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An Approach of Diagnosis Based On The Hidden Markov Chains Model

Karim Bouamrane, Amel Djebbar, Baghdad Atmani

Abstract

Diagnosis is a key element in industrial system maintenance process performance. A diagnosis tool is proposed allowing the maintenance operators capitalizing on the knowledge of their trade and subdividing it for better performance improvement and intervention effectiveness within the maintenance process service. The Tool is based on the Markov Chain Model and more precisely the Hidden Markov Chains (HMC) which has the system failures determination advantage, taking into account the causal relations, stochastic context modeling of their dynamics and providing a relevant diagnosis help by their ability of dubious information use. Since the FMEA method is a well adapted artificial intelligence field, the modeling with Markov Chains is carried out with its assistance. Recently, a dynamic programming recursive algorithm, called 'Viterbi Algorithm', is being used in the Hidden Markov Chains field. This algorithm provides as input to the HMC a set of system observed effects and generates at exit the various causes having caused the loss from one or several system functions.

Key words: Diagnosis, Markov Chain, Hidden Markov Chain (HMC), FMEA, Viterbi Algorithm.

1 Introduction

Under the effect of multiple causes as wear or deformations etc, equipment tends to worsen in the course of time. These deteriorations can fail down system operations (breakdown), decrease outputs, reduce or decrease quality and may be increase operation costs. Today, industrial materials availability control makes possible industry action on the production regularity, manufacturing costs, its competitiveness and commercial success.

Selling more and better is not only a better installation control mode proposition but also a fast owner mode intervention and installation maintenance of equipments that guaranties an optimum production satisfaction. Maintenance computerization aims to optimize reliability and equipment availability. Belavilacqua [3] shows that 80 percent of the production systems downtime, following random breakdowns is devoted to the diagnosis maintenance and only 20 percent of this time is used for repair itself. In order to satisfy the new market requirements, each enterprise must provide an identification and an effective and rapid localization of failures and their causes. Thus, each time a failure occurs, it will be identified and immediately corrected. This performance realization requires expert technician or specialized maintenance engineer supervision, knowing the equipment perfectly. Since the production process became complex, including several factors and situations, the diagnosis requires important technical skills and a great experiment, being difficult to find in only one human. For this reason, the Markov Chains are one of the tools used for the maintenance diagnosis. Article continuation is organized in four sections. Section 2 presents a diagnosis definition. Section 3 defines the various existing methods of diagnosis. Section 4 details the developed diagnosis approach. Section 5 deals with an illustrative example.

2 Definition of the diagnosis

Diagnosis is defined as a process of exact failure cause localization. Once the failure is detected, it is the responsibility of the maintenance engineer to recognize the effects, to analyze information, to interpret the various error messages and indications, and to leave with the true diagnosis of the situation in term of components having caused the failure and the reason of their failures. When the diagnosis is completed, the replacement or the repair of the component at the origin of the failure is the following defect correction stage. The companies are thus confronted with this double economic challenge:

- to increase the productivity by increasing availability of their equipments production;
- to reduce the maintenance costs.

Diagnosis methods are mainly classified according to the used knowledge type [2],[4],[9],[10],[11],[12],[13],[16],[17],[18].

3 Markovian approach for diagnosis

Among the methods of diagnosis quoted previously, we choose the diagnosis by Markov Chain and more precisely the Hidden Markov Chain (HMC) because they make it possible to deal with dubious information problem. The interest to add a hidden layer lies in the ridge in which the failing component is not directly observable. On the other hand, what are observed are the effects having generated this failure [5] [1].

3.1 Discrete time Markov Chain

It is a Markovian discrete states process where observations and states are identical. States are related by probabilistic transitions. A following Markov Chain (MC) models operation:

1. A set of states N: a finite state system where each state is represented by a node. The trajectories between states are symbolized by directed arcs. We denote n_i *the* n^{th} state visited by the system,
2. A distribution: $\pi i = P(n0 = i)$ on the initial state. With a known probability, the state can then evolve, and pass from $n_i = i$ *to* $n_{i+1} = j$. Generally, this probability depends on the sequence of states occurrence since the initial moment. But in the case of the first order Markov models, dependence stops at a previous moment n.

$$P(n_{i+1}/n_0 = i_0, \dots, n_{i-1} = i_{i-1}, n_i = i) = P(n_{i+1} = j/n_i = i) \quad (1)$$

3. The transitions probabilities of the Markov chain are specified by a matrix of transition $A = a_{ij}$

$$a_{ij} = P(n_{i+1} = j/n_i = i), \forall i, j \in n \tag{2}$$

with

$$\Sigma a_{i,j} = 1, \forall i, j \in n \tag{3}$$

Thus, the built model takes the name of Markov Chain.

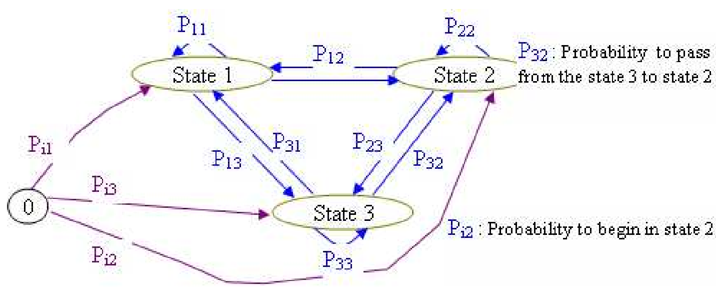

Figure 1. Markov Chain Model

Definition 1: A Markov chain is defined by: $\lambda = (N, \Pi, A)$ With N a finished spaces state, Π a probability distribution on the initial state and A the transition probabilities matrix.

3.2 Hidden Markov Chain

It is a Markov chain where the states are not the same as observations. Each state will generate an observation. It is said that the states are hidden (they are not directly observed). In a Hidden Markov Model (HMM), the states $N = (n_1, n_2, \ldots, n_n)$, are non observable, however they emit observable signals $O = (O_1, O_2, \ldots, O_n)$ which are balanced by their probability. It is characterized by:

1. The states $N = \{n_1, n_2, \ldots, n_n\}$,

2. The transition matrix $A = \{a_{ij} = P(n_j/n_i\}; \Sigma a_{i,j} = 1$

3. The initialization vector $\Pi = \{\pi_i = P(n_i)\}; \Sigma\pi_i = 1$
4. Probabilities that the state n_i emits the signal of observation o_k. They are gathered in an emission matrix $B = \{b_i(o_k) = P(o_k/n_i)\}; \Sigma a_{ij} = 1$

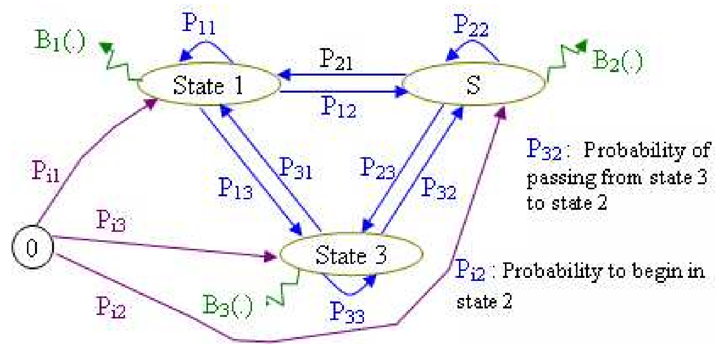

Figure 2. Hidden Markov Chain Graph

Definition 2: A Hidden Markov Chain is defined by:

$$\lambda = (N, \Pi, A, B) \tag{4}$$

With N – a finite state, Π – an initial distribution probability state, A – the transition probabilities matrix and B – the observation probabilities matrix. A Hidden Markov Chain is a Markov chain of order one with non observable states (emission of a signal) and B – the observation probabilities matrix.

3.3 Application of Markovian modeling to the diagnosis

Since Markov chains and more specifically Hidden Markov chains Model (HMM) can deal with uncertain information problems, we opted for their use as a solution for the diagnosis problem. The use of a hidden layer in our case lies in the ridge that the component failure is not directly observable. But, what were observed are effects that produced this failure. In diagnosis, the order one ergodic Markov model, figure

(3), lets any state be reached from any other one within a finite number of transitions. This type of model is more general and interesting when the model represents a following process statements evolution.

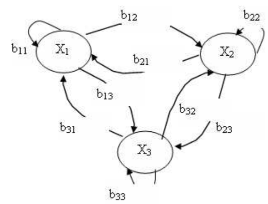

Figure 3. The Ergodic Topology

The HMM that we consider for the diagnosis has the following characteristics [6], figure (4):

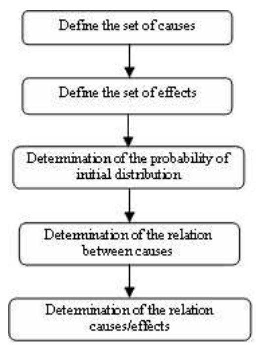

Figure 4. General diagram of Diagnosis by HMM

1. each state is a breakdown state;

2. each observation is an observed effect on the system;

3. the initial probability Π of the HMM states: this distribution on the set N of the states is supposed known; it represents the confidence which we have on the operation system;

4. the transition probabilities matrix between states: it depends on the connections of cause and effects between the breakdown states.

5. Matrix emission probabilities: it depends on the relationship between the failure effects and causes.

The diagnostic system based on the model Hidden Markov chains for an industrial process is constructed in two steps:

Step 1: Construction of the model for each system. This step is carried out using a solution of the evaluation problem and learning to estimate efficiently the optimal parameters of the model in order to maximize the probability of the observed sequence.
Step 2: Assess the following statements. This step is carried out using a solution to the problem of recognition. Once the parameters of HMM constructed and optimized, the defining of the set of statements that have caused the system breakdown is still pending.

The diagnostic system by Hidden Markov Chains works like figure (5):

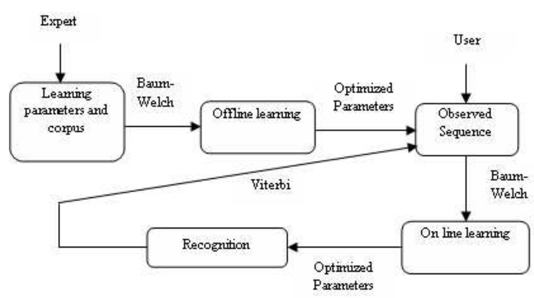

Figure 5. Diagnostic System Functioning

Phase 1: Once the various parameters associated with HMM are entered, the diagnostic system performs offline learning with a corpus of learning (sequence of observations) provided by the expert and using Baum-Welch algorithm.

Phase 2: Once the maintenance operator enters the failure of the observed effects in the system, an online learning will be done using the Baum-Welch algorithm.
Phase 3: Finally, the system will determine the sequence of the optimal failure statements in the sense of the post maximum likelihood, and this is estimated recursively by the Viterbi algorithm [8].

The approach Characteristic The Markovian approach performance depends on the system knowledge a priori richness. Indeed, the real process modeling based on HMM is effective if the model parameters are correctly estimated because the latter have a direct influence on the obtained results. The Markovian model combinative explosion phenomenon is well known: the number of states increases exponentially according to the breakdown number.

4 Illustrative example

The case study was carried out on the ANABIB[1] Company equipment in order to improve its maintainability. Indeed, being given the heavy investment in this sector, the machines often function in two teams. Any breakdown can cause non recoverable delays for the production service. In the context of an effectiveness preoccupation, we choose the most critical company equipment. It is about a machine illustrated in figure (6) which, starting from a steel reel, gives a structural shapes named "Skelp". It ensures the forming and welding operation.

We had carried out cutting of the machines into a subset and then into bodies by specifying each element functions and by using the various functional analysis methods [19] [20] [21]. Then, we were brought to identify for each body all its modes of failures, their possible causes, their respective effects and repair measurements to be applied using FMEA analysis [14]. This phase was not easy because the company does not have Computer-Assisted Maintenance and Management software.

[1]ANABIB: Public Economic Enterprise of the iron and steel sector in Algeria

Figure 6. Forming-Welding machine

The principal failures of this equipment are as follows: 1. wear ball. 2. wear bearing. 3. wear roll.

Effects observed: 1. Bad forming. 2. Oil leakage.

Since Markovian methods are used, work consists in a correct problem specification. That is done by the states set determination which represents in this case the set of the failures quoted previously, the calculus of the transition probability which is defined by the failure rate hh such as hh= 1/COAT (Correct Operation Average Time) and the calculus of appearance probability of each effect determined by the frequency factor of FMEA table. Thus, we can build:

1. The transition matrix A with the states set as lines and columns.

A =

0.3	0.5	0.2
0	0.3	0.7
0	0	1

2. The observation matrix B with the various states as lines and the observed effects set as columns.

B =

1	0
0.5	0.5
0	1

The initial probabilities vector Π such as $P(\pi_i) = 1/\text{numbers of}$ causes.

Π =

0.33
0.33
0.33

If we supposed that the observed sequence O = bad forming, bad forming, oil leakage, oil leakage after application of the Viterbi algorithm, we obtained:
- The matrix δ :

δ =

0.33	0.09	0	0
0.16	0.08	0.02	0.03
0	0	0.05	0.05

- The matrix ψ :

ψ =

0	0	0	0
0	0	0	1
0	1	1	2

- The sequence of states having generated $N*$ is wear ball, wear roll, wear bearing, wear bearing.

5 Conclusion

In the new economic context, the survival of small, average and large company depends on their ability to maintain their productivity. To achieve this goal, the company is brought to control the system production and to improve products quality.

We discussed in this article the necessary tool to develop a Markov Chain diagnostic system and more particularly the Hidden Markov chain model. We proposed the hidden Markov chain model in order to be able to mitigate the difficulties related to the realization of a diagnosis system. Indeed, the use of an FMEA analysis for Markovian modeling makes it possible to facilitate the construction of the used model for the diagnosis.

The FMEA Analysis for the presentation of the effect/cause relations as for the determination of the probabilities of the signals emitted by the various considered states and the HMM adapted to take into account of incomplete and dubious information makes it possible to obtain coherent results and to provide a relevant help to the diagnosis.

Finally, the use of the Viterbi recursive dynamic programming algorithm enabled us to determine the failures sequence affecting the system. From a prospective point of view, this work will continue with the development of various tools for diagnosis quoting the Bayesian networks and the expert systems in order to determine the most relevant tool by using a multi criterion method for outclassing using various criteria such as the response time, the development cost.

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Karim Bouamrane, Amel Djebbar,
Baghdad Atmani

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Computer Science Department,
Faculty of Science, University of Oran,
BP 1524 El M'Naouer 31000 Oran, Algeria;
E–mail: *bouamrane.karim@univ − oran.dz*, *bbatmani@yahoo.fr*