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Probabilistic temporal reasoning and its application to fossil power plant operation

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Abstract

Many real-world applications, such as industrial diagnosis, require an adequate representation and inference mechanism that combines uncertainty and time. In this work, we propose a novel approach for representing dynamic domains under uncertainty based on a probabilistic framework, called temporal nodes Bayesian networks (TNBN). The TNBN model is an extension of a standard Bayesian network, in which each temporal node represents an event or state change of a variable and the arcs represent causal–temporal relationships between nodes. A temporal node has associated a probability distribution for its time of occurrence, where time is discretized in a finite number of temporal intervals; allowing a different number of intervals for each node and a different duration for the intervals within a node (multiple granularity). 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. Given this model, we can reason about the probability of occurrence of certain events, for diagnosis or prediction, using standard probability propagation techniques developed for Bayesian networks. The proposed approach is applied to fossil power plant diagnosis through two detailed case studies: power load increment and control level system failure. The results show that the proposed formalism could help to improve power plant availability through early diagnosis of events and disturbances.

Keywords: Bayesian networks; Temporal reasoning; Diagnosis; Prediction; Power plants

1. Introduction

Applying artificial intelligence techniques to real time environments presents a great challenge. Among the specific characteristics that these systems must include, are the ability to manage uncertainty and temporal aspects. Temporal intelligent systems typically are much more complex than atemporal ones. In a temporal model each variable and its interactions with other variables must be taken in account over multiple points of time. These systems 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 (Allen, 1983; Cooper et al., 1989; Maiocchi and Pernici, 1991; Haddawy, 1996; Van Beek and Manchak, 1996). The exact timing information for things like lab-test results, occurrence of symptoms, observations, measures, as well as faults, can be crucial in this kind of application.

For example, in medicine, representing and reasoning about time is crucial for broad reasoning tasks like prevention, diagnosis, therapeutic management, prognosis and discovery. Temporal information can be quite crucial in settings like ‘blood test B was taken 5 h after drug D was administered to the patient’ (Santos, 1996) or ‘what is the state of the patient 10 min after an automobile accident had occurred’ (Hanks et al., 1995). In planning is also critical in situations such as ‘the variability of an employee’s arrival time at work and the relationships between the time of arrival and later events’ (Santos and Young, 1996). In industrial diagnosis, dealing with time is important in settings like ‘if the drum level is high and the pressure in the drum increases minutes later, look for an increase of feedwater flow 5 min before, preceded by an augmentation in the current of the feedwater pumps, 3 min before the detection of increase of feedwater flow’ (Arroyo-Figueroa et al., 1998). In these

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domains, the relationship between each two events (cause and effect) is a function of the time occurrence of the events.

Industrial diagnosis requires the ability to deal with uncertainty and time. For the first one (imprecise process knowledge, imprecise signals, availability), the ideal representation should handle uncertainty in a principled and unambiguous way with declarative semantics. An ideal representation would also be sound and complete, as well as amenable to machine-learning and explanation methods (Díez, 1994). For the second one, the ideal representation should satisfy the following requirements: time expressiveness (sound and flexible time model); computational tractability (adequate temporal reasoning that allows examination of the variable interactions over multiple points of time); and temporal knowledge acquisition (amenable to machine-learning methods for process evolution knowledge acquisition) (Aliferis and Cooper, 1995).

In this paper we propose a novel approach for representing temporal aspects on a probabilistic framework. We suggest building an extension of a standard Bayesian network that facilitates temporal representation and reasoning with uncertainty and time. The temporal model is called 'temporal nodes Bayesian network'. In this graphical model, each temporal node represents an event or state change of a variable and the arcs represent causal–temporal relationships between the nodes. 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. The goal is to represent complex systems changing over time. Given evidence about the past and present state of the system, predict the system's future state. Also, given a future state determine the most probable cause. The proposed approach is applied to fossil power plant diagnosis through a detailed case study. The paper is organized as follows. Section 2 presents a brief overview of Bayesian networks. Section 3 presents the proposed approach and shows the application of the temporal model to a simple example, the diagnosis and prediction of events of the drum level of a steam generator. In Section 4 we describe a complete application of the formalism with four experiments including prediction and diagnosis. Section 5 presents a brief description of previous probabilistic temporal models. In Section 6 we present the main conclusions and future work.

2. Bayesian networks

Bayesian networks (BN), also known as probabilistic networks, causal networks or belief networks, are a formalism for representing uncertainty in a way that is consistent with the axioms of probability theory (Pearl, 1988; Neapolitan, 1990). A Bayesian network (BN) is a graphical structure (directed acyclic graph) composed of nodes and arcs. Each node corresponds to an entity of the real world (variable) and each link gives direct information about the dependency relationships between the variables involved. These dependency relationships are parameterized by conditional probabilities required to specify the underlying distribution. In particular, qualitative knowledge is represented by the topology of the network and quantitative knowledge is represented by the conditional probability distribution of the variables. Inference with BN's is based on probabilistic reasoning. This consists of instantiating the input variables and propagating their effect through the network to update the probability of the hypothesis variables.

A BN has a number of important properties, including a declarative semantics based on probability theory, efficient and complete inference algorithms and several machine learning and explanation methodologies. There are exact and approximate inference algorithms for probabilistic reasoning and special case algorithms and corresponding conditions that allow tractable inference. Great attention has been given and substantial results obtained, in the field of automated learning of BN from data. Nowadays, there is an important trend in the study of BN's capabilities for dealing with decision, causal, temporal and planning models (Poh et al., 1994; Horvitz and Seiver, 1997; Maxwell et al., 1997).

Although BN's are not designed to model temporal aspects explicitly, recently Bayesian networks have been applied to temporal reasoning under uncertainty (Kanazawa, 1991; Nicholson and Brady, 1994; Ngo et al., 1995; Aliferis and Cooper, 1996; Ibarguengoytia et al., 1996; Santos and Young, 1996; Arroyo-Figueroa et al., 1998). Prior temporal modelling techniques have often made a trade-off in expressiveness between semantics for time and semantics for uncertainty. Therefore, to integrate uncertainty and time, it is necessary to have a combined approach integrating strong probabilistic semantics for representing uncertainty and expressive temporal semantics for representing temporal relations. Unfortunately, the resulting model is usually extremely complex and computationally intractable. Hence a successful model must make a trade off between expressiveness and computational efficiency.

3. Temporal nodes Bayesian network

In a standard Bayesian network, each node represents a random variable and each arc represents a probabilistic dependency (causal relationship) between two nodes. In the case of a temporal nodes Bayesian network (TNBN), each temporal node is also a random variable but it represents the temporal interval in which a change of state occurs (Arroyo-Figueroa and Sucar, 1998). That is, instead of associating a state to each value of the node, we associate state changes and their corresponding temporal interval. Each arc represents a causal–temporal relationship between two temporal nodes. The model implies that there is at most one state change for each variable in the temporal range of interest. Formally, a temporal node is defined as:

Definition 1. A Temporal Node (TN) is an ordered pair (ξ, τ), in which ξ is a state or value of a random variable and τ is a time interval associated to the change of state of the random variable. Σ defines the set of states or values of the random variable and Θ defines the set of time intervals associated with the random variables. One of the states in Σ is considered as initial state.

In a TNBN each temporal node is connected by at least by one arc. Intuitively each arc represents a causal–temporal relationship between temporal nodes.

Definition 2. The joint probability distribution for the temporal nodes (Π) is defined by the probability of each ordered pair (value of the node) given the values of its parents and the a priori probability for root nodes (without parents).

As each temporal node is defined by a time interval, it is possible to generate a set of qualitative temporal relationships based on the thirteen relations of interval algebra (Allen, 1983). Formally a set of temporal relationships between each pair of temporal node is defined as follows:

Definition 3. A qualitative temporal relationship (TR) describes a relation between two temporal nodes $A(\xi a, \tau a)$ and $B(\xi b, \tau b)$ where A is considered the 'cause' and B is considered the 'effect'. Formally, a TR is written as $A(\Phi)B$ where Φ is the set of qualitative temporal relationships between two temporal nodes based on the thirteen relationship defined by the interval algebra.

Φ is defined by the 13 temporal relations of Allen's interval algebra $\{b, b_i, m, m_i, o, o_i, s, s_i, d, d_i, f, f_i, e_q\}$. These relations constitute a set of temporal constraints that help to validate the consistency of the model and facilitate the acquisition of the quantitative temporal knowledge of the domain (probabilities).

Finally, a TNBN is a directed acyclic graph with a finite set of temporal nodes and a finite set of temporal–causal relationships.

Definition 4. A Temporal node Bayesian network (TNBN) is a 4-tuplet, TNBN = (ξ, τ, Φ, Π), where:

ξ is a set of states or values for each random variable.
τ is a set of time intervals associated with each change of state or value of the random variables.
Φ is the set of qualitative temporal relationships between the time intervals that define each temporal node.
Π is the set of a priori probabilities for root temporal nodes and the set of conditional probability distributions for the other.

3.1. An example of TNBN application

This section shows the use of TNBN as a model to solve a temporal reasoning tasks applied to the operation of a fossil power plant. As an illustrative example, we present the drum level disturbance when a power load increment occurs. 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. Fig. 1 shows a simplified diagram of a drum system in a fossil power plant. One of the main problems in the drum is to maintain the level for safe operation.

For purpose of the example, assume the following hypothetical case. The drum is a tank with a steam valve at the top, a feedwater valve at the bottom and a feedwater pump which provides water to the drum. When an augmentation in the current of the feedwater pump occurs, the feedwater flow inside the drum tank increases. This could lead to an increase in the drum level to a dangerous level. The control system must open the steam valve in order to increase the steam flow. This will lead to a reduction of the water level in the drum tank so that the level will decrease to safe levels. Another cause of an increase of the feedwater flow is the increase in the opening of the feedwater valve. This will also lead to an increase in the drum level to a dangerous level, but this increase takes more time to occur.

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 a *disturbance*. In the example, the feedwater flow increase (FWF) can be caused by two different disturbances, a power load increment or a control system failure. These disturbances are characterized respectively by the FW pump current augmentation (FWP) and FW valve opening increase (FWV), see Fig. 1. To determinate which of both disturbances are present is a complicated task. We need additional information to determine which is the real cause. One of these is temporal information. We can select the hypothesis of failure according to the time interval in which the event occurs. In order to reason about the sequence of facts and disturbances that occur, we require a temporal representation.

The process dynamics can provide important temporal information about the relation between events. For instance, the dynamics of the FW pump (FWP) is faster than the dynamics of the FW valve (FWV). When a FW pump current augmentation occurs the FW flow increase (FWF) is detected 1 minute 30 secs later and when a FW valve opening increase occurs the FW flow increase (FWF) is detected 2 minutes 30 secs later. Also, the steam valve increase (STV) is detected 1 min after the current augmentation

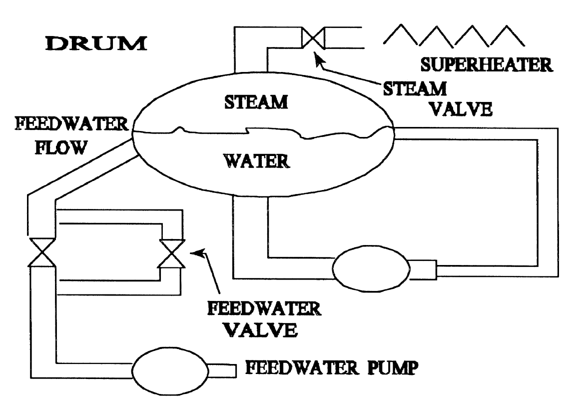

Fig. 1. Steam generator drum system.

and the drum level high condition (DRL) is detected 6 min after the FW flow increase detection.

According to the temporal information, a net with five temporal nodes forms the temporal Bayesian network for this example: two root nodes (feedwater pump current augmentation and feedwater opening valve increase), one intermediate node (feedwater flow increase) and two leave nodes (steam valve increase and drum level high condition). Each temporal node of the network has two times intervals. The definition of each time interval is according to the temporal information of the process. Using definition 1 each temporal node can be defined as follows:

Feedwater pump	FWP = {(true, [0:30–1:30]),(true,[1:30–2:30]),(false,[0–7:30])}
	Σ_{FWP} = {true, false}
	Θ_{FWP} = {[0:30–1:30], [1:30–2:30], [0–7:30]}
Feedwater valve	FWV = {(true,[1:30–2:30]),(true,[2:30–3:30]),(false,[0–7:30])}
	Σ_{FWV} = {true, false}
	Θ_{FWV} = {[1:30–2:30], [2:30–3:30], [0–7:30]}
Feedwater flow	FWF = {(true,[0:30–2:00]),(true,[2:00–3:30]),(false,[0–7:30])}
	Σ_{FWF} = {true, false}
	Θ_{FWF} = {[0:30–2:00], [2:00–3:30], [0–7:30]}
Drum level	DRL = {(true,[4:30–6:00]),(true,[6:00–7:30]),(false,[0–7:30])}
	Σ_{DRL} = {true, false}
	Θ_{DRL} = {[4:30–6:00], [6:00–7:30], [0–7:30]}
Steam valve	STV = {(true,[0:30–1:00]),(true,[1:00–2:00]),(false,[0–7:30])}
	Σ_{STV} = {true, false}
	Θ_{STV} = {[0:30–1:00], [1:00–2:00], [0–7:30]}

Where true means the event's occurrence and the temporal range of interest is from 0–7 minutes 30 secs. A temporal node has associated a probability distribution for its time of occurrence, where time is discretized in a finite number of temporal intervals, allowing a different number of intervals for each node and different duration for the intervals within a node (multiple granularity). For instance, the table of the conditional probability matrix for the temporal node FW flow increase (FWF) is shown in Table 1 and Fig. 2 depicts the temporal nodes Bayesian network for the drum level system with the a priori probabilities for each temporal node.

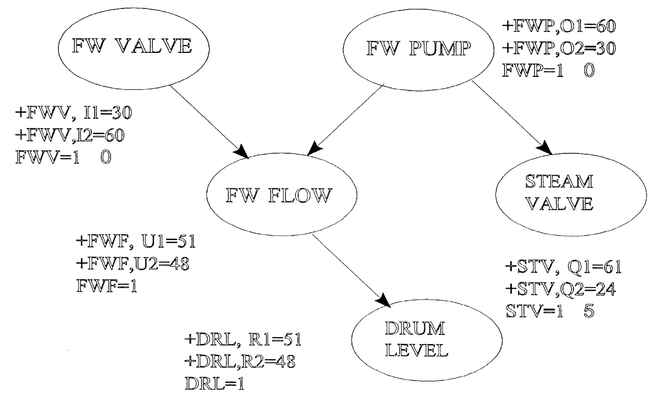

Fig. 2. Temporal node Bayesian network for drum level example.

TNBN can be seen as a natural extension of Bayesian networks, so the properties of TNBN are parallel to the properties of BN. The inclusion of time intervals into the network is unconstrained. However, it is necessary to make a trade off between the temporal expressiveness and the complexity. An advantage of this kind of representation is the ability to predict and diagnose events and the time interval of their occurrence. Given this model, we can reason about the probability of occurrence of certain events using standard probability propagation techniques developed for Bayesian networks. This consists of instantiating the input temporal variables (this can be any variable in the network)

Table 1
Conditional probabilities for FW flow increase node.

FW pump	True [0:30-1:30]	True [1:30–2:30]	False [0–7:30]
FW valve	True [1:30–2:30]		
True [0:30–2:00]	0.70	0.40	0.10
True [2:00–3:30]	0.30	0.60	0.90
False [0–7:30]	0	0	0
FW valve	True [2:30–3:30]		
True [0:30–2:00]	0.60	0.25	0
True [2:00–3:30]	0.40	0.75	0.9990
False [0–7:30]	0	0	0.001
FW valve	False [0–7:30]		
True [0:30–2:00]	0.999	0.90	0.001
True [2:00–3:30]	0.001	0.05	0
False [0–7:30]	0	0.05	0.999

and propagating their effect through the network to update the probability of the hypothesis variables (diagnosis and prediction). The reasoning mechanism starts when a temporal variable is instantiated and the probability distribution of all temporal nodes is updated. In the next section, we present the preliminary results obtained by using the temporal Bayesian network model for the power load increment and level control system failure in the drum.

4. Experimental results

In order to demonstrate the utility and application of the temporal node Bayesian network for representing dynamic domains, we present in this section the diagnosis and prediction of events when a power load increment or when a control system failure occurs in the steam generator drum system. According to the example depicted in Section 3, there are two possible causes of an increase in the FW flow (FWF): a FW pump current augmentation (FWP) and a FW valve opening increase (FWV). Each one is characterized by a power load increment and by a control system failure. We present four experiments. The first experiment shows the events prediction when a FW pump current augmentation (FWP) occurs. The second experiment shows the events prediction when a FW valve opening increase (FWV) occurs. The third experiment presents the events diagnosis when a drum level condition occurs in both time intervals. The fourth experiment shows the events diagnosis and prediction when a FW flow increase is detected.

4.1. Experiment 1: prediction

For the case of event prediction, the analysis begins when some event is detected. Suppose that a FW pump current augmentation (FWP) is detected at time 17:40:00 (17 hours, 40 minutes), see Fig. 3. According to the temporal information, the next event, the FW flow increase (FWF), can occur at the next minute. To confirm which is the time interval, we require the time of occurrence of the next event, in this case the FW flow increase (FWF). Now suppose that FW flow increase (FWF) occurs at time 17:41:05 (17 hours 41 minutes and 5 secs). Propagating the temporal evidence, we obtained that the drum level high condition might occur in the time interval 17:45:35 to 17:45:05 with a probability of 95%. Hence, the time interval for FW pump current augmentation (FWP) is the difference of the times of occurrence of both events $\alpha = (t_{FWP} = t_{FWP}) = 1$ minute 5 secs. The difference corresponds to the first time interval. Propagating the temporal evidence, we obtained that the drum level high condition might occur in the time interval 17:45:35 to 17:45:05 with a probability of 95%. This event occurence may be characterised by a power load increment.

4.2. Experiment 2: prediction

Now suppose that FW valve opening increase (FWV) is detected at time 17:20:00. This is an initial event and according to the temporal information, it is expected the next potential event, the FW flow increase (FWF), occurs 2:00 minutes later. Assume that a FW flow increase (FWF) is detected at time 17:22:30. Hence the time difference of the events occurence is 2 minutes 30 secs, this corresponds to the second time interval. Propagating the temporal evidence, we obtained that the drum level high condition might occur in the time interval of 17:28:30 to 17:30:00, with a probability of 95%. This event occurence may be characterised by a control system failure. Fig. 4 depicts the propagation of evidences for this case.

4.3. Experiment 3: diagnosis

For diagnosis, the inference mechanism gives the most probable cause of a disturbance. The analysis begins when some event is detected. Suppose that a drum level high condition (DRL) is detected at 17:50:45. Assume that the event occurs in the first time interval, then the most probable cause is a FW pump current augmentation (FWP) with a probability of 76% (see Fig. 5). If the event occurs in the second interval, then the most probable cause is a FW valve opening increase (FWV) with a probability of 70% (see Fig. 6).

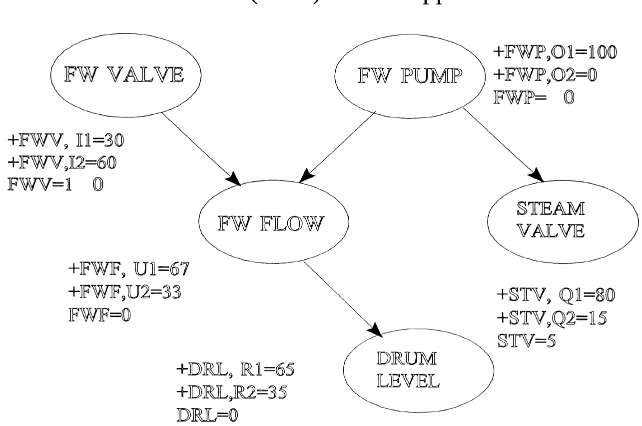

Fig. 3. The FW pump current augmentation occurs at the first time interval.

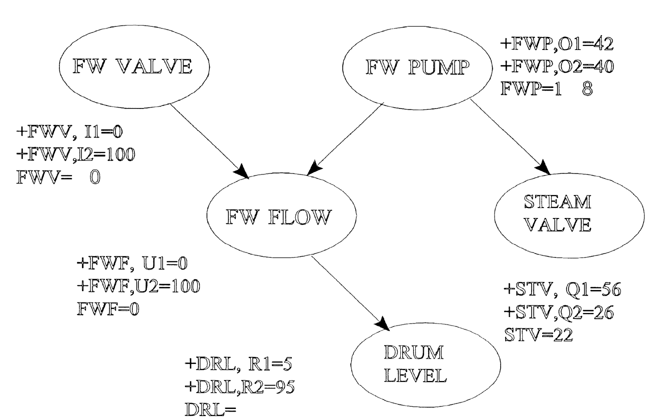

Fig. 4. The FW valve opening increase and the FW flow increase occur at the second time interval.

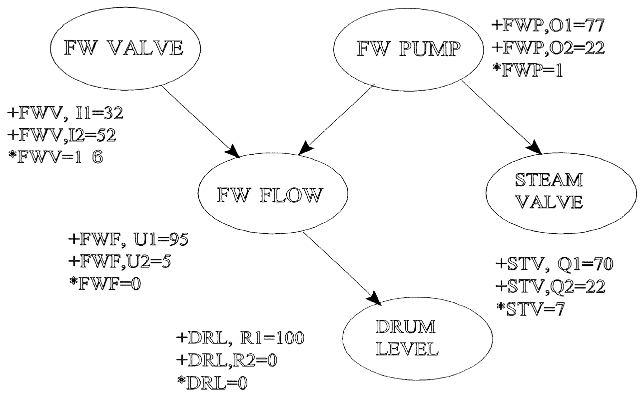

Fig. 5. The drum level high condition occurs at the first time interval.

4.4. Experiment 4: prediction and diagnosis

With this formalism it is possible to predict and diagnose events at the same time. Suppose that at time 17:42:35 a FW flow increase (FWF) is detected. Assume that the drum level high condition (DRL) occurs at time 17:47:55, this time of occurrence corresponds to the first time interval of the drum level high condition (see Fig. 7). Hence, the most probable initial event is a FW pump current augmentation (FWP) with a probability of 79%. Now, suppose that the drum level high condition (DRL) is detected at time 17:49:00, in the second interval, then the most probable cause is a FW valve increase with a probability of 72%. This reasoning mechanism makes it possible to answer queries about the probability that an event takes place over a time interval, such as the drum level high event occurred 1 minute 30 secs after the feedwater flow increase occurred. What is the most probable disturbance (cause)?

These experiments show the advantages of using temporal information for diagnostic and prediction tasks in industrial plants. This information is important for situations in which the operator must take the best control action. The prediction of variable state changes and their time of occurrence are fundamental for early diagnosis of the disturbances in fossil power plants. The proposed temporal probabilistic model has also been applied in other dynamic domains, such as medical diagnosis, with promising results [Arroyo-Figueroa and Sucar, (1998)]. We consider that TNBN can be used for temporal reasoning tasks under uncertainty that involve prediction and diagnosis in real time complex environments.

5. Related work

Significant research has been done exploring probabilistic networks that are evaluated at each point in time. 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. The ‘time net’ of Kanazawa (Kanazawa, 1991) is a kind of Bayesian network based on a formal declarative semantic. Events are considered to occur at an instant of time, while facts are considered to occur over a series of time points. The ‘dynamic belief networks’ (DBN) (Nicholson and Brady, 1994) consider a dynamic Bayesian network where the network has certain structure at time t_i and a different structure at time $t_i + 1$. The DBN is built dynamically, reflecting the dynamic changes in the environment. The network of exogenous events and endogenous changes (Hanks et al., 1995) is a probabilistic model for reasoning about the system as it changes over time. An exogenous event generally refers to an instantaneous change in the process state. Endogenous changes are modelled 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.

Other authors propose the use of time intervals as the primitive temporal notion. Santos (1996) proposed a model based on the ‘temporal abduction problem (TAP)’. In the TAP, each event has an associated interval during which the event occurs. Relationships between events are expressed as directed edges from cause to effect. The TAP

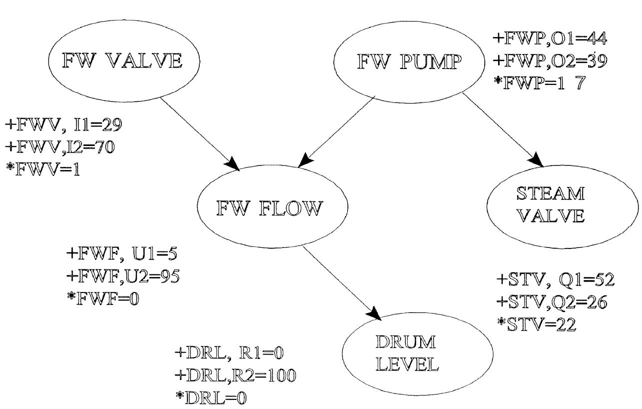

Fig. 6. The drum level high condition occurs at the second time interval.

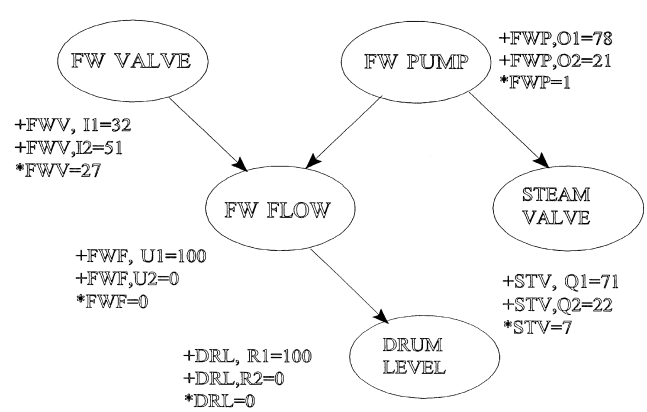

Fig. 7. The FW flow increase and the drum level high condition occur at the first time interval.

has strong interval-based temporal semantics, but lacks strong probabilistic semantics. Later, Santos and Young (1996) proposed a new model, the 'probabilistic temporal network (PTN)'. Bayesian networks provide the probabilistic basis for the management of uncertainty. Allen's interval algebra and its thirteen relations provide the temporal basis (Allen, 1983). 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). These approaches are based on time-intervals and consider the temporal relationships between events. The time-constrained models provide a trade off between both strong uncertainty and temporal semantics, but the models are difficult to apply to real time environments because of their computational complexity.

Aliferis and Cooper (1996) proposed an extension of Bayesian networks called modificable temporal Bayesian networks with single-granularity (MTBN-SG). 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. As indicated by their 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 represent recurrence and feedback. This model provides an expressive representation of temporal and atemporal information. The main problems with this model are that it is not compatible with standard Bayesian networks and that it only supports a single granularity for the size of the time step. Extending the model to support multiple granularity appears problematic, it is difficult to combine two events with different time ranges. Also, the acquisition of quantitative information appears a big problem because of the excessive number of probabilities required.

In summary, previous probabilistic temporal models are, in general, based on variable states that are replicated at different times. A static probabilistic model of the system is built and replicated at various time points and directed temporal links are drawn between nodes of the different 'static' slices. The resulting models are 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 TNBN 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 a different number of temporal intervals for each node and a different duration for each interval within a node.

6. Conclusions and future work

This paper presented the definition and application of an approach for dealing with uncertainty and time called temporal nodes Bayesian network (TNBN). A TNBN 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 seen as a trade off between the complexity and the accuracy needed for depicting the knowledge of the domain. 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.

Although many BN variants have been introduced for temporal modelling, we believe that the TNBN is a good candidate for diagnosis and prediction of events in real complex environments, such as industrial diagnosis. 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. It also facilitates temporal knowledge acquisition and allows efficient inference using standard probability propagation techniques. The formalism satisfies the requirements of temporal knowledge acquisition, low computational cost and temporal expressiveness.

In order to demonstrate the ideas present in the article, the formalism was applied to the diagnosis and prediction of events and disturbances during the operation of the drum of a fossil power plant. The results are consistent with the event occurrence of the real plant and they show the necessity to model temporal concepts in this type of domain. The formalism could help to improve power plant availability through early diagnosis of events and disturbances.

Our future work will focus on developing and validating our approach with additional experiments on prediction and diagnosis of events in real-world applications, such as medical diagnosis and industrial process diagnosis. We are also developing a temporal knowledge acquisition mechanism and an intelligent diagnostic system shell applied to fossil power plants for the operators to evaluate it.

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