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THE PRINCIPLES OF INFORMATION GROUPING IN PROCESS DIAGNOSTIC SYSTEM

This paper focuses on problem information grouping to detect potentially dangerous situation in critical applications. The method combines the problem of group division (the classes) and the definition of the main object in each group is offered. The numerical algorithm of the information grouping is given.

diagnosis, fault isolating, problem of group division, fuzzy set, graph model

Introduction

When a technological system in operation is close to its limits, it is essential for the operators to have a clear knowledge of its operation state. In recent years, increasing attention has been given to methods of identifying the potential factors that would affect to analyze the operation systems.

Many special algorithms and methods have been proposed in the literature for analysis the process instability. But these traditional methods require significantly large computations and are not efficient enough for real-time use in the technical management system. Hence, there is a need for an alternative approach, which can quickly detect a potentially dangerous situation and alleviates the technological system from possible collapse.

One of the ways of the problem decision is the development of the express-diagnostics methods, which are capable to control process of the system fault detection due to automatic information grouping.

In developing algorithms grouping for diagnostics goals it is necessary to solve the following problems:

1. Grouping of events set.
2. Definition of the main object in each group.

Typically, two stages of decision making are reduced to realization by methods of the cluster analysis:

1) building the mutual distances graph between objects of the grouping;

2) searching for a set of tops on the graph that corresponds the group characteristics [1].

Such decisions are characterized by significant redundancy of computing operations.

It has been argued that it is caused by the first stage realization when it is necessary to search the shortest ways in graph on the whole set of arcs. And at the second stage the group shaping is made by direct searching for among the set of grouping objects (the graphs tops), which can be shortened by the more efficient decision at the first stage.

Additionally, the most existing methods do not give any instructions concerning to automatic choice of the main objects in the group.

In this work the method combines the problem of group division (the classes) and the definition of the main object in each group is offered.

Statement of the problem

First level modeling task is presented as an analytical graph model of the grouping problem for system failure diagnosis with fuzzy data.

For mathematical statement of the problem the following indications are incorporated

The bipartite graph $\mathcal{G}(H, P, E)$, with n tops is considered to be given (fig. 1).

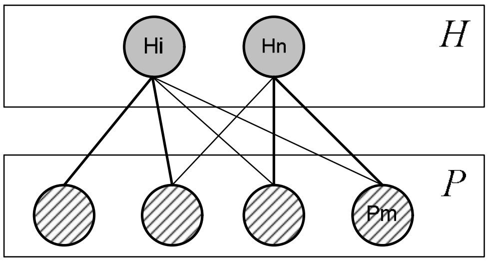

Fig. 1. Generalized diagnostic graph

Tops of the first part of a graph ($H = \{h_1, ..., h_i, ..., h_n\}$) are the fault events (deviation of system parameters); $i = 1, \ldots, n$ – an index, in which the fault events are numbered.

Tops of the second part of the graph $P = \{p_1, \ldots, p_j, \ldots, p_m\}$ are the causes of failure (the faults), $j = 1, \ldots, m$ – an index, which numbers the causes of failure, $E = \{e\}$ – sets of arcs.

The graph $\mathcal{G}$ corresponds to the binary fuzzy relation $\mathcal{P}_{\mathcal{G}}$ which consists of all pairs $<h_i, p_j>$. A real number from the interval [0,1] is determined for each pair $<h_i, p_j>$. This number is equal to the membership function $\mu_{\mathcal{G}}(e_k)$ for the arc $e_k \in E$ which corresponds to this pair of the tops.

C_∂ – is a cost of the diagnosis mistake. It is an expert-determined value which depend on the searching direction selection: as to the most dangerous incurable deviation, as to the most probable defect and etc.

k_d – is a coefficient of the confidence of diagnostic search. It is defined as a ratio of amount of deviations which can be distinguished on the chosen set to the total number of possible deviation, caused by i's fault;

The analytical statement is a problem of covering bipartite graph $\mathcal{G}(H,P,E)$ by subgraph $\mathcal{G}'(H', P', E')$, $\mathcal{G}' \delta\, \mathcal{G}$; that contains only chosen set of tops as a result of fixed overshoots.

Moreover possible decision is a ranked set, characterizing all possible faults in the system under the given importance of stability relationship (degree of membership $\mu_{\mathcal{G}}(<h_i, p_i>)$). Each set component is grouped $g^i = (\{h_i\}, P^i, E^i)$, $h_i \in H'$, $P^i \,\delta\, P'$, $E^i \,\delta\, E'$ with the centre in the defined top h_i from the first part and the set P^i tops from the second P part.

On the set of the graph's $\mathcal{G}$ possible decisions the objective function F as a generalized optimization criterion is determined

$$F_{\sum}(\omega, R(x)) = \sum_{i=1}^{2} \omega_i R_i(x) \to \min, \qquad (1)$$

where, $R(x) = \{R_1(x), R_2(x)\}$ – is a vector of a partial criteria (the risks); $\omega = \{\omega_1, \omega_2\}$ – are the weight ratios for significance of the partial criteria.

The problem is to find such a decision where both the risk R_1 and the risk R_2 are small.

According to the defined criteria, $R_1(x)$ can be factored as a $-k_d$ and $R_2(x)$ as a C_∂:

$$R_1 = -k_d;$$
$$R_2 = C_\partial.$$

It means the choice of such a reason sequences to get the maximum value of the coefficient of the confidence of diagnostic search with minimum cost of the diagnosis mistake (C_∂) on the set of the possible graph decisions:

$$\begin{gathered} k_d \to \max; \\ C\partial = \sum C(p_j) \to \min. \end{gathered} \qquad (2)$$

The algorithm of the information grouping

The algorithm of the information grouping includes 3 stages of the result determination.

At the initial stage the preliminary grouping procedure for each deviation registered of the system variables is carried out.

For solving first part of the task the main characteristics of the fuzzy relations are used [2].

The general concept of α-level, in particular. It is understood as a ordinary ratio $P\alpha = \{(<h_i, p_j> \mid \mu_X<h_i,$

p_j>)≥α} (∀<h_i, p_j>∈ P_G), where α – is a certain real number from interval [0,1] i.e. α ∈ [0,1].

The peculiarity of the model used is the two-level structure of one of the graph part; the objective factor require such structure: a set of fault reasons P can include both simple (having only one top) and complex P^*, $P^* \subseteq P$ the causes of failure which are due to the reserve elements within the object diagnosed. That provide the additional functional reliability to the object. In this case a set of complex causes of failure is described as binary fuzzy relation :

$$H \times P^*: \mathcal{P}_1 = \{<h_i, p_l^*>, \mu(<h_i, p_l^*>)\};$$

$$P^* \times P: \mathcal{P}_2 = \{<p_l^*, p_j>, \mu(<p_l^*, p_j>)\}.$$

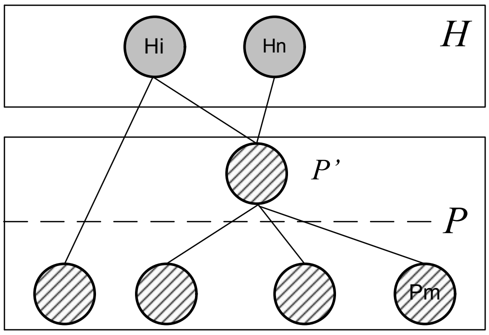

Fig. 2. Structured diagnostic graph

The analysis of the component overshoot causes is executed as a composition of the binary fuzzy relations $H \times P^*$: $P_1 = \{<h_i, p_l^*>, \mu(<h_i, p_l^*>)\}$ and $P^* \times P$: $P_2 = \{<p_l^*, p_j>, \mu(<p_l^*, p_j>)\}$. And the membership function is defined as a max-min convolution of the fuzzy relations [3].

Therefore, the graph arc e_k = <h_i, p_j> with the beginning in the top h_i and the end in the top p_j, and with the membership function value is related to each tuple of the fuzzy relations <h_i, p_j> ∈ $\mathcal{P}_G$.

Thereinafter, for each deviation registered the fuzzy matrixes are built. Then they are decomposed into the relations of equivalence which are configured as an equal α-leves.

The system of the classes (the groups) for all possible α-levels is built. Each group describes the overshoots which can appear in either development of the process. This procedure implies the division and grouping source decisions set according to the principle of membership α-level.

The results of the preliminary grouping can be used both as benchmark data for solving of the optimization task and as preliminary result of system diagnosing , being a set of possible solutions.

The second stage - a procedure of ordering the graph tops is executed when two or more deviations are registered. The iterative algorithm of ordering the graph tops $G = (H, P, E)$ is in alternating fixing one of the groups along coordinate axis and moving of each top of the other group into the geometric centre of the coordinates of the tops connected to it of the opposite group. The analogue of the ordering the fuzzy bipartite graph tops will be renumbering lines and column of its matrix such that the more value of a variable, the closer it must be to the main diagonal. Formally this is the problem of the minimization of function with $(m + 1)(n + 1)$ variables

$$J(h_0,...,h_n, p_0,...,p_m) = \\ = \sum_{i=0}^{n} \sum_{j=0}^{m} \mu_{ij} (p_j - h_i)^2 \to \min_{p_j, h_i}, \tag{3}$$

where μ_{ij} – an element of the fuzzy graph matrix, defining the degree of coherence *i's* top with *j's* top; p_j and h_i – numbers (coordinates) of reordered lines and columns.

To prevent shrinkage of graph lines and columns in a point the restriction is introduced:

$$\max_{j,l} \{ |p_j - p_l| \} = m. \tag{4}$$

The problem of conditional optimization (3) – (4) can be solved using the method of the projected gradient and is arranged as a iteration process with initial approach $p_j^0 = j$, *k*-iteration of which is:

$$h_i^k = \frac{p_0^{k-1}\mu_{i0} + p_1^{k-1}\mu_{i1} + \cdots + p_m^{k-1}\mu_{im}}{\mu_{i0} + \mu_{i1} + \cdots + \mu_{im}}, \ i = 0, ..., n;$$

$$P_j^k = m(\overline{P}_j - \min_l \overline{P}_l) \Big/ (\max_l \overline{P}_l - \min_l \overline{P}_l), \quad j = 0, ..., m.$$

Final sorting of last approximation to P_j and H_i assigns the optimum order of numeration lines and columns.

The matrix reordered allows each deviation registered to match the list of the possible reasons (the diagnosis) in the sequences of the removing from the main diagonal.

The final stage considers the optimization task (1). The result of the problem solution is a final ranging of partial criteria in the sequence of the reduction of their importance in accordance with the searching criteria chosen. Normalization of the local criteria is made before solving multi-criterion task [4].

Considering the standardization of partial criteria made the problem of the determining the most critical tops is reduced to solving a single-criterion task of the optimization:

$$F = \max(\omega_1 K_N + \omega_2 C_N). \tag{5}$$

The cycle of grouping is completed by presentation of diagnosed faults in form of the causes chains, close to the desired solution.

Conclusion

Analyzing the obtained results grouping we came the conclusion that it is possible to organize the procedure of fault search in fuzzy graph G one by one without whole combinatorial search by presenting fuzzy matrixes as a equivalence relation. However, in this case it may occur that the reason caused the fault will be absolutely ignored, and that is pointed out by calculated value of the diagnostic search confidence factor.

The algorithms given use the limited number of elements from the sets of fault events and causes of failure, as well as expert determined rates. Evidently the quality of grouping and evaluating significantly depends on choosing initial parameters and model structure.

The results of calculations made have shown that this principles let quickly define possible directions of fault search according to strategy chosen before, which is of great importance for efficient fault isolating.

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