HYPOTHESES EVALUATION ABOUT THE STATE OF THE CRITICAL PROCESS

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Abstract

In this paper the theory of the hypotheses evaluation about the instantaneous state of the safety-related critical processes has been described. Firstly, the critical processes (CP) are characterised. Fuzzy state images of the monitored process are defined by the composition of process variables. The hypotheses about the possible states of the safety-related critical process are set and the finite sets of the system states in discrete state space are defined. Secondly, the hypotheses are evaluated using fuzzy logic from their credibility point of view. The set of the weighted statements about the instantaneous state of the monitored process is a result.

Keywords: safety-related critical process, fuzzy state images, process monitoring, hypothesis, hypotheses evaluation, credibility value

1 INTRODUCTION

Safety-related critical process is a continuous or discrete technological process whose dysfunction effected by its own error or control error could cause damage to properties, health, human lives and environment [Molnárová, 1999]. System's tools for analysis and synthesis of control systems used in safety-related critical applications are similar to conventional. They are also appended with tools for identification of the failure states and with tools for affect analysis of the particular failure group, which is dominant from the safety point of view. Control precision and its safety rate depend on information quality about the actual state of the safety-related CP.

2 CONTROLLING AND CONTROLLED PROCESS AS A SAFETY-RELATED CRITICAL PROCESS

Assume that the control system (Fig. 1) is defined by $\langle Y, P, U, \omega, \beta, U_0 \rangle$, where Y is a set of inputs, which monitors the instantaneous state of controlled process.

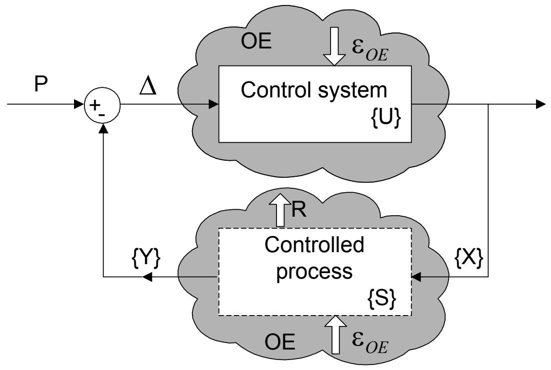

Fig. 1 Interaction between controlled process and operational environment

Finite set P includes all requirements of superior control system (operator) to transfer controlled process into new target state from set S. U is a finite set of states, $\omega : P \times \Delta \times U \rightarrow U$ is a transition function, $\beta : U \rightarrow X$ is an output function and $U_0 \in U$ is an initial state of the control system.

Controlled process can be described as a subsystem with a finite set of discrete states (Fig. 1). Input variables are commands of the control system *{X}*, output variables are process variables *{Y}*. The instantaneous state of the controlled process is determined by state variables *{S}*. Behavioural analysis of the controlled process redounds to description of state trajectory.

The controlled process as a subsystem is affected by operating environment (OE) with its defined set of stressors ε_{OE}. The mechanism of the controlled process safety level reducing, its dysfunction or breakdown could be summarised into following groups:

- consequence of the controlled process correct response to an incorrect command of the control subsystem,
- consequence of the faulty or unpredictable response of the controlled process to a correct command,
- consequence of the failure intervention of the operational environment to a correctly working controlled process,
- consequence of the failure intervention of the operational environment to an incorrectly working controlled process (failure cumulation).

The methods for the analysis of dynamic systems can be used for behavioural analysis of the controlled process following its external exhibition, i.e. in accordance with measurable parameters, which are changing in time. The subsystem of the controlled process is described with parameters $\langle X, Y, S, \delta, \alpha, S_0 \rangle$, where *X, Y* and *S* are sets of inputs, outputs and states of the controlled process, respectively. $\delta : X \times S \rightarrow S$ is a transfer function (determining system's dynamic), $\alpha : S \rightarrow Y$ is an output function and $S_0 \in S$ is an initial state. Thus, $S(t+1) = \delta(U(t), S(t))$, $Y(t) = \alpha(S(t))$. The operational environment effects the controlled process behaviour with a set of stressors ε_{OE}. In this case, subsystem of the controlled process can be rewritten with variables $\langle X, \varepsilon_{OE}, Y, S, \delta, \alpha, S_0 \rangle$, which create non-deterministic or stochastic model of the controlled process according to status of occurrence and influence.

Therefore, at the description of controlled process behaviour the sets of states, inputs and outputs of the process should be divided into *correct* subset (correct in defined time) and *failure* subset [Balažovičová, 2002].

From the operational environment point of view, every failure form of the transition and output functions is potentially dangerous. Thus, rate R goes towards value of accident probability of the operational environment. Whether dysfunction of the controlled process causes accident or not, depends on instantaneous operative conditions of the operational environment.

To summarise, they are two parallel random processes, in which mutual interaction are determining in case of accident occurrence. For example, incorrect result of the railway track circuit state monitoring does not cause railway accident while the train appears in observed section.

3 SAFETY-RELATED CRITICAL PROCESS MONITORING

Process monitoring is an action of gaining real images about the selected process features. The monitoring system is a complex of technological and software tools, which allow monitoring.

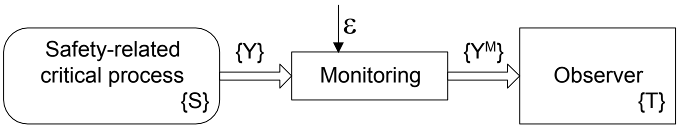

Fig. 2 Model of the safety-related critical process monitoring

Let safety-related critical process be a monitored object Fig. 2 with finite number of defined states $\{S\}$. Process monitoring can be described with transformation $M: Y \rightarrow Y^M$, $M^\varepsilon : Y \xrightarrow{\varepsilon} Y^{M^\varepsilon}$, where $Y \in \{Y\}$ are the output process variables of the monitored process, M is a correct transformation, executed by monitoring subsystem, M^ε is an incorrect transformation under interference influence ε. As a consequent, correct variable $Y \in \{Y\}$ is noticed by observer as an image $Y^{M^\varepsilon} \in \{Y\}$.

Exact regulation or exact control in closed loop can be achieved only with following qualified monitoring, i.e., which provides real images about the controlled process state with adequate credibility. Firstly, state decomposition of the control system and controlled process is needed.

4 STATE DECOMPOSITION OF THE CRITICAL PROCESSES

Let $\{S\}$ be a state space of the safety-related critical process and contains *E* states according to Fig. 3: $\{S\} = \{S^K\} \cup \{S^\varepsilon\} \cup \{S_{margin}\}$, where $\{S^K\} = (S_1, S_2, ..., S_k)$ is a subset of all correct (failure-free) states, $\{S^\varepsilon\} = (S_{k+1}, S_{k+2}, ..., S_e)$ is a subset of all considered failure states, $\{S_{margin}\} = (S_{e+1}, S_{e+2}, ..., S_E)$ is a subset of states irrelevant to the control function. Subset $\{S^K\}$ includes states, which are from the control safety point of view critical (menace rate of the operational environment is not negligible) and states, which can be integrate to the group of safety, non-hazardous states. There is an assumption, that all states from the subset $\{S^\varepsilon\}$ are potentially dangerous. The control system is in charge to generate commands that minimise the risk.

The control system that is in observer-role (Fig. 2) generates control variables based on obtained state-images and corresponding control algorithm. For detailed behaviour description, finite set of state-images $\{T\}$ has to be defined. The elements of this set are images of the instantaneous state from set $\{S\}$ of the controlled process, obtained by transformation:

$$T(t): T \times Y(t), \tag{1}$$

where *T* is an composition algorithm $Y(t) \rightarrow T(t)$. The elements of the set $\{Y\}$ are in practice represented by measurement of the physical variables of the controlled process. They are electrical variables. The set of state-images $\{T\}$ consists of subset T^K correct and subset T^ε incorrect images:

$$\{T\} = \{T^K\} \cup \{T^\varepsilon\}, \ where$$
$$T^K(t): T \times Y^K(t) \Leftrightarrow T^K(t) \equiv S^K(t)$$
$$T^\varepsilon(t): T \times Y^\varepsilon(t) \Leftrightarrow T^\varepsilon(t) \neq S^K(t) \tag{2}$$
$$T^\varepsilon(t): T^\varepsilon \times Y^K(t) \Leftrightarrow T^\varepsilon(t) \neq S^K(t)$$
$$T^\varepsilon(t): T \times Y^\varepsilon(t) \Leftrightarrow T^\varepsilon(t) \equiv S^\varepsilon(t), \ if \ \alpha_j^\varepsilon : S_j^\varepsilon \to Y_k^\varepsilon$$

The definition of the set of state-images $\{T\}$, which are observed by the observer, results in conditions, under which deformation of the actual state perception can occur. Observer has to provide to the control system qualified estimation of the actual process state. During the conventional monitoring, this estimation is discrete and can be incorrect. Fuzzy logic principles allow quantifying estimation credibility by state pseudo-partition [Balažovičová, 2002].

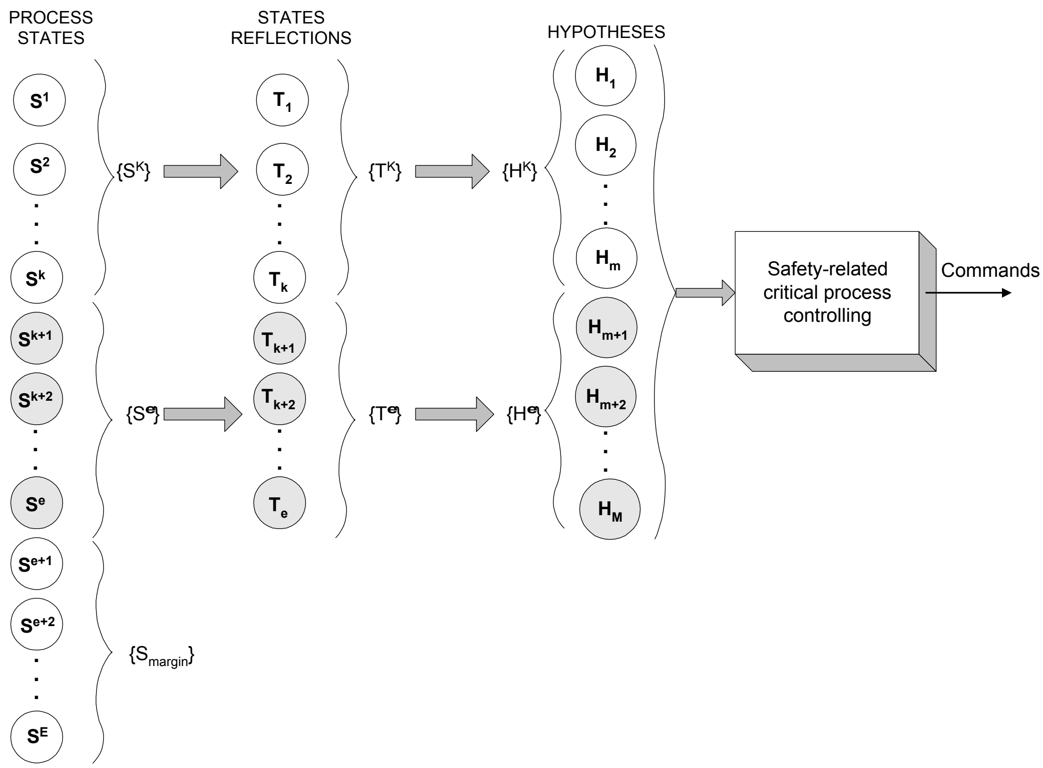

Fig. 3 Creation of the state-images and hypotheses setting

Successful monitoring of the safety-related critical process requires solutions to the following problems:

1. to set the hypotheses relevant to particular kind of process risk and its control algorithm,
2. to quantify the degree of coincidence between the hypotheses and safety-related critical process real state,
3. to define threshold values of the hypotheses credibility accepted by control system.

Multicriterial control of the safety-related critical process differs from the conventional control mainly by algorithms based on set hypotheses about the process state relevant to particular kind of risk.

5 HYPOTHESES SETTING

Let $\langle X, \varepsilon_{OE}, Y, S, \delta, \alpha, S_0 \rangle$ be a description of monitored non-deterministic continuous process [Balažovičová, 2002]. Let *S* be a finite and discrete state space. Observer evaluates the instantaneous state of the process by scanned physical variables $(y_1, y_2, ..., y_n)$. In ideal case, real state $S_i(y_1^i, y_2^i, ..., y_n^i)$ has been perceived as $T_i \in T^K$, $T_i \equiv S_i$. Due to stressors and failures mentioned above and process dynamics, deformation of the state perceiving could be occurred: $S_i \to T_j \neq T_i$. Providing safety-related CP, it is important to ensure that incorrect perceived state does not belong to set of regular states T^K. Incorrect perception can be detected only if $T_j \in T^{\varepsilon}$.

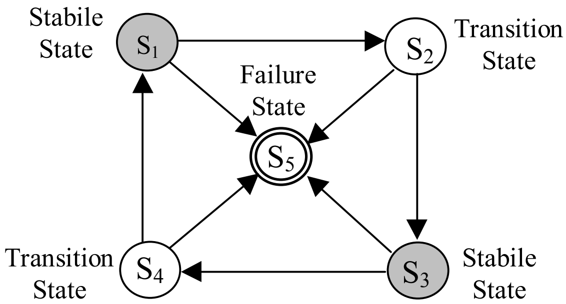

Fig. 4 State decomposition of the safety-related CP

The set of hypotheses $H = \{H_1, H_2, ..., H_5\}$ about the actual state of the safety-related CP consists of following hypotheses:

$$
\begin{aligned}
&H_1(t): T_i(t) = S_1,\\
&H_2(t): T_i(t) = S_2,\\
&H_3(t): T_i(t) = S_3,\\
&H_4(t): T_i(t) = S_4,\\
&H_5(t): T_i(t) = S_5.
\end{aligned}
\tag{3}
$$

The mission for the safety-related CP observer is to create the state model of the CP, which is involved not only all expected process states, but also algorithm images of all transition among states. Example of the state decomposition of the simple two-state safety-related CP is depicted in Fig. 4. To ensure achieving credible information for control system, there has to be decided, which hypothesis is true in time *t*. Inasmuch as criterions for hypothesis evaluation are based on static and dynamic analysis of measured physical variables, it is obvious that this evaluation can not be crisp. It will depend not only on evaluation of absolute values and gradients of state variables, but also on sequence features of safety-related CP. Multicriterial fuzzy decision making is considered as a suitable method.

Hypotheses are the set of statements about the instantaneous state of the controlled process. They are set to the state-images that represent state of the controlled process relevant to control algorithm.

Let set M hypotheses about the instantaneous state of the monitored process with S states $M \le E$. The hypotheses about the marginal states of the controlled process are not needful for the control algorithm, then $M \le e$. About the k correct process state m hypotheses could be set, $m \le k$. Similarly, about the $(e-k)$ failure process state $(M-m)$ hypotheses could be set, $(M-m) \le (e-k)$, see Fig. 3.

The observer creates the set of state-images $\{T\}$ following process variables $\{Y\} = (y_1, y_2, ..., y_p)$. Process variables are the systems of input variables which are used for creating the rules for state-images $T_1, T_2, ..., T_e$ and coupled with integro-differential functions $\psi(y_1), \psi(y_2), ..., \psi(y_p)$ compose a extended systems of input variables. Hypothesis H_h can be set only according to the assignment:

$$H_h : T_g, h = 1,2,...,M, \; g = 1,2,...,e, \text{ where}$$
$$T_g : \left(y_1, y_2, ..., y_p \middle| \psi(y_1), \psi(y_2), ..., \psi(y_p)\right)_{T_g}, \tag{4}$$

where ψ is an integro-differential function for computing the gradient and median of the continuous process variables. e is a overall number of correct and failure process state, Fig. 3. Assignment $T_g : \left(y_1, y_2, ..., y_p \middle| \psi(y_1), \psi(y_2), ..., \psi(y_p)\right)_{T_g}$, $g = 1,2,...,e$ is defined by fuzzy partition. Fuzzy partition creates domains divided into essential number of subspaces. Using fuzzy partition of the extended system of input variables, finite number of subspaces η_a, $a = 1,2,...,A$ is formed:

$$\eta_a = (\tilde{y}_1, \tilde{y}_2, ..., \tilde{y}_p) | \; \tilde{\psi}(y_1), \tilde{\psi}(y_2), ..., \tilde{\psi}(y_p), \tag{5}$$

where $y_1^{a1} \le \tilde{y}_1 \le y_1^{a2}$; $y_2^{a1} \le \tilde{y}_2 \le y_2^{a2}$; ...; $y_p^{a1} \le \tilde{y}_p \le y_p^{a2}$ and

$$\psi^{a1}(y_1) \le \tilde{\psi}(y_1) \le \psi^{a2}(y_1); \psi^{a1}(y_2) \le \tilde{\psi}(y_2) \le \psi^{a2}(y_2); ...; \psi^{a1}(y_p) \le \tilde{\psi}(y_p) \le \psi^{a2}(y_p).$$

Domains $\aleph_b, b = 1,2,...,B$; $B \le A$ are developed by combination of subspaces see Fig. 5:

$$\aleph_b = \bigcup_{i=a_1^b}^{a_2^b} \eta_i \text{, kde } a_1^1 > a_2^1; \; a_1^1, a_2^1, i = 1,2,...,A; \; b = 1,2,...,B \tag{6}$$

Subspaces creating the particular domains must be conjunctive.

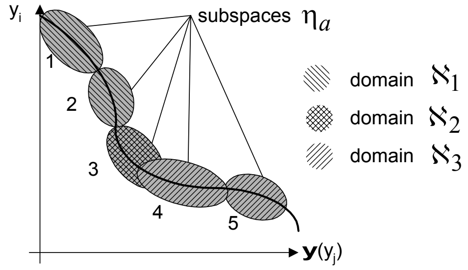

Fig. 5 Example of the subspaces and domains of the extended process variables

The image of the monitored process state is defined by fuzzy partition of the extended system of the process variables with one following method:

1. One state image T_b is allocated to every domain $\aleph_b, b=1,2,...,B$; $B \leq A$ i.e. $T_b : \aleph_b$, $b=1,2,...,B$. Example: $T_1 : \aleph_1 \equiv \eta_1 \cup \eta_2$; $T_3 : \aleph_3 \equiv \eta_4 \cup \eta_5$ in Fig. 5.
2. If the domain is created with exactly one subspace, then to every subspace $\eta_a, a=1,2,...,A$ one state-image will be assigned T_a , i.e. $T_a : \eta_a$, $a=1,2,...,A$. Example: $T_2 : \aleph_2 \equiv \eta_3$ in Fig. 5.
3. Combination of the methods ad 1) and ad 2).

Let state-images T_i , T_j , where $i, j=1,2,...,e$ are set to domains $\aleph_{b_1}, \aleph_{b_2}$, where $b_1, b_2 = 1,2,...,B$, which are creating an adjacent segment of the domain chain. If $\aleph_{b_1} \subset \aleph_{b_2}$ or $\aleph_{b_2} \subset \aleph_{b_1}$, for example $\aleph_2, \aleph_3$ in Fig. 5, then these state-images are non-crisp. If the domains meet each other in one point, then state-images are crisp (Fig. 5). To ensure for control system to obtain credible information, there is a necessity to decide which hypotheses is true in selected time *t*. Some methods for this hypotheses evaluation are presented in [Balažovičová, 2002]. Criteria for hypotheses evaluation are based on static and dynamic analysis of the measured physical variables. Their evaluation could neither binary nor unique. This evaluation depends not only on evaluation of absolute values and gradients of state variables but also on sequence features of the safety-related critical processes. Multicriterial fuzzy decision making is considered as a suitable method [HONG, 2000].

Let $H = \{H_1, H_2, ..., H_m\}$ be a set of hypotheses and let $C = \{C_1, C_2, ..., C_n\}$ be a set of criteria. Assume that the characteristics of the hypotheses H_i are represented by the vague set $H_i = \{(C_1, [t_{i1}, 1-f_{i1}]), (C_2, [t_{i2}, 1-f_{i2}]), ..., (C_n, [t_{in}, 1-f_{in}])\}$, where t_{ij} indicates the degree to which the hypothesis H_i satisfies criteria C_j, f_{ij} indicates the degree to which the hypothesis H_i does not satisfy criteria C_j, $t_{ij} \in [0,1]$, $f_{ij} \in [0,1]$, $t_{ij} + f_{ij} \leq 1$, $1 \leq j \leq n$, and $1 \leq \mathrm{i} \leq \mathrm{m}$.

Let $1 - f_{ij} = t^*_{ij}$, where $1 \leq \mathrm{j} \leq \mathrm{n}$ and $1 \leq \mathrm{i} \leq \mathrm{m}$. In this case, H_i can be written as:

$$H_i = \{(C_1, [t_{i1}, t^*_{i1}]), (C_2, [t_{i2}, t^*_{i2}]), ..., (C_n, [t_{in}, t^*_{in}])\}, \text{ where } 1 \leq i \leq m . \tag{7}$$

Assume that there is a decision-maker who wants to choose a hypothesis which satisfies the criteria $C_j, C_k, ..., C_p$ or which satisfies the criteria C_s . This decision-maker's requirement is represented by the following expression $C_j \; AND \; C_k \; AND \; ... \; AND \; C_p \; OR \; C_s$.

In this case, the degrees to which the hypothesis H_i satisfies and does not satisfy the decision-maker‘s requirement can be measured by the evaluation function *E*:

$$\begin{aligned} E(H_i) &= ([t_{ij}, t^*_{ij}] \wedge [t_{ik}, t^*_{ik}] \wedge ... \wedge [t_{ip}, t^*_{ip}]) \vee [t_{is}, t^*_{is}] = \\ &= [\min(t_{ij}, t_{ik}, ..., t_{ip}), \min(t^*_{ij}, t^*_{ik}, ..., t^*_{ip})] \vee [t_{is}, t^*_{is}] = \\ &= [\max(\min(t_{ij}, t_{ik}, ..., t_{ip}), t_{is}), \max(\min(t^*_{ij}, t^*_{ik}, ..., t^*_{ip}), t^*_{is})] = \\ &= [t_{Hi}, t^*_{Hi}] = [t_{Hi}, 1 - f_{Hi}], \end{aligned} \tag{8}$$

where $\wedge$ and $\vee$ denote the minimum operator and the maximum operator of the vague values, respectively; $E(H_i)$ is a vague value, $1 \leq \mathrm{i} \leq \mathrm{m}$, and

$$t_{Hi} = \max(\min(t_{ij}, t_{ik}, ..., t_{ip}), t_{is}), \qquad t^*_{Hi} = \max(\min(t^*_{ij}, t^*_{ik}, ..., t^*_{ip}), t^*_{is}). \tag{9}$$

Definition 1: Let $x = [t_x, 1 - f_x]$ be a vague value, where $t_x \in [0,1]$, $f_x \in [0,1]$, $t_x + f_x \le 1$. The score of x can be evaluated by the score function Æ shown as follows:

$$Æ(x) = t_x - f_x, \tag{10}$$

where $Æ(x) = [-1,+1]$.

Based on the score function *Æ*, the degree of suitability to which the hypothesis H_i satisfies the decision-maker's requirement can be measured as follows:

$$Æ(E(H_i)) = t_{H_i} + t^*_{H_i} - 1 \tag{11}$$

where $Æ(E(H_i)) \in [-1,+1]$. The larger the value of $Æ(E(H_i))$ the more the suitability to which the hypothesis H_i satisfies the decision-maker's requirements, where $1 \le i \le m$.

Let $Æ(E(H_1)) = p_1$, $Æ(E(H_2)) = p_2, \ldots, Æ(E(H_m)) = p_m$. If $Æ(E(H_i)) = p_i$ and p_i is the largest value among the values $p_1, p_2, \ldots, p_m$, then the hypothesis H_i is his best choice.

The correct setting and objective evaluation of the hypotheses about the actual state of controlled safety-related CP is a requisite condition for precise and safety control. Select package of hypotheses *H* needs to be optimal not only from number of the expected operative-states point of view, but also from operative condition among them. Therefore, it must go out from substantial behavioural analysis of the controlled process. For example, the package of hypotheses (4) set at state diagram in Fig. 4 would be sequential insufficient, if transition $S_1 \to (S_2) \to S_3$ was not finished (because of some operative reason) and state S_1 was the target state. The existence of the absorbing failure-state (S_5 in Fig. 4) is another condition for correct setting of the hypotheses about the actual state of the safety-related CP.

The method for hypotheses evaluation determines the hypotheses credibility $Æ(E(H_i))$ in extreme sense: if $0 < Æ(E(H_i)) < 1$, then hypothesis credibility is $H_i \in [0,1]$, and vice-versa , if $-1 < Æ(E(H_i)) < 0$, then hypothesis non-credibility is $H_i \in [0,1]$.

For hypotheses evaluation about the actual state of safety-related CP, there can be used either a less sensitive formulation of the credibility $V(H_i) \in [0,1]$, which bound of the non-credibility is $V(H_i) = 0$ and represents only values $Æ(E(H_i)) \ge 0$:

$$V(H_i) = \left\langle \begin{array}{c} Æ(E(H_i)), \text{if } 0 < Æ(E(H_i)) < 1 \\ 0, \text{if } -1 < Æ(E(H_i)) < 0 \end{array} \right., \; i = 1, \ldots, n, \tag{12}$$

or a more sensitive formulation which bound of the non-credibility is $V(H_i) = 0{,}5$:

$$V(H_i) = 0{,}5.(Æ(E(H_i)) + 1). \tag{13}$$

In control system, the selection of the most credible hypothesis is performed by next two approaches:

a) *relative selection* – at safety-related non-critical states:

$$H_{opt} = H_j \Big|_{V(H_j) = \max(V(H_i))}, \; i = 1, \ldots, n; \tag{14}$$

b) absolute selection – at safety-related critical states:

$$H_{opt} = \left\langle \begin{array}{c} H_j \Big|_{V(H_j) = \max(V(H_i)) > V_{\min}} \\ H_k : T_k \in T^{\varepsilon} \Big|_{V(H_i) < V_{\min},\ k \ne i} \end{array} \right., \; i = 1, \ldots, n. \tag{15}$$

An estimation of the minimal hypothesis credibility value $V_{\min}$, which is still accepted by control system, is noticeable. This is an assignment $H_i \rightarrow V(H_i)_{\min} \in [0,1]$, while threshold value $V(H_i)_{\min}$ of the safety-related relevant hypotheses (i.e. hypotheses about the actual state $S_i \in S^K$, which is safety-related critical) is higher than the threshold value $V(H_j)_{\min}$ of the hypotheses about the actual state $S_j \in S^K$, $j \neq i$, which is non-critical. In extreme cases, $V(H_i)_{\min} = 1$ may be required. In this situation, control safety rate determined by the input credibility is high, but generally to the prejudice of control reliability.

Function analysis of the conventional control of the critical processes assumes the control algorithm decomposition to the elementary safe control function f_i^B. For the control optimisation of the system with goal-oriented behaviour it is necessary to choose tools for the description, modelling and model analysis which are enable increasing the control precision. For the safety-related critical processes these tools have to ensure multicriterial control. It could be expected that equation is changing into:

$$\textit{if} \quad [c_1(V_1), c_2(V_2), \ldots, c_n(V_n) \,|\, c_{n+1}(B_{n+1}), c_{n+2}(B_{n+2}), \ldots, c_m(B_m)] \quad \textit{then} \quad f_i^B, \qquad (16)$$

where $c_j(V_j)$, $j = 1,2,\ldots,n$ are the technological control conditions completed with weight information about their plausibility and $c_k(B_k)$, $k = n+1, n+2, \ldots, m$ are interlocking (protective) conditions completed with weight information about their safety rate.

6 CONCLUSION

Fuzzy set theory application for the safety-related critical process controlling allows quantifying the credibility of the information accessed to the control algorithm. The method for the safety-related critical process controlling based on fuzzy decision making mentioned in this paper exploits a new approach for the monitoring of the safety-related critical process attributes. This method is based on hypotheses setting and their evaluation. The method can be described and summarised as in Fig. 7.

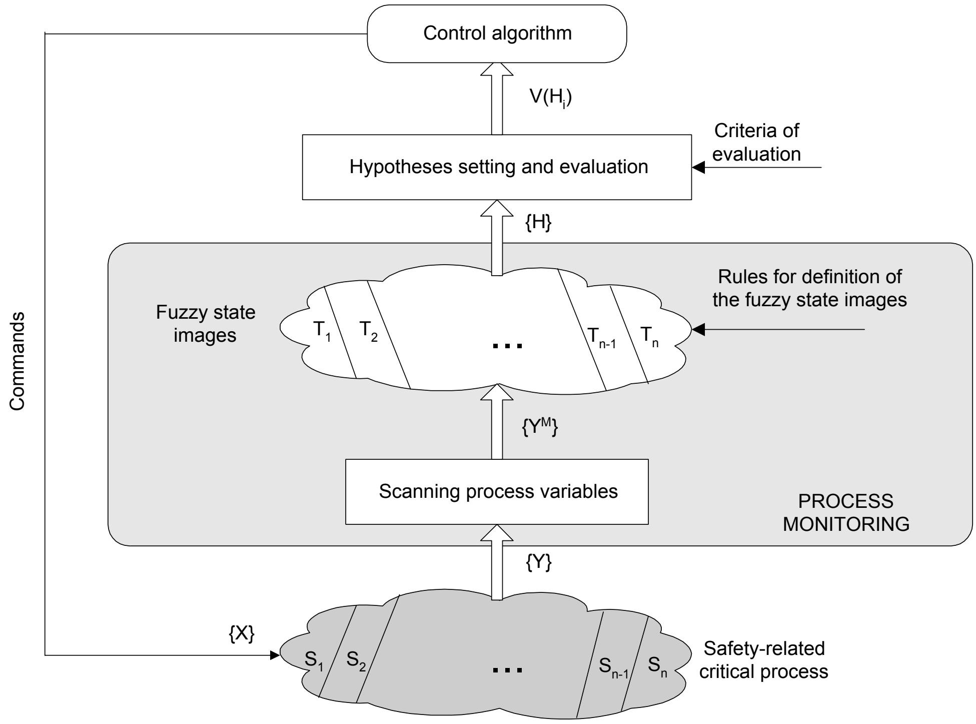

Fig. 7 Spracovanie procesných veličín pozorovateľom

The information about the safety-related critical process obtained with the mentioned method is above standard compared with conventional method. According to the parallel evaluation of these hypotheses, the information is also redundant.

The aim of the optimal controlling of the safety-related critical processes is to achieve its high quality. The quality criteria are reliability, safety and control precise. The optimal control also minimises the human factor influences, but according to the quality it does not take any responsibilities from human factor.

This work has been supported by the Grant Agency of the Slovak Republic VEGA, grant No. 1/8261/01 „The Use of Artificial Intelligence for Critical Processes Controlling".

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