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A FUZZY APPROACH OF THE OPTIMAL ANALYSIS BASED OF FAILURE STATES IN MANUFACTURING SYSTEMS

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Abstract: This article proposes an algorithm for prognosis in optimal analysis of manufacturing systems. Uncertain knowledge of such task requires for specific reasoning and adaptive model base of fuzzy logic analyzes. The proposed method performs the interfaces between the results provided by the fuzzy supervision model and the algorithm witch identify the real state of the monitored system. The supervisory system sends failure signals described in a fuzzy approach. These ones represent inputs values in the system of failure optimal analysis which identifies the current degradation states by recurrent identification cycle. The proposed algorithm has also predictive component capable to determine the possible evolution of the system state towards a critical state of failure.

Keywords: fuzzy logic, prognostic, optimal analysis, manufacturing system

1. INTRODUCTION

The maintenance activity combines different methods, tools and techniques in order to reduce maintenance costs in same time with increasing reliability, availability and security of equipments. Actually the maintenance is far away to be only a research area of interest. The industrials also show a growing interest in this thematic; see recent papers dedicated to "CBM", condition-based maintenance (Jardine et al., 2006) and (Ciarapca et al., 2006).

Initial maintenance framework was delimited by the necessity of "perceiving" phenomena, next, of "understanding" them, and finally, of "acting" consequently. In concordance with the actual demands for triple performance, rather than understanding a phenomenon which has just appeared like a failure, it seems convenient to "anticipate" it's manifestation in order to act consequently and resort to protective actions. This is what could be defined as the "prognostic process". The main idea of prognostics is to optimize the maintenance policies according to certain criteria like risk, cost, reliability and availability (Dragomir, 2008).

The fuzzy supervision provides refined information for actions of optimal analysis of system's performance indicators. The major difficulty consists in the identification of mathematical models appropriately to these indicators. In a fuzzy approach will also have to integrate the fuzzy variable's values. We concentrate our study on the optimal analysis of information given by fuzzy monitoring tools.

The supervision of discrete events systems needs taking into consideration some specific reasoning and modeling methods put on our disposal by the artificial intelligence techniques. The fuzzy logic provides the environment to exploit the fuzzy information which seen from the qualitative point of view offers more refined results than the classic logic. From this point of view in the category of modeling instruments, the Fuzzy Petri Network (FPN) is an adequate instrument for studying the discrete events systems described by such fuzzy information.

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A very complete study of various approaches regarding the existent Fuzzy Petri networks was published by J. Cardoso and B. Pradin-Chezalviel in (Cardoso et al., 1993). Various types of logic (classic, linear and fuzzy) (Cardoso et al., 1993), (Feldbaum, 1973), (Minca et al., 2003a, c) used in system's description; generate two main categories of FPN models: the first class of models is represented by the fuzzy expert systems. Another class of applications is modelated through RdPF models which express information's vagueness (Cardoso et al., 1993).

Using a temporal fuzzy research, FPN modeling instrument allows generalization of the analysis upon the production system from the point of view of fault's tracking down and diagnosis. The FPN model the state of error's temporal evolution expressed trough a descriptive instrument: fault tree analysis (ADD).

The propagation and temporal variation of errors are evaluated through temporal sections on network's marking levels. Through his interface, the instrument provides selective fuzzy information from the point of view of the faults gravity of the detection. This information represents the inputs in an algorithm of cyclic identification of system's state modelated through an objective function.

Considering the benefits that prognosis may bring to the security, economics and resource management fields, we propose in this article a method based on Fuzzy Petri networks and predictive maintenance techniques in order to obtain an optimal analysis of the manufacturing systems.

Firstly, a numerical method which locates the current state through the information given by the fuzzy supervision model is proposed. The considered objective function aggregates the performance indicators or the analytical expressions of system's state.

This one expresses the system's reliability in operation and is exclusively dependent on the error variables situated on the error critical curve (Minca, 2004) of the FPN temporal model. Secondly, the identified tools are used in order to take into account the system's dynamic and to predict (Dragomir et al., 2007), (Dragomir et al. 2008) its future behavior according to its actual state and other imposed performance variables or constraints.

2. FUZZY PETRI NETS FOR FAULTS DETECTION AND LOCALISATION

2.1. *Analytical methods for identifying the critical states of the manufacturing systems*

Lets consider a n-dimensional space which describes the objective function $f : R^n \rightarrow R^n$,

$f(x_1, x_2,..x_n)$ which describe the critical of dynamics system. We shall propose an algorithm who analyzes the current state of the system in order to predict a future state of the system that can be assimilated with a failure, called critical state of the system.

For the set $\{a_1, a_2,..a_{n+m}\}$ of possible errors to appear in system's operation, we consider the set $\{a_1, a_2,..a_n\}$ which represents the set of crucial errors in system's maintenance action.

These errors are those situated on the critical error curve in a Petri network specialized in modeling the maintenance function (FPN). The model (Fig. 1) is based upon the causal relation between these events expressed by ADD (Pradin 1993), respectively the apparition of errors and their propagation. (Minca et al., 2003a, b, c).

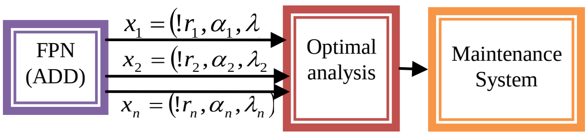

Figure 1. Block schema for optimal analysis of manufacturing systems

The model built with the FPN specialized networks shows intermediary error states which can be critical from human expert point of view (Fig. 2).

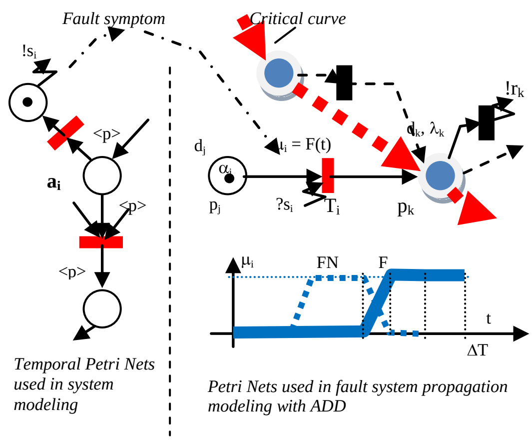

Figure 2. The FPN based on ADD for manufacturing monitoring systems modelling

The fuzzy aspect of the modeling is expressed through fuzzy values $\{\alpha_1, \alpha_2, ..\alpha_n\}$ associated to the variables which define the critical errors, errors shown by the model through $\{!r_i\}_{i=\overline{1,n}}$ signals (Looney, 1988, Racoceanu 2002, Proos 2001) .

The $x_1, x_2, ..x_n$ variables are in correspondence with the set of states that define the critical error curve $\{x_1 \equiv s_1, x_2 \equiv s_2, ..x_n \equiv s_n\}$. The $\{s_1, s_2, ..s_n\}$ states corresponding to the critical curve lead the supervised system into states of critical weakness if the limit value associated to its error state is exceeded by the fuzzy value which describes the system's state in the FPN associated model: $\alpha_k \geq \lambda_k$.

We define the critical reliability state, n-uplet $\{x_1, x_2, ..x_n, f(\bullet)\}$ corresponding to the minimum value of function f (Fig.3). The evolution of the system towards state $C \in \{f(x_1, x_2, ..x_n)\}$ imposes the movement of the point corresponding to system's current state on a level track descendant from current point **A** towards point **C** (Fig. 3).

We define the system's state corresponding to point **C** state of critical reliability of the supervised system where $C = \min\{f(x_1, x_2, ..x_n)\}$.

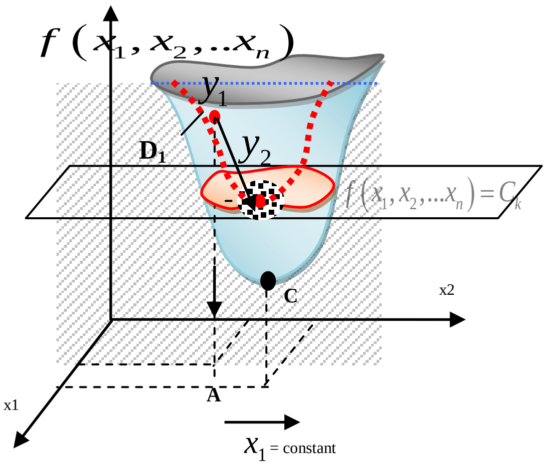

Figure 3. Analytical representation of loss function based on considered faults in FPN and ADD

The information provided by the supervision system in the case of system's evolution towards the state of critical reliability, shows worsen states of the supervised system through the additive apparition of new errors. We consider the initial state y_1 (Fig.4). In a temporal approach, it corresponds to the evolution error state generated by the apparition of a critical error $d_1 = x_1$, while the other errors $(n-1)$ remain stationary.

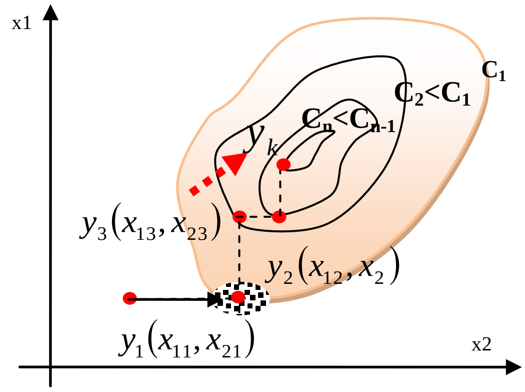

Figure 4. Graphical representation of isolevel curves associated to critical status identified with faults monitoring system

Accordingly to the optimal numeric techniques for searching a minimum value of a variable n function, these states can be determined through evaluation of the objective function $f(x_1, x_2, ..x_n)$ for the condition $(x_1, ..x_{i-1}, x_{i+1}..x_n) = const.$

The problem is transforming into a classical problem of successive linear search (Soare, 2001, Popeea 1996), on direction of coordinate axes of R^n systems, of relative minimum value of one variable function.

The correspondent state of the supervised system at the appearance of d_1 error is represented by D_1 curve obtained by sectioning $f(\bullet)$ with cu plan $(x_2, x_3, ..x_n) = const.$. If the d_1 error is worse for system's state of reliability, then it will set the current state in a circled nucleus $y_2 = \min\{f(x_1, (x_2, x_3, ..x_n) = const)\}$.

The line $\overline{d_{12}} = (y_1, y_2)$ is obtained by plan projection $(x_2 O x_1)$ of $\left(\overrightarrow{y_1 y_2}\right) = \overrightarrow{Oy_2} - \overrightarrow{Oy_1}$ vector where y_2 point is situated on the level curve $f = C_1$. The point y_2 can vary on the domain $(y_2 - \delta_2, y_2 + \delta_2)$.

The value $\delta_i = \alpha_i$ is given by the temporal fuzzy supervision system designed to emit fuzzy signals for warning about the appearance of an error situated on the critical error way. The appearance of the next error d_2 leads the system into y_3 state correspondent to

(1) $y_3 = \min\{f(x_2, (x_1, x_3, ..x_n) = const)\}$.

The current state of the system becomes a point from $(y_3 - \delta_3, y_3 + \delta_3)$. Through augmentation, the appearance of the last error d_k will lead the system into the critical error way:

(2) $y_{k+1} = \min\{f(\bullet), (x_1, ..x_{k-1}, x_{k+1}..x_n) = const\}$.

The system's current state becomes a point from the interval $(y_k - \delta_k, y_k + \delta_k)$ where δ_k corresponds to the fuzzy value attached to the signal announcing the appearance of d_k error.

If the state of the supervised system gets worse through the appearance of all n errors, then it will be in a state of reliability in degraded operation which doesn't exactly mean that it is the critical one. The analysis instrument becomes efficient if we introduce the independent variable "t" into the set of variables of the objective function, correspondent to an orthogonal direction from space R^n.

The function which describes the state of reliability in operation gets the form of a specific model for the evolutionist systems:

(3) $\Phi : R^{n+1} \to R^{n+1}, \Phi(f(x_1, x_2, ..x_n), t)$.

It shows the dynamic aspect of system's supervision.

Proposition 1:

If a system's error state is continuous, the system can develop towards the state of critical reliability in operation correspondent to the minimum value of the objective function $\Phi(f(x_1, x_2, ..x_n), t)$.

The presence of time variable on one of the coordinate axes shows the non stationary aspect of a system in a certain weakness state. The analysis has the aspect of some stationary cyclic evaluations on the n rectangular axes axe as well as a temporal one through evaluation of the objective function in each new moment $\Phi(f(x_1, x_2, ..x_n), t + k \cdot \Delta t)\big|_{k \notin Z+}$.

Proposition 1 :

(4) If $\|y_{n+1} - y_n\| < \varepsilon$

(5) $\delta_m = \dfrac{\sum_{k=2}^{n+1} \delta_k}{n} > \left(\dfrac{\lambda_1 + \lambda_2 + ..\lambda_n}{n} + \varepsilon' \right)$

the system is in a state of critical reliability $y_{n+1} = \min\{\Phi(\bullet)\}$, where Φ is the objective function which describes the reliability in operation of it, depending on the critical error states that the system has in time and $(n+1)$ represents the last direction (last variable x_{n+1}) in a cycle of identification/evaluation of system's state.

2.2. *Algorithm for identifying the critical state of the manufacturing systems*

The method for dynamic identification of the state of reliability in operation appeals to system's state identification algorithm by searching the state in space R^{n+1} with variable steps on the directions of the coordinate axes (Fig. 5). The dynamic aspect of the analysis is determined by the input data, respectively the fuzzy signals $\{!r_i\}_{i=\overline{1,n}}$ emitted by the FPN model.

The analytically determination of critical state in operation supposes the of $(x_{1i}, x_{2i}, ..x_{ni}, t_i)$ n-uplet on the characteristic of function $\Phi(f(x_1, x_2, ..x_n), t)$. If the series $\{X_i\}_{i=1,n+1}$, $X_i = (x_{1i}, x_{2i}, ..x_{ni}, t_i)$ leads to a convergent evolution of the function Φ towards its minimum point, it is a minimized series for Φ and system's state leads towards the critical state in operation of the system. The analysis is based on monitored data at every Δt moment. In each $t \to t + \Delta t$ moment the $\{!r_i\}_{i=\overline{1,n}}$ signals are obtained.

After it, there is a complete cycle for identification of the current state of the system in relation with evolution model of function Φ.

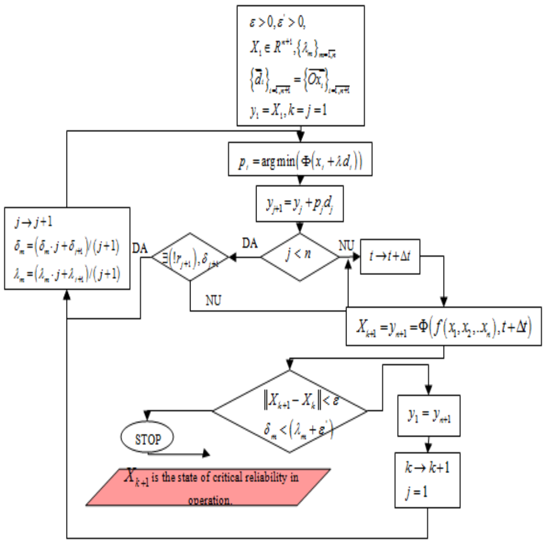

Figure 5. Logical schema of critical states of manufacturing system identified through fuzzy output of the monitoring system

The algorithm is cyclic and indicates a movement on the characteristic $\Phi\left(f\left(x_1, x_2, ..x_n\right), t\right)$ by smaller and smaller steps/levels. From a moment t_n the algorithm can't distinguish anymore the difference between states. This moment is obtained in relation with the condition $\left\| y_{n+1} - y_n \right\| < \varepsilon$ and indicates a limit of the method.

The method's limit can be verified through comparison between the theoretical conclusion of the numeric calculus algorithm which can indicate the system failure and its real state which can be sever but not yet fatal.

The method's accuracy consists in having a higher number of analysis points for the supervised system. Processing the data is a time-consuming operation and the result can sometimes be wrong because of the stop condition (not so restrictive) $\left\| y_{n+1} - y_n \right\| < \varepsilon$.

3. PROGNOSIS EVALUATION OF IDENTIFIED FAULTS

3.1. Statement on the prognosis concept

Many health monitoring technologies have been developed. They however have traditionally focused on fault detection and isolation within an individual subsystem.

The researchers in this area are just beginning to address the concepts like prognostics or prognostic integration technologies across subsystems and systems. Hence, the ability to detect and isolate impending faults or to predict the future situation of a system is currently a high priority research topic.

In this context, (Dragomir et al., 2007) has redefined the prognosis "as the association of a prediction and an assessment processes" (Fig. 6). The main requirements ensured by a predictive analysis at all levels of a system through prognosis are resuming as follows:

- identify and assess the degradation degree of components of the analyzed system (local treatments),

- correlate causes with effects from the prediction point of view: first at the local level, and next at the global level of the process, - learn from scenarios the influence of partial entities on the whole system with neural networks,

- coordinate the local predicted states with the global performance criteria (from local prediction to global prognostic) (Gouriveau et al., 2008).

In this context, in the following sections the identified faults with the proposed algorithm will be evaluated from predictive maintenance objectives point of view.

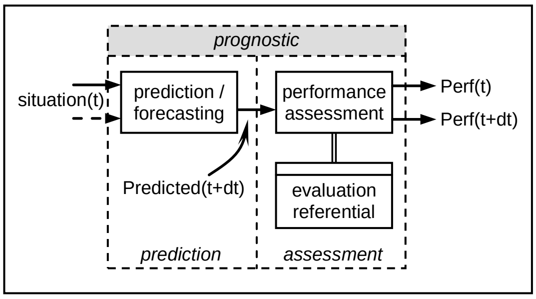

Figure 6. Prognostic as a prediction and assessment process (Dragomir et al., 2007)

3.2. Evaluation of the predicted state of the system

From the health-management point of view, relationship between function, structure and behavior can be difficult to identify (complexity of the process, lack of knowledge, complicated causal relations, etc.). These considerations make harder the modeling step, even impossible.

This is the main reason that led researchers to associate dependability tools like "fault trees". Yet, a monitoring process must deal with it, and artificial intelligence should be valorized to support a global prognostic.

The primary function of the prognostic in (Dragomir et al., 2007) acceptation is to project the current health state of equipment into the future by taking into account estimates of future usage profiles. In order to support this acceptation, in the first sections of this article has been proposed an algorithm.

The second function of the proposed prognosis concept allows to evaluate the identified critical states as follows:

- if the forecast situation of the ''degraded'' system is considered as ''safe'' in relation with imposed preformande limits or ''satisfactory'' to perform the system goals, no action needs to be planned. The system will evolve to another acceptable degraded state and it can drift under control.

- if the forecast situation is not acceptable, several maintenance alternatives must be investigated through the prognosis process. Then, the results of the different assessments will be used by the aided-decision-making module to select, by comparison, the most efficient maintenance policy.

4. CONCLUSIONS

In this paper, a classical numerical method dedicated to indicator's modeling: a system's critical reliability in operation has been implemented. It is based upon general methods of numeric search of multivariable function's extremes in test points. The associated algorithm is based upon fuzzy information provided by the FPN dedicated model of supervision. The route generated by the representation of current state predicts the closeness or not of the system towards the critical state located in the extreme point.

The originality of the presented methods consists in the temporal aspect's integration and fuzzy logic introduction of the variable independent of time and of fuzzy values associated with the variables of objective function.

The researches and the developments described in the second part of the paper are still in progress.

To conclude, let us underline a point of interest of the global work which is not discussed in the paper. From the industrial point of view, this work is in coherence with actual maintenance trends like "e-maintenance systems" or "intelligent sensors networks" and with the increasing interest for emerging technologies like "web-services".

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