{\tau}$ is the time interval associate to the change of variable value.

There is a default state of no change that corresponds to the initial value (generally the "normal" value), associated to the temporal range of the node. The values of each TN can be seen as the "cross product" between the set of values (Σ) and the set of time intervals (T), except for the default state, which is associated only to the temporal range of interest (TR).

TNs are connected by edges. Each edge represents a causal-temporal relationship between TNs. The conditional probability distribution for each node is defined as the probability of each ordered pair (σ_i,τ_i) given the ordered pairs of its parents (σ_j, τ_j).

As a TN is defined by a set of time intervals, we can relate these time intervals based on Allen's temporal algebra [13]. In a TN the definition of the default state is associated to temporal range of interest, TR. A temporal relationship between the time intervals of a TN is defined as:

Definition 2. The possible temporal relationships between TR with the time intervals, Ti, of a node are: *start* (si), *during* (di) and *finish* (fi). The temporal relationship between each pair of time intervals is *meet* (m): Ti $\{m\}$ Tj.

The definition of TN based on Allen interval's for the accident example was presented in Fig 4. Finally, a Temporal Bayesian Network of Events (TBNE) is defined as:

Definition 3. A TBNE is defined as TBNE $= (V, E)$, where V is the set of temporal nodes and E is the set of edges.

In each temporal node, the temporal intervals are relative to the parent nodes, that is, no absolute temporal reference exists. This makes the representation more general; but, for its application, we need to associate these relative times to the actual or absolute times of the observed events. We developed a mechanism for transforming the relative times to absolute, based on the timing of the observations. In the next section, we present the definition of the inference mechanism.

4. Inference Mechanism

As we mentioned before, the temporal intervals in each node are relative to its parents. When an initial event is detected, its time of occurrence "fixes" temporally the network. The timing of the observation is used as temporal reference for the other events. This means that the actual timing of the events represented in the network is dynamic. For definition of the inference mechanism, we need to define some additional parameters:

τc (*time of occurrence*): is the actual time when an event is detected. As the network does not have any temporal reference, the time of occurrence of the initial event fixes temporally the network.

α (*time delay*): is the absolute value of the difference between the time of occurrence of a pair of events, $\alpha = |tc_i - tc_{ii}$, where tc_i is the time of occurrence of the first event and tc_{ii} is the time of occurrence of the second event.

These parameters are used by the inference mechanism for determining the actual time intervals of occurrence of each event. The mechanism consists of 3 basic steps, which are as follows.

Step 1. Event detection and time interval definition
When an initial event is detected, its time of occurrence, "τc_{initial}," is utilized as temporal reference for all the network. There are two possible cases, depending on the position of the *initial* node in the network: (a) the initial event corresponds to a root node, and (b) the initial event corresponds to an intermediate or leaf node.

1-(a). In the first case, the actual value of the node can be determined (root nodes are always instantaneous events).

1-(b). For the second case, it is not possible to determine the value of the variable, because the event could be associated to any time interval for the state. It is necessary to wait for a second observation to determine the interval. When the next event is detected, its time of occurrence, $\tau c_{\text{posterior}}$, is utilized for definition of the time interval associated with the real time occurrence function, $\alpha = |\tau c_{\text{initial}} - \tau c_{\text{posterior}}|$. The value of α is used to set the time interval of the child node considering the parent node as the initial event. This step is applied recursively to subsequent events.

Step 2. Propagation of the evidences
Once the value of a node is obtained (time interval and associated state), the next step is to propagate the effect of this value through the network to update the probability of other temporal nodes. It can be use any standard algorithm for probability propagation.

Step 3. Determination of the past and future events
With the posterior probabilities, we can estimate the potentially past and future events based on the probability distribution of the each temporal node.

If there is not enough information, for instance there is only one observed event which corresponds to an intermediate node, the mechanism handles different *scenarios*. The node is instantiated to all the intervals corresponding to the observed state, and the posterior probabilities of the other nodes are obtained for each scenario. These scenarios could be used as a set of possible alternatives, which will be reduced when another event occurs.

5. Empirical Results

The proposed representation and inference mechanism is applied for fault diagnosis and prediction in a subsystem of a thermal power plant. We consider the drum level control system with four potential disturbances: a power load increase (**LI**); a feedwater pump failure (**FWPF**); a feedwater valve failure (**FWVF**); and the spray water valve failure (**SWVF**). The drum is a subsystem of a fossil power plant that provides steam to the superheater and water to the water wall of a steam generator. The drum system is composed of three systems: feedwater, water steam generator and superheater steam system. One of the main problems in the drum is to maintain the water level in safe operation state. Figure 6 shows a simplified diagram of the power plant's systems.

In the process, a signal exceeding its specified limit of normal functioning is called an *event*, and a sequence of events that have the same underlying cause are considered as a *disturbance*. To determine which of the disturbances is present, is a complicated task, because there are similar sequence of events for the four main disturbances. We need additional information in order to determine which is the real cause. In particular, the temporal information about the occurrence of each event is important for an accurate diagnosis. For example, a feedwater flow increase (FWF) can be caused by two different events: the feedwater pump current

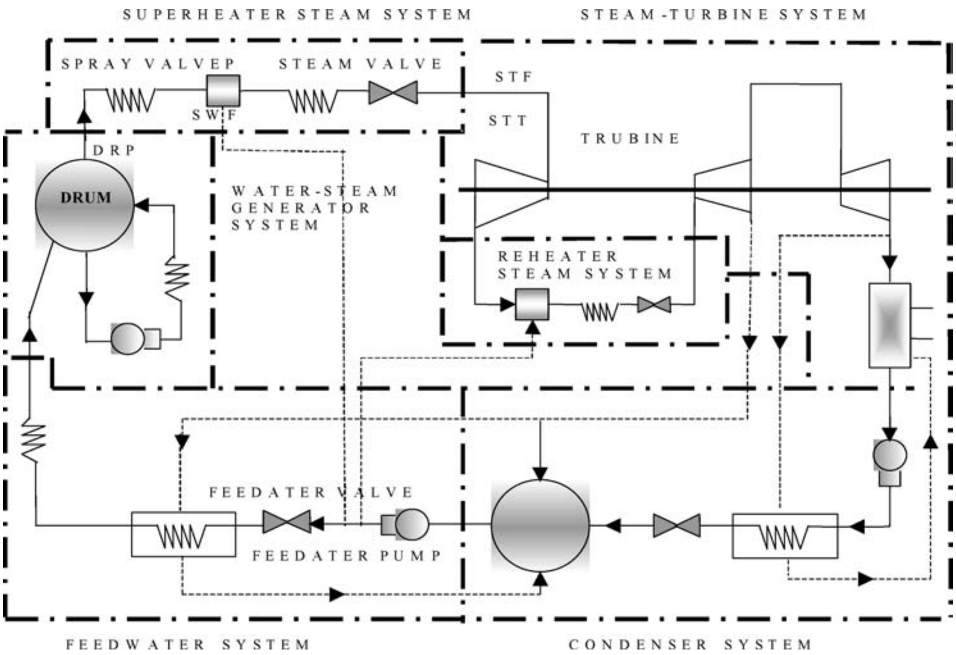

Figure 6. A simplified diagram of thermal power plant.

augmentation (FWP) and feedwater valve opening increase (FWV). We can use the time difference between the occurrence of each event, FWV-FWF and FWP-FWF, for selecting the "cause" of the increase of the FW flow.

According to the process data, the time interval between a pump current augmentation and an increase of the flow (FWP-FWF) is from 25 to 114 seconds. The time interval between the valve opening increase and an increase of the flow (FWV-FWF) is from 114 to 248 seconds. Hence, if the flow increase occurs in the first time interval, the probable cause is an augmentation of the pump; but if the flow increase occurs in the second time interval, the probable cause is a valve opening increase. Figure 7 shows a TBNE that represents the events of the steam drum system of a steam generator and the definition and prior probabilities of the temporal nodes. The network structure was defined based the knowledge of an expert operator. The definition of the time intervals for each temporal node was obtained based on knowledge about the process dynamics combined with data from a simulator.

Once the structure and time intervals were defined, the required parameters were estimated from data. The process data-base was generated by a full scale simulator of a 350 MW thermal power plant. We selected 80% of this database (800 data) for parameter learning and 20% (200 data) for evaluation. The network was evaluated using two scores: % accuracy and % of relative Brier score (total square error). The % of accuracy was evaluated by number of correct predictions of unknown variables.

The Brier score is defined as: $\text{BS} = \Sigma_{i=1}^{n}(1 - P_i)^2$. Where P_i is the marginal posterior probability of the correct value of each node given the evidence. The maximum Brier score is: $\text{BS}_{\text{MAX}} = \Sigma^{n}(1)^2$. The % of relative Brier score is defined as:

$$\text{RBS (in \%)} = \{1 - (\text{BS}/\text{BS}_{\text{MAX}})\} \times 100$$

The test methodology includes three basic steps: (i) assign a value to a subset of nodes, (ii) propagate the evidence and (iii) compare the posterior probabilities of the nodes with the actual values. The assigned nodes were selected for 3 sets of tests: (1) *Prediction*: root nodes are observed (LI, FWPF, FWVF and SWVF); (2) *Diagnosis*: leaf nodes are observed (STT, STF and SWF); and (3) *Prediction and diagnosis*: intermediate nodes are observed (STV, FWP, FWV and SWV).

Table 1 shows the results of the evaluation for the three sets of tests in terms of the mean and the standard deviation for both scores. These results show

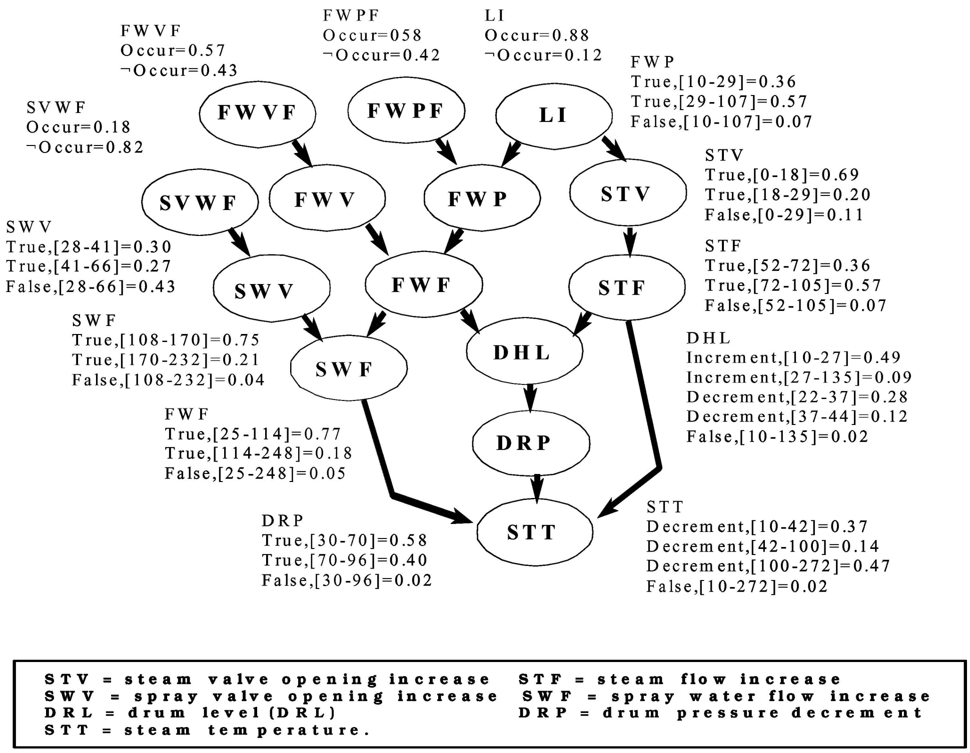

Figure 7. TBNE for the steam drum system.

the prediction and diagnosis capacity of the temporal model in a real process. Both scores are between 80 and 95% for all the set of tests, with better results when intermediate nodes are observed, and slightly better results for prediction compared to diagnosis. We consider that these differences have to do with the "distance" between assigned and unknown nodes, and with the way that the temporal intervals were defined. We are encouraged by the fact that the model can produce a reasonable accuracy in times that are compatible with real time decision making.

Table 1. Empirical evaluations results.

Parameter	μ	σ
Prediction		
% of RBS	87.37	9.19
% of Accuracy	84.48	14.98
Diagnosis		
% of RBS	84.25	8.09
% of Accuracy	80.00	11.85
Diagnosis and Prediction		
% of RBS	95.85	4.71
% of Accuracy	94.92	8.59

6. Related Work

BN's usually represent a static causal model for certain domain. That is, the nodes represent the values of the variables at a time point and temporal relations are not considered. However, recently BN have been applied to model temporal relationships.

The first group are the formalisms based on time point as the primitive temporal notion. The network is arranged into "time slices" representing the system's complete state at a single point in time. Time slices are duplicated over a predetermined time grid representing the temporal range of interest and, directed temporal links are drawn between nodes of the different "static" slices. The DBN is built dynamically, reflecting the dynamic changes in the environment. Some recent applications of DBN are model of time net by Kanazawa [14], model for sensor validation by Nicholson and Brady [15], a method for reasoning with

DBN by Kjaerulff [12], a model for audio-visual speech recognition by Murphy [10].

The second group are the formalisms based on time intervals as the primitive temporal notion. The first case is the model based on the temporal abduction problem (TAP) by Santos [2]. In TAP, each event has an associated interval during which the event occurs. Relationships between events are expressed as directed edges from cause to effect within a weighted directed acyclic graph structure. The TAP has strong interval-based temporal semantics but lacks strong probabilistic semantics. Later, Santos and Young proposed the probabilistic temporal network (PTN) [16]. In a PTN, the nodes of the network are temporal aggregates and the edges are the causal/temporal relationships between aggregates. Each aggregate represents a process changing over time. The temporal aggregates are temporal random variables, defined by an ordered pair (random variable plus Allen's intervals). This approach is based on time-intervals and considers the temporal relationships that occur between the events. Another model is the network of probabilistic events in discrete time (NPEDT) by Galan and Diez [4]. Under this approach, time is discretized in intervals and each value of a variable represents the instant at which a certain event may occur. The NPEDT is modeled by temporal noisy gates, which facilitate the acquisition and representation of temporal knowledge.

The third group is the formalisms based on extensions of BN. For instance, the "Network of exogenous events and endogenous changes" by Hanks et al. [11]. This representation is a probabilistic model for reasoning about the system as it changes over time, both due to exogenous events and endogenous changes. An exogenous event generally refers to an instantaneous change in the process state. Endogenous changes are modeled using a local inference model, a simple arbitrary linear model. All the previous approaches are based on point models of time, and as such require that events occur instantaneously. It is difficult to consider that events take place at time points, often it is more natural to consider events taking place over time intervals. Another model is the "Modificable Temporal Bayesian Networks with Single-granularity (MTBN-SG) by Aliferis and Cooper [1]. A MTBN-SG is an extended time-sliced Bayesian network defined over a range of time points. The temporal graph is a directed graph (possibly cyclic) composed of nodes and arcs corresponding to 3 types of variables; ordinary, mechanism and time-lag quantifier variable. As indicated in the name, the MTBN-SG model only supports a single granularity for the size of the time step in any given network. The resulting graph can have cycles to allow expressions of recurrence and feedback.

In summary, previous probabilistic temporal models are, in general, quite complex for realistic applications, so they do not satisfy the knowledge acquisition and computational tractability criteria. These models support a single granularity and it is difficult to extend them for multiple granularity. In contrast, the TBNE model is based on representing changes of state in each node. If the number of possible state changes for each variable in the temporal range is small, as it is in many practical problems, the resulting model is much simpler. This facilitates temporal knowledge acquisition and allows efficient inference using standard probability propagation techniques. Also, the model supports in a natural way multiple granularity, with different number of temporal intervals for each node, and different duration for each interval within a node.

7. Conclusions

This paper presented the definition and application of an approach for dealing with uncertainty and time called Temporal Bayesian Network of Events (TBNE). A TBNE generates a formal and systematic structure used to model the temporal evolution of dynamic process. TBNE model is an extension of Bayesian networks for dealing with temporal information. Each event or state change of a variable is associated with a time interval. The definition of the number of time intervals and their duration for each node is free (multiple granularity) and can be see as a trade off between the complexity and the accuracy needed for depicting the knowledge of the temporal domain.

The formalism satisfies the requirements of temporal knowledge acquisition, low computational cost and temporal expressiveness. The main difference with previous probabilistic temporal models is that the representation is based on state changes at different times instead of state values at different times. This makes the model much simpler in many applications in which there are few changes for each variable in the temporal range of interest.

The temporal information in a TBNE is relative, that is, no absolute temporal reference exists. We developed a mechanism for transforming the relative times to absolute. The temporal reasoning mechanism is based on the propagation of probabilities and gives the time of occurrence of events or state changes with some probability value. The mechanism has three main steps: (1) event detection and time interval definition; (2) evidence propagation through the net; and (3) determination of past and future events. If there is not enough information, the mechanism handles scenarios. These scenarios could be use as a set of possible alternatives, which will be reduced when another event occurs.

In order to demonstrate the ideas present in this article, the formalism was contrasted with a DBN for a simple medical example. An empirical evaluation is presented for the diagnosis and prediction of events in the drum level system of a thermal power plant with good results.

Although many BN variants have been introduced for temporal modeling, we believe that the TBNE can be used for the diagnosis of a cascade of anomalies arising with certain delays; this situation is typical in the diagnosis of medical and industrial processes. In contrast, DBN, using time slices, seem more adequate for monitoring the evolution of a system that fluctuates around its normal state, specially if there is a cyclic pattern.

Our future work will focus on validating our approach in other domains, such as planning and student modeling. Also, we will incorporate qualitative temporal constraints that could facilitate knowledge acquisition and validating of the temporal consistency of the model.

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