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SADEP—a fuzzy diagnostic system shell—an application to fossil power plant operation

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Abstract

Artificial Intelligence applications in large-scale industry, such as fossil fuel power plants, require the ability to manage uncertainty and time. In these domains, the knowledge about the process comes from experts' experience and it is generally expressed in a vague-fuzzy way using ill-defined linguistic terms. In this paper, we present a fuzzy expert system shell to assist an operator of fossil power plants. The fuzzy expert system shell, called SADEP, is based on a new methodology for dealing with uncertainty and time called Fuzzy Temporal Network (FTN). The FTN generates a formal and systematic structure used to model the temporal evolution of a process under uncertainty. The inference mechanism for a FTN consists in the calculation of the possibility degree of the real time occurrence of the events using the fuzzy compositional rule Sup_min. A FTN can be used to recognize the significance of events and state variables with respect to current plant conditions and predict the future propagation of disturbances. SADEP was validated with the diagnosis of two detailed disturbances of a fossil power plant: a power load increment in the drum level and a water condenser pump failure. The evaluations performed in this work indicate that SADEP can potentially improve plant availability through early diagnosis of disturbances that could lead to plant shutdown.

1. INTRODUCTION

In the last 10 years the operating conditions of fossil power plants have changed. The size and complexity of power plants have increased significantly. Today, the operation of power plants must be optimal considering fuel costs and environmental regulations. As a result of these changes, the supervision and control systems of large-scale industrial plants, such as fossil power plants, are becoming more complex.

Under fault situations, the operator of the fossil power plant must interpret each measurement that is received and determine which is the condition of the equipment in order to make a proper operating decision. The complexity of the decisions that the operator is required to make is continually increasing along with the severity of the consequences of an error in judgement. In addition, the ability to respond quickly, can often be the decisive factor in the prevention of a developing malfunction.

A fossil power plant can be described by a great variety of processes interacting between state variables, events, and disturbances. In this domain, the state variables change over time in response to both internal and external disturbances as well as the transition of time itself. In the process, a signal exceeding its specified limit of normal functioning called as an event, and a sequence of events that have the same underlying cause are considered as a disturbance. During disturbances, the operator must determine the best recovery action according to the type and sequence of the signals received. Current control systems do not provide the means for intelligent interpretation of sensor data, fault diagnosis, copying with large process disturbances or predicting the consequences of control actions. In a major upset, the operator may be confronted with a large number of alarms but very limited help from the system, concerning the underlying plant condition. To understand the plant condition will require the time consuming task of analyzing the incoming data before any action is taken. As a result, there is a strong tendency to design

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supervision and control systems with artificial intelligence techniques (Shirley et al., 1990; Wong et al., 1994; Arroyo-Figueroa & Villavicencio, 1994; Cellier & Nugica, 1995; Dorr et al., 1997).

Industrial applications of artificial intelligence require the ability to manage uncertainty and reason about changes in time. Research in this area involves new knowledge representation and inference mechanism to deal with uncertainty and time. Temporal systems have the ability to reason about past, present and future events, as well as the order in which they occur (Allen, 1983). Different approaches for temporal reasoning under uncertainty have been proposed using different models (Hanks et al., 1995; Chen, 1995; Aliferis & Cooper, 1996; Santos & Young, 1996; Arroyo-Figueroa et al., 1996). Each approach is characterized for a time model and a data manipulation technique. The time-uncertainty model is usually represented by a directed acyclic graph (DAG) (Pearl, 1988). Each node represents an event that describes the state of the process while an arc between two nodes represents the transformation between two states.

In the context of fossil power plants, the knowledge of the process evolution comes from experts' experience, but this experience is generally expressed in a vague-fuzzy-imprecise way using ill-defined linguistic terms such as 'during a long period of time'. We need a technique to handle this kind of information. Fuzzy logic has shown its ability to handle uncertain knowledge and information (Zadeh, 1983; Sugeno, 1985; Zimmerman, 1985; Terano et al., 1987; Dubais & Prade, 1988; Von Altrock, 1996). Using fuzzy logic each linguistic term can be defined by a normalized possibility distribution. Moreover, the temporal relation between two fuzzy instants can be defined based on conditional possibility.

In this paper, we present the design, implementation and validation of a fuzzy expert system to assist an operator of fossil power plants. The expert system called System for Analysis and Diagnosis of Events and Disturbances (SADEP), is a Shell based on fuzzy logic to deal with time and uncertainty. Firstly, we show how fuzzy logic can deal with uncertainty and time, and present a novel methodology called Fuzzy Temporal Networks (FTN). Afterwards, we present the design and development of an expert system to assist an operator of a fossil power plant based on FTN. Finally, we illustrate its application in a fossil fuel power plant with two detailed examples. In the first example, a power load increment in the drum level is diagnosed; and in the second example, a condenser pump failure is diagnosed.

2. FUZZY TEMPORAL MODEL

In the large-scale industry, the process knowledge is usually described in a fuzzy, imprecise and vague way. Additionally, the process information is generally imprecise and incomplete, and it changes over time. These problems suggest that any successful representation should handle uncertainty and time in a principled and unambiguous way. An ideal representation would also be sound and complete, facilitate efficient inference, as well as be amenable to explanation methods.

One of the most important characteristics of fuzzy logic, proposed by Zadeh (1965), in expert systems applied to engineering, is its capacity for capturing uncertainty and understanding in human experience, with regard to the description and operation of a process (Zimmerman, 1996). These positive properties of fuzzy logic suggest building a technique for uncertainty–time modeling. The uncertainty in the experts' knowledge about the temporal evolution of process and the occurrence of events can be represented and handled using fuzzy logic and possibility theory.

A representation for handling uncertainty and temporal reasoning using fuzzy logic was proposed by Chen and Terrier (1993). Their approach consists in to extend the possibility theory in order to include temporal reasoning. Chen and Terrier defined a fuzzy instant by a possibility distribution. The distance between two fuzzy instants is also characterized in terms of another possibility distribution. Two numerical measures, possibility and necessity are defined to determine relations between two instants. The temporal distance between two instants describes the time delay between the occurrence of two events. For temporal reasoning, Chen and Terrier proposed a temporal expression evaluation, which consists of computing the degree of satisfaction of a real measurement value with fuzzy linguistic terms.

We propose a novel methodology called Fuzzy Temporal Network (FTN) based in the work of Chen and Terrier. A FTN is a graphical representation (DAG) for dealing of uncertainty and time. A FTN shows the expert's knowledge and experience over the process evolution. In the net a node describes an event (fact) and an arc describes a temporal numerical relation between two nodes (events). A FTN is a formal and systematic structure used to model the temporal evolution of a process with uncertainty. The principal characteristic of the FTN is its capacity to handle temporal linguistic expressions about the occurrence of events. These linguistics expressions are represented using possibility distributions that they can be built using process data.

2.1. Definition of a FTN

In this section we will formalize the components of a FTN.

Definition 1. A FTN is defined as $FTN=\{Tn,Tr,J,\alpha,\Phi,\lambda\}$, where each of the components is described as follows.

Definition 2. A Tn (temporal network) is a directed acyclic graph composed by nodes and arc with three types of variables.

Definition 3. The first type of variable is a *process variable* that belongs to an observable (directly or indirectly) phenomena. A process variable can be associated with a time point (event) or a time interval (fact). A fact variable has a continuous value at each time within the temporal range of the model. This time can be specified or not, and can only be constrained by causal associations of the fact variable with others variables in the model. The set of all process variables is denoted by *N*. Each process variable is represented by a node with a symbolic name.

Definition 4. The second type of variable is a *causal variable* (also called an 'arc variable') that corresponds to causal mechanisms between variables. The set of all causal variables is denoted by *P*. In the graph, casual variables are represented by an arc between two process variables. A causal variable can take two feasible values: active or inactive. The mechanism of inference in the network establishes the activation of the causal variables.

Definition 5. The third type of variable is a *temporal variable*, corresponding to the time between two process variables: N_i (the cause) and N_j (the effect). The set of temporal variables is denoted by β. Every temporal variable is represented in the graph as a square node associated with an arc.

A process variable, for its place at the temporal network, can be initial, terminal or intermediate and for its relation with others variables can be immediate or adjacent.

Definition 6. A process variable is called *initial* if it does not have any incoming arcs (causal variables). A process variable is *terminal* if it does not have any outcoming arcs (causal variables). Otherwise a process variable is called *intermediate*.

Definition 7. A process variable N_j is called *immediate variable* with respect to another variable *Ni* if there is a causal variable from N_i to N_j.

Definition 8. A process variable N_i is called *adjacent* of N_j with respect to N_k if N_k is *immediate variable* to N_i and also to N_j.

Definition 9. A temporal range is defined as $Tr=[t_1,....,t_n]$, where t_1 is the initial point of interest and t_n is the last point of interest.

Definition 10. α is defined as a real time occurrence function of the process variable.

Definition 11. *J* is the possibility distribution of the fuzzy linguistic terms between two process variables. Each linguistic term associated to a temporal variable can be described by a possibility distribution.

Definition 12. Φ is defined as the *possibility degree* associated to the corresponding process variable or causal variable. The value is between 0 and 1.

Definition 13. λ is the threshold of possibility degree pre-defined by operators. In practice, when λ becomes too low over a process variable, the reasoning stops.

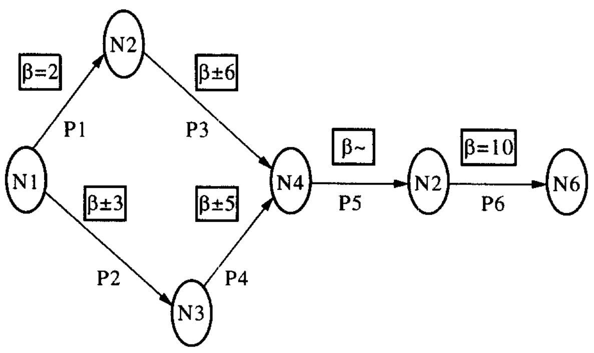

FIGURE 1. FTN for the drum level system.

2.1.1. An Example of a FTN. In this section we give an example of using a FTN model to represent and apply temporal knowledge. Figure 1 presents a small FTN that captures part of the causal and temporal knowledge about an industrial process. Table 1 gives the specification for the FTN of the example and Table 2 gives the possibility distributions associated with each temporal variable. The model is based on the following knowledge obtained from an expert operator of a fossil fuel power plant:

"If the *drum level* is **high** and the *pressure in the drum* **increases** several minutes later, look for about 5 min

TABLE 1
Parameter and variable specifications for the FTN of Fig. 1

Temporal range=1–20 min, Temporal unit=min

VARIABLES:

- a) Process variables:
  - Events:
    - N1 *augmentation in the current of feedwater pumps*
    - N2 *increase in the opening of feedwater valve*
    - N3 *increase of the feedwater flow*
    - N5 *increase in the pressure in the drum*
  - Facts:
    - N4 *drum level high*
    - N6 *drum level normal*
- b) Causal variables:
  - P1=[N1→N2]
  - P2=[N1→N3]
  - P3=[N2→N4]
  - P4=[N3→N4]
  - P5=[N4→N5]
  - P6=[N5→N6]
- c) Temporal variables:
  - β(P1)=2 min
  - β(P2)=about 3 min
  - β(P3)=about 6 min
  - β(P4)=about 5 min
  - β(P5)=several minutes
  - β(P6)=10 min

NODES:

- a) Initial process variable [N1]; Terminal process variable [N6].
- b) Immediate process variable: N1=[N2,N3]; N2=[N4]; N3=[N4]; N4=[N5]; N5=[N6]
- c) Adjacent process variable: N2=[N3]; N3=[N2]

TABLE 2
Temporal possibility distributions for the FTN of Fig. 1

$\mu_{2\,\mathrm{min}} =$	$\begin{cases} 1 \text{ If } t=2 \\ 0 \text{ Otherwise} \end{cases}$
$\mu_{\mathrm{about}\,3\,\mathrm{min}} =$	$\begin{cases} 1 \text{ If } 12.75 \geq t \leq 3.25 \\ -1/0.75(t)+4/0.75 \text{ If } 3.25>t\leq 4 \\ 1/0.75(t)-2/0.75 \text{ If } 2\geq t<2.75 \\ 0 \text{ Otherwise} \end{cases}$
$\mu_{\mathrm{about}\,6\,\mathrm{min}} =$	$\begin{cases} 1 \text{ If } 5.75 \geq t \leq 6.25 \\ -1/0.75(t)+7/0.75 \text{ If } 6.25>t\leq 7 \\ 1/0.75(t)-5/0.75 \text{ If } 5\geq t<5.75 \\ 0 \text{ Otherwise} \end{cases}$
$\mu_{\mathrm{about}\,5\,\mathrm{min}} =$	$\begin{cases} 1 \text{ If } 4.75 \geq t \leq 5.25 \\ -1/0.75(t)+6/0.75 \text{ If } 5.25>t\leq 6 \\ 1/0.75(t)-4/0.75\text{If } 4\geq t<4.75 \\ 0 \text{ Otherwise} \end{cases}$
$\mu_{\mathrm{several\ minutes}} =$	$\begin{cases} 1 \text{ If } 1.75 \geq t \leq 2.25 \\ -1/0.75(t)+3/0.75\text{If } 2.25>t\leq 3 \\ 1/0.75(t)-1/0.75 \text{ If } 1\geq t<1.75 \\ 0 \text{ Otherwise} \end{cases}$
$\mu_{10\,\mathrm{min}} =$	$\begin{cases} 1 \text{ If } t=10 \\ 0 \text{ Otherwise} \end{cases}$

before an **increase** of *feedwater flow* preceded by an **augmentation** in the *current of the feedwater pumps* about 3 min before detection of increase of feedwater flow. Another confirmation can be found if the *opening of feedwater valve* **increases** 2 min after the **augmentation** in the *current of the feedwater pumps* and about 6 min before the high drum level. In this case, it is expected that 10 min after, the increasing of pressure in the drum, the level drum of steam generator will become normal."

2.2. Evaluation of a FTN

The inference mechanism for FTN is described in this section. A FTN can be applied to supervision, diagnostic and prediction tasks. The reasoning mechanism is based on the calculation of the temporal distance between two fuzzy instants. A numerical measure, possibility degree, has been defined to determinate these relations. The inference mechanism over the FTN is achieved by the calculation of the possibility degree of each node given the occurrence of some events.

The possibility degree is calculated for each node and arc based on the real occurrence of an event(s). It is supposed that there is not uncertainty over detected events. This hypothesis implies that for all initial nodes, their possibility degree value is one once the correspondent event has been detected. For intermediate and terminal nodes the calculation of the possibility degree is obtained by the fuzzy compositional rule sup_min

For an arc(causal variable) the possibility degree $\Phi(P_i)$ is calculated by:

$$\Phi(P_i)=\min(\Phi(N_j),MD\pi)$$

where P_i is the causal variable between the node N_j (the cause) and N_i (the effect), $\Phi(N_j)$ is the forward possibility degree (cause node) and MD_Π the membership degree of the real time occurrence of the node N_i (the effect).

For a node (process variable), the possibility degree $\Phi(N_i)$ is calculated by the superior of all possibility degrees of the arcs $\Phi(P_i^N)$ that arrive to the node N_i (the effect):

$$\Phi(N_i)=\mathrm{Sup}(\Phi(P_i^1),....,\Phi(P_i^N))$$

In the net, we have three states related with the process variables (nodes): active, when the event has been detected; potentially active, when the event would be detected in the next time interval; and non-active, when the event has not been detected.

There are three possible ways to terminate the propagation: (1) when a terminal node is reached; (2) when the possibility degree value is lower than a threshold (λ); and (3) when there are not immediate nodes in the way. The threshold determines the delay permitted in the network and it is pre-defined by the operator.

We can identify three main steps in the procedure: (1)detection of the event occurrence; (2)determination of the possibility degree of the arcs $\Phi(P_i)$ and the nodes $\Phi(N_i)$; and (3) propagation of the possibility degree through the net until the termination conditions are satisfied.

3. IMPLEMENTATION OF SADEP

SADEP is a computer tool for building, validating and running FTN (Solis, 1997). SADEP can be used to recognize the significance of events and state variables in relation to current plant conditions and predict the future propagation of disturbances. The computer tool allows the semi-automatic building of a FTN. To construct a FTN the knowledge engineer should specify the parameters associated to each one of the nodes and the possibility distributions to each one of the arcs. These possibility distributions can be generated by process data. SADEP also facilitates the validation of the FTN. The process values of the nodes can be read from the keyboard as requested by the system. Further, the system allows the on-line application of the net. The process values of the nodes can be read from a data acquisition system.

Structurally, SADEP has five main modules: the knowledge base; the consultation objects; the fuzzy temporal inference engine; the plant data acquisition and the man-machine interface. SADEP has been programmed in C++ under Windows 3.1 on a PC Pentium, using a structural methodology for analysis and design. The architecture of SADEP is shown in Fig. 2.

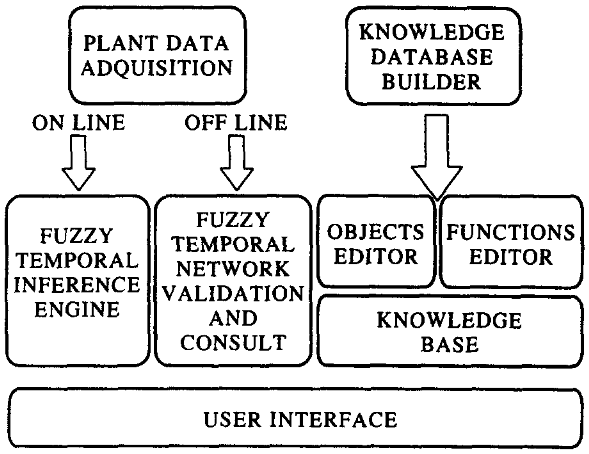

FIGURE 2. Architecture of SADEP.

3.1. The Knowledge Base

The knowledge base in SADEP is organized as objects and functions. Each class of objects is defined by its attributes. A node is an object that represents an event or fact (description of a process variable) and an arc is an object that represents the temporal relation between two events. The functions are the possibility distributions. Each fuzzy linguistic term is modeled by one of the three kinds of possibility distribution functions: triangular, trapezoidal or cosine.

The purpose of the knowledge base builder is the semi-automatic construction of the fuzzy temporal net. Hence, the knowledge base builder has two editors; the object editor, for events and arcs, and the possibility distribution functions editor. The object editor defines the network structure: number of nodes (events), description of the events, and description of the temporal relations between events. The functions editor defines the possibility distributions, these functions represent the temporal aspect of the net by fuzzy linguistic terms. Each module has a friendly man–machine interface.

3.2. Object Consultation

This module has the purpose of showing the information of any node or arc in the FTN. It facilitates the analysis and validation of the information of each object in the net. Once that the net is built with the object and function editors, it is possible to modify the structure, whether adding or eliminating nodes. On the other hand, in a similar manner, it shows the information with regard to the operative state of a node when SADEP is in the on-line operating mode.

3.3. Fuzzy Temporal Inference Engine

The real-time inference engine in SADEP reasons about the current state of the process. The reasoning formalism implemented within SADEP is the fuzzy temporal mechanism described previously. Once the knowledge base has been built, the knowledge engineer can then start the reasoning process. The inference engine operates on the network contained in the knowledge base, keyboard values (off-line operating mode) or simulated values (on-line operating mode) of the process domain. The inference engine has the following function: it evaluates the possibility degree for each node and it determines when the termination conditions apply.

3.4. Plant Data Acquisition

SADEP has two operating modes: on-line; and off-line. In the off-line operating mode, the engineer introduces the process information through the keyboard. In the on-line operating mode, the process information is obtained from a power plant simulator. The power plant simulator emulates the dynamic behavior of key state variables, such as flow, pressure and temperatures of the process equipment. The simulator is a full-scale simulator of steam power plant, called MICROTERM (Palomares et al., 1992).

3.5. Man–Machine Interface

This module has been designed for displaying the results of the supervision and diagnostic tasks. In this module, the engineer can follow the state of each node and arc in the net structure. The module shows graphical displays and a brief written description of the event occurrence until the FTN mechanism reaches the termination condition (fault). The man–machine interface has been designed in order to facilitate the dialogue between users and the system. The programming interface is based on the Application Style Guide of Microsoft Windows (Microsoft Press, 1995).

One of the most important characteristics of the SADEP is the use of a linked double list with headers for the building of the fuzzy temporal Net. Each substructure defines a specific attribute necessary for the construction of the net. The matrix dependence is a two-dimensional vector that allows the knowledge database to be built in two steps. In the first step the network structure is defined and in the second step the possibility distributions functions are defined. This structure permits the easy knowledge representation, implementation and the evaluation. Furthermore it enables the code optimization and suitable use computer memory.

4. EXPERIMENTAL RESULTS

This version of SADEP has been tested and validated using two illustrative examples taken from the operation of a power plant. In the first example, a power load increment in the drum level is diagnosed; and in the second example, a cool water pump fault in the condenser is diagnosed. Nevertheless, SADEP can be applied to different domains such as clinical diagnosis, sensor validation and other time-relevant diagnosis under uncertainty.

The evaluation of SADEP is divided into two broad categories: basic demonstration tests and exploratory tests. The objective of the basic demonstration test is to determine how SADEP behaves during situations in which the system is expected to behave well. In contrast, the exploratory test is designed to study the behavior of SADEP during non-ideal conditions.

4.1. First Experiment

The drum is a subsystem of the fossil power plant that provides steam water to the superheater and water liquid to the water wall of a steam generator. The drum is a tank with a steam water valve at the top and feedwater pumps, which provide water. One of the main problems in the drum is to maintain the level in safe operation, see Fig. 3. There are many disturbances that affect the operation of the drum level; one of them is a power load increment. To show the application of SADEP, we take the example presented in Section 2.1, the description of the disturbance in the drum level by a load increment in the fossil power plant.

The analysis is performed as follows. The selected disturbance (power load increment) is first simulated on the MICROTERM 300 training simulator. During these simulations, SADEP is actively performing its analysis and the relevant real-time performance is recorded. At the same time, all the data from the simulator that SADEP needs for its analysis is sent. The analysis begins when an augmentation in the current of feedwater is detected at time 8:00:00 (node N_1), see Fig. 4. During the test, the value of the reliability threshold is designated as 0.3. N_1 is an initial node, hence its Φ function value is 1. The mechanism continues with two potentially activated nodes, N_2 and N_3.

At $t=8{:}02{:}00$, the flow increase, N_2, is detected. The real occurrence function is $\alpha(N_2)=t_2$, where $t_2=2$ min. The Φ function for the causal variable $\Phi(P_2)$ is determined with the membership degree obtained by the possibility distribution '2 min' $MD_{P2}=1$ and $\Phi(P_2)=\min(\Phi(N_1),MD_{P2})=1$. Finally the Φ function for the process variable N_2 is $\Phi(N_2)=\sup(\Phi(P_2))=1>0.3$. The procedure continues along the route where N_2 is found. Now, the node N_4 is the potentially activated node, see Fig. 5.

The feedwater valve is opened at 8:03:30 (node N_3).

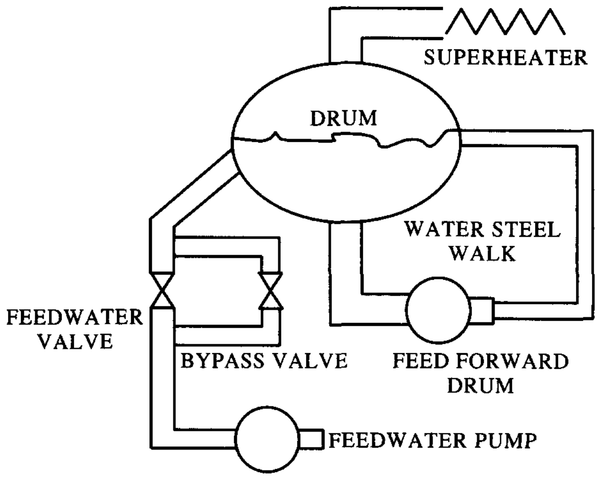

FIGURE 3. Drum level system.

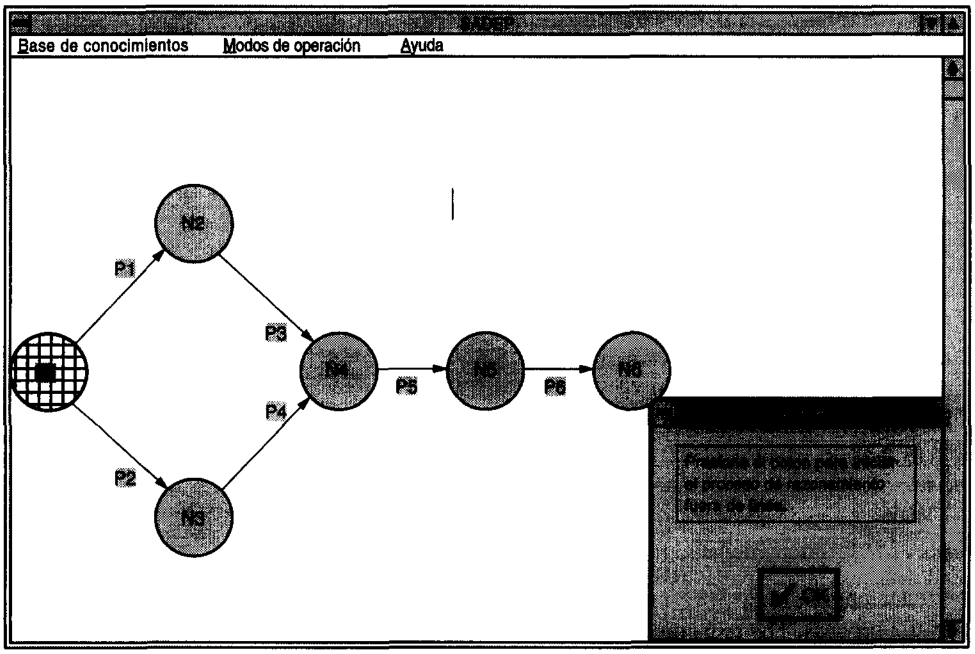

FIGURE 4. Initial step mechanism for the drum level example.

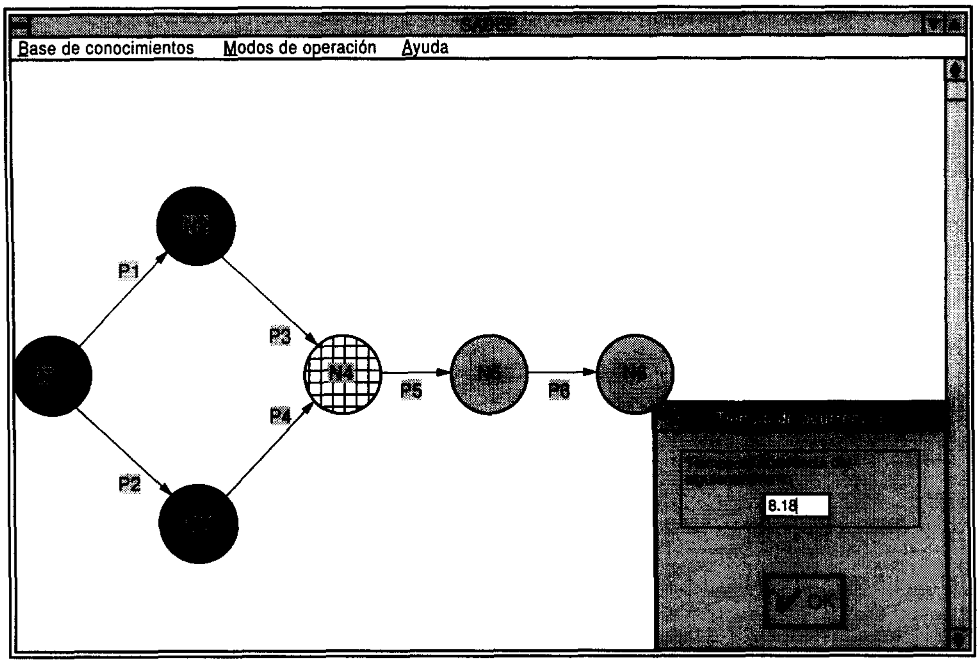

FIGURE 5. Nodes N2 and N3 activated.

The real occurrence function is $\alpha(N_3)=t_3$, where t_3=3:30 min. We determinate the Φ function for the causal variable $\Phi(P_2)$ with the membership degree obtained by the possibility distribution 'about 3 min' $MD_{P2}=0.67$ and $\Phi(P_2)=\min(\Phi(N_1),MD_{P2})=0.67$. Hence the Φ function for the process variable N_3 is $\Phi(N_3)=\sup(\Phi(P_2))=0.67>0.3$. The procedure continues along the route where N_3 is found. Now, the node N_4 is the potentially activated node, see Fig. 5.

A high drum level is detected at $t=t_1+8{:}18$ (node N_4). In this case, we have two adjacent process variables with two real occurrence function $\Phi(N_4)_{N2}=t_4$, where t_4=6:18 min and $\Phi(N_4)_{N3}=t_4$, where t_4=4:48 min. For each causal variable, its Φ function should be determined: $\Phi(P_3)=\min(\Phi(N_2),MD_{P3})=0.93$, where $MD_{P3}=0.93$ is obtained by the possibility distribution 'about 6 min', and $\Phi(P_4)=\min(\Phi(N_3),MD_{P4})=0.67$, where $MD_{P4}=1$ is obtained by the possibility distribution 'about 5 min'. Hence the Φ function for the process variable N_4 is $\Phi(N_4)=\sup(\Phi(P_3),\Phi(P_4))=0.93>0.3$. The procedure continues along the route where N_4 is found, see Fig. 6. Now, node N_5 is the potentially activate node. The reasoning procedure continues in the same way until one of the terminal conditions is satisfied.

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4.2. Second Experiment

The condenser is a subsystem of a fossil power plant that cools the steam coming from turbine to bring it back to the liquid state. Assume that the condenser is a tank with the steam valve at the top. It has an air valve which maintain the tank conditions and a water pump which provide cool water to a number of isolated steel tubes in a bundle without mixing the cool water with the steam, see Fig. 7.

Figure 8 presents a FTN that captures part of the causal and temporal knowledge about the cool water pump fault. Table 3 gives the specification for the FTN of the example and Table 4 gives the possibility distributions associated with each temporal variable. The model is based on the following knowledge obtained from an expert operator of a fossil fuel power plant and it depicts a possible cool water pump fault:

> "If the *temperature inside the condenser* tank is **high** and comes to a dangerous level, and the *pressure* in the condenser **increases** 2 min after, look several minutes before for a strict **decrease** in the *current of the cool water pump* preceded by a **decrease** in the opening of the *steam valve* 4 min after the detection of high temperature. Another confirmation of the fault can be found if the *opening of air valve increases* 5 min after the detection of high temperature. In this case, look for a **decrease** in the condenser pressure 5 min after the decrease of steam valve or 4 min after the increase of air valve. If this is the case the condenser tank **temperature** becomes normal 5 min after the detection of the pressure decrease in the tank."

In order to determine the effect of SADEP on operator performance twenty different disturbances were run, with and without the SADEP system, during regularly scheduled operator training sessions. The responses of the operators were recorded. In addition to this information, the plant parameters, alarms, controller settings and valve positions were recorded. Six different disturbances

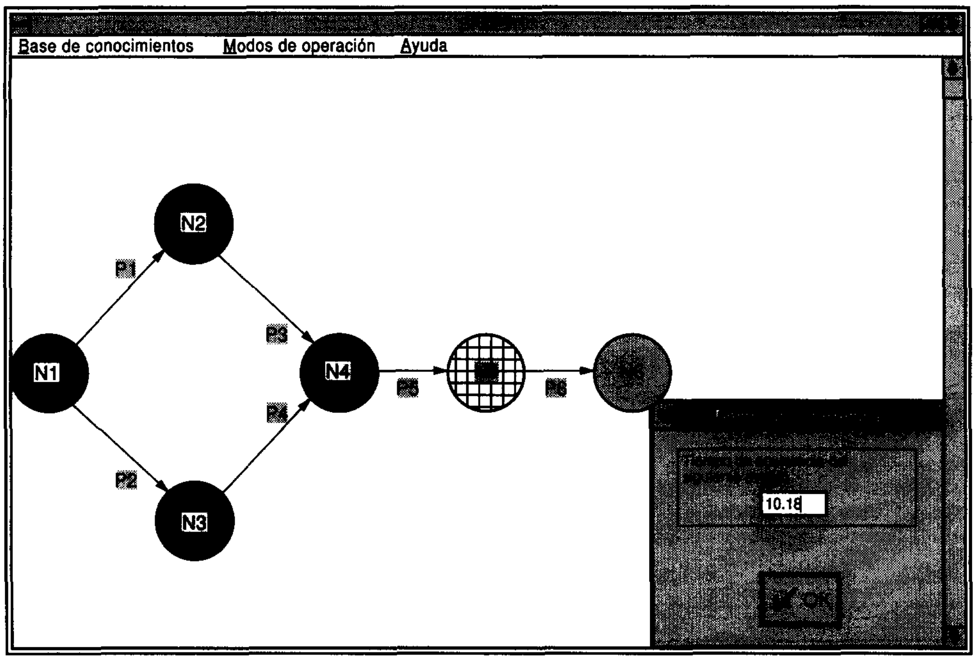

FIGURE 6. High drum level is detected.

were used for the performance evaluation. Four of these disturbances were associated with the feedwater system and two with the condenser system. The results of this performance evaluation indicated that SADEP provides

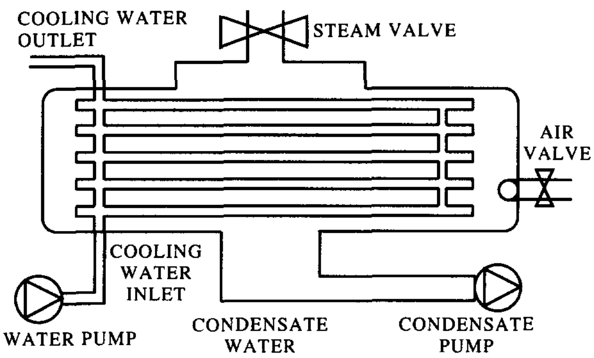

FIGURE 7. Condenser system.

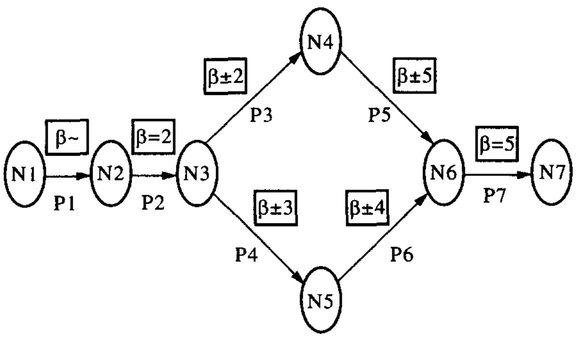

FIGURE 8. FTN for the condenser system.

TABLE 3
Parameter and variable specifications for the condenser system

Temporal range = 1–16 min Temporal unit = min

VARIABLES:

a) Process variables:

Events:

- N1 *decrease in the current of the cool water pump*
- N3 *increase in the pressure of the condenser*
- N4 *decrease in the opening of the steam valve*
- N5 *increase in the opening of the air valve*
- N6 *decrease in the pressure of the condenser*

Facts:

- N2 *temperature high*
- N7 temperature *normal*

b) Causal variables:

- P1 = [N1→N2]
- P2 = [N2→N3]
- P3 = [N3→N4]
- P4 = [N3→N5]
- P5 = [N4→N6]
- P6 = [N5→N6]
- P7 = [N6→N7]

c) Temporal variables:

- β(P1) = several minutes
- β(P2) = 2 min
- β(P3) = about 2 min
- β(P4) = about 3 min
- β(P5) = about 5 min
- β(P6) = about 4 min
- β(P6) = 5 min

NODES:

a) Initial process variable [N1]; Terminal process variable [N7].
b) Immediate process variable: N1 = [N2]; N2 = [N3]; N3 = [N4,N5]; N4 = [N6]; N5 = [N6]; N6 = [N7]
c) Adjacent process variable: N4 = [N5]; N5 = [N4]

the operators with earlier and more precise diagnosis of the disturbances that the existing alarms and instrumentation of the MICROTERM simulator. As result, it is observed that the operator is consistently able to take the proper corrective action with less of a challenge to the protection system.

5. CONCLUSIONS AND FUTURE WORK

This paper presented the design and implementation of a demonstration-type event and disturbance analysis system shell (SADEP). This system can be used to assist the operator in real-time assessment of plant disturbances and in this way contribute to the safe and economic operation of power plants. Development of SADEP was initially motivated by the desire to improve plant availability through early diagnosis of disturbances that could lead to plant shutdown.

The development of an expert framework for event and disturbance analysis has been a primary objective throughout the project. The framework is based on an extension of a new methodology for dealing with uncertainty and time called FTN. The FTN generates a formal and systematic structure used to model the temporal evolution of a process under uncertainty. The inference mechanism for a FTN consists in the calculation of the possibility degree of the real time occurrence of the events using the fuzzy compositional rule Sup_ min. This methodology has been made in terms of a C++ computer program that has been implemented on a PC Pentium computer with a man–machine interface based on the Application Style Guide of Microsoft Windows. SADEP has been elaborated using a structural methodology for analysis and design. The implementation objective was to demonstrate the technical performance of FTN methodology for a limited number of disturbances in two selected plant subsystems, the drum level feedwater system and the condenser system.

TABLE 4
Temporal possibility distributions for the FTN of condenser system

$$\mu_{\text{several minutes}} = \begin{cases} 1 \text{ If } 1.75 \geq t \leq 2.25 \\ -1/0.75(t) + 3/0.75 \text{ If } 2.25 > t \leq 3 \\ 1/0.75(t) - 1/0.75 \text{ If } 1 \geq t < 1.75 \\ 0 \text{ Otherwise} \end{cases}$$

$$\mu_{2\text{ min}} = \begin{cases} 1 \text{ If } t = 2 \\ 0 \text{ Otherwise} \end{cases}$$

$$\mu_{\text{about 2 min}} = \begin{cases} 1 \text{ If } t = 2 \\ -t + 3 \text{ If } 2 > t \leq 3 \\ t - 1 \text{ If } 1 \geq t < 2 \\ 0 \text{ Otherwise} \end{cases}$$

$$\mu_{\text{about 3 min}} = \begin{cases} 1 \text{ If } 2.75 \geq t \leq 3.25 \\ -1/0.75(t) + 4/0.75 \text{ If } 3.25 > t \leq 4 \\ 1/0.75(t) - 2/0.75 \text{ If } 2 \geq t < 2.75 \\ 0 \text{ Otherwise} \end{cases}$$

$$\mu_{\text{about 5 min}} = \begin{cases} 1 \text{ If } t = 5 \\ -t + 6 \text{ If } 5 > t \leq 6 \\ t - 4 \text{ If } 4 \geq t < 5 \\ 0 \text{ Otherwise} \end{cases}$$

$$\mu_{\text{about 4 min}} = \begin{cases} 1 \text{ If } 5.75 \geq t \leq 6.25 \\ -1/0.75(t) + 6/0.75 \text{ If } 6.25 > t \leq 7 \\ 1/0.75(t) - 5/0.75 \text{ If } 5 \geq t < 5.75 \\ 0 \text{ Otherwise} \end{cases}$$

$$\mu_{5\text{ min}} = \begin{cases} 1 \text{ If } t = 5 \\ 0 \text{ Otherwise} \end{cases}$$

The results of the performance evaluation tests indicate that the SADEP can assist the operator in responding to plant disturbances. Two types of disturbances were modelled in detail for the drum level system and the condenser system, and these were subject to testing, using data from the training simulator. The tests confirmed the ability of the SADEP to properly diagnose disturbances under abnormal situations. The primary benefits of the system are: (a) an early and precise diagnosis of the disturbances; and (b) an improvement in the timeliness of the operator's corrective action. The evaluations performed in this work indicate that SADEP can potentially improve plant availability through early diagnosis of disturbances that could lead to plant shutdown. The results of the validation show that the fuzzy expert system is successful for this domain.

At present, the fuzzy expert system is just a prototype to be tested before it is installed in a real fossil power plant. However, the prototype has shown the benefits and capability of this kind of system to diagnose fossil power plant operations. Our future work will be focused on developing and integrating our approach in a real time diagnostic system. Furthermore, the simulator test environment appears to produce more conservative results than the ones that may be observed in real plant operations.

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