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HYBRID CONTROL PROBLEMS OF COAL FLOTATION PROCESS

ZAGADNIENIE STEROWANIA HYBRYDOWEGO PROCESEM FLOTACJI WĘGLA

In Poland, the most often used control systems of a coal flotation process are based on a doses stabilization system. An operation of this system is limited to the stabilization of reagent doses, based on measurements of concentration and feed flow intensity. In practice, the flotation process is running under conditions of different industrial disturbances. These are reasons that doses stabilization system, in many cases, doesn't stabilize the process qualitative parameters. This problem can be solved by the feedback control system. In order to practically use formulated control algorithms, it is necessary to determine dynamic models describing the input and output behaviour of the flotation process. High changes of mineral characteristics and plant properties can be a cause of significant changes of model parameters. It can makes that sensitivity limits of a conventional control system will stay overflow. In order to ensure a required control quality, there is necessary to tune control algorithm during algorithms realization. It can be realized by a hybrid control system.

In the paper rules for a design of the hybrid control system have been presented. Basic assumptions of the hybrid control system have been given. A fuzzy logic for description of dynamic models of coal flotation process has been applied. The analytical examples of dynamic models parameters determining based on a knowledge base system have been presented. A numerical example a formation of the flotation process dynamic model has been shown.

Key words: flotation process, identification, dynamic models, fuzzy models, hybrid control.

Stosowane w Polsce układy sterowania procesem flotacji węgla związane są z układami stabilizacji dawek odczynników flotacyjnych. Jednak ze względu na zakłócenia występujące w procesie flotacji stosowanie tych układów nie zapewnia stabilizacji jakości produktów wzbogacania. Możliwość taką stwarza zastosowanie pętli sprzężenia zwrotnego w układzie sterowania. Obecnie prowadzone są badania teoretyczne dotyczące układów automatycznej regulacji zawartości popiołu w odpadach z procesu flotacji węgla. W celu wykorzystania

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opracowanych algorytmów regulacji na obiekcie przemysłowym, niezbędna jest eksperymentalna weryfikacja przyjętych modeli dynamicznych. Modele dynamiczne są użyteczne przy założeniu, że sterowany obiekt jest stacjonarny. Dzięki temu wystarcza jednorazowa identyfikacja obiektu i zakłóceń oraz jednorazowe nastawianie parametrów przyjętego algorytmu regulacji. Założenia te jednak często są niesłuszne. Właściwości dynamiczne obiektu przemysłowego mogą się zmieniać w bardzo szerokim zakresie. Dlatego w celu zapewnienia wymaganej jakości sterowania konieczne jest dostrajanie algorytmu regulacji podczas realizacji tych algorytmów. Jednym ze sposobów takiej realizacji jest układ regulacji adaptacyjnej w pętli sprzężenia zwrotnego obiektu.

Innym podejściem do realizacji dostrajania parametrów regulatora jest zastosowanie układu regulacji z systemem opartym na wiedzy (KBS — knowledge based system). System KBS, związany z nadzorowaniem operacji w pętli zamkniętej, jest systemem uzupełniającym i rozszerzającym konwencjonalny algorytm sterowania. Regulator taki można nazwać systemem ekspertowym z nadzorem (SECS — supervisory expert control system), a sterowanie tego typu *sterowaniem hybrydowym*. System SECS wykorzystuje podstawy logiki rozmytej.

W artykule podano zasady tworzenia modeli rozmytych TSK oraz ich zastosowanie do opisu dynamiki obiektu. Omówiono koncepcje sterowania hybrydowego przemysłowego procesu flotacji węgla. Przedstawiono podstawowe założenia takiego sterowania. Podano przykłady analityczne wyznaczania parametrów modelu dynamicznego flotownika na podstawie bazy wiedzy (KBS) oraz zmierzonych w poprzednich chwilach czasu wartości wielkości wyjściowej i wielkości wejściowej obiektu.

Przedstawiono przykład obliczeniowy wyznaczania parametrów modelu dynamicznego flotownika. Na podstawie badań symulacyjnych otrzymano przebieg czasowy wielkości wyjściowej modelu obiektu i porównano z przebiegiem czasowym otrzymanym na podstawie pomiarów obiektu przemysłowego.

Słowa kluczowe: proces flotacji, identyfikacja, modele dynamiczne, modele rozmyte, sterowanie hybrydowe.

1. Introduction

In Poland, the most often used control systems of a coal flotation process are based on a system presented in figure 1. An operation of this system is limited to the stabilization of reagent doses, based on measurements of concentration (C_n) and feed flow intensity (V_n).

The unitary doses of the collector and frother (D_k, D_s) are loaded into the controller memory by flotation machine operator. Then, the values of frother and collector intensity are calculated by the programmable controller. This system also monitors a tailings ash content A_0 (Błaszczyk & Kaczmarczyk, 1990), (Kaczmarczyk & Kostorz, 1988).

In practice, the flotation process is running under conditions of different industrial disturbances. These are reasons that doses stabilization system, in many cases, doesn't stabilize the process qualitative parameters.

This problem can be solved by the feedback control system. In Poland there is no feedback control system of the coal flotation process with feedback for the

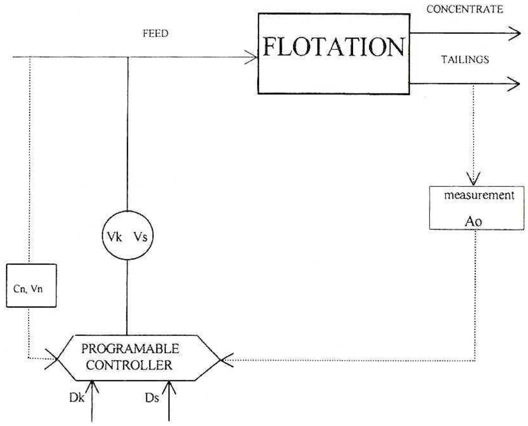

Fig. 1. A schematic diagram of the doses stabilization system

qualitative parameters stabilization in an industrial application. At the Department of Electrical Engineering and Automation in Mining a theoretical research concerning the feedback control system of the coal flotation process have been conducted. Because of an existence of industrial applications of tailings ash content gauge (a measurement signal A_0 in figure 1) and its relatively good accuracy, this research have been concentrated on tailings ash content stabilization in the feedback system. (Kalinowski & Kaula, 1997a), (Kalinowski & Kaula, 1997b), (Kaula, 1997).

In order to practically use formulated control algorithms, it is necessary to determine dynamic models describing the input and output behaviour of the flotation

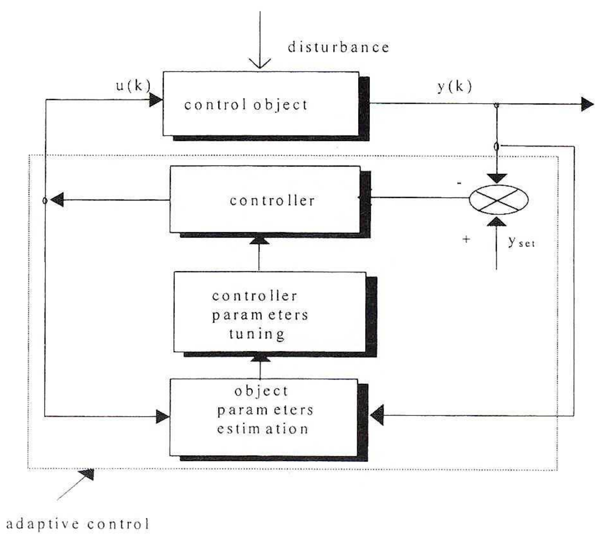

Fig. 2. Scheme of an adaptive control system

process. It can be obtained using the input-output identification. These dynamic models are useful, if the controllable system is time-invariant and the disturbances have only specific nonstationarities. In this case, there suffices only a one-time identification of the disturbances and system, as well as a one-time adjustment of the control algorithm parameters. These assumptions are often wrong. Dynamic properties of the industrial object can change in a wide range.

Big changes of mineral characteristics and plant properties can cause significant changes of model parameters and can overflow robustness limits of a conventional control system. The result of this situation can be:

— a decrease of a disturbance dumping,
— a decrease of a control quality,
— a system unstability in an extreme case.

In order to ensure a required control quality, there is necessary to tune control algorithm during operation. It can be realized by an adaptive control system (figure 2) (Niederliński et al., 1995). For this system, controller parameters by the on-line identification of the parametric model are determined.

2. Idea of the hybrid control

Another approach for the controller parameters tuning based on plant parameters identification is an application of a control system with a knowledge based system (KBS). KBS is the control system which expands robustness and error reliability, because it includes knowledge. This knowledge cannot be included in an

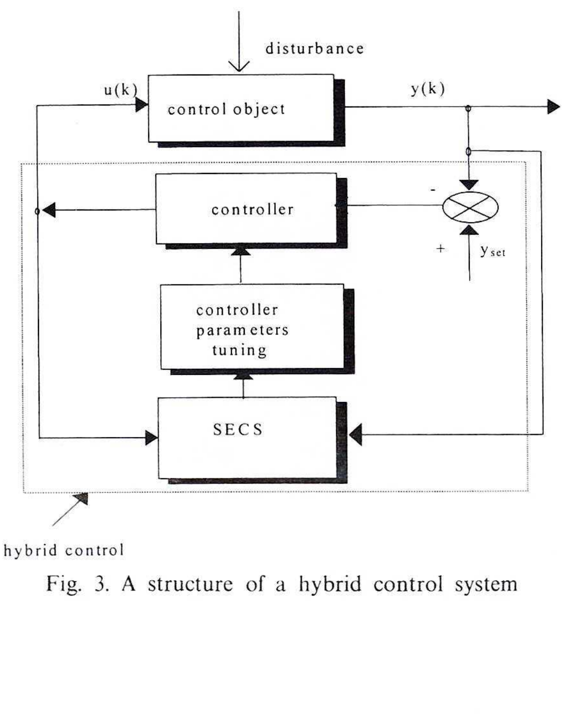

Fig. 3. A structure of a hybrid control system

analytical model, on which is based design of the conventional control algorithm (Driankow et al., 1996), (Yager et al., 1995). KBS, connected with a supervising operation in a feedback loop, is the extending and complementary system for the conventional control algorithm.

This kind of a controller can be called "supervisory expert control system" (SECS), and such control — the hybrid control (figure 3). SECS uses fuzzy logic basis.

2.1. Application of TSK fuzzy models for an object dynamics description

The required control quality can be obtained by a tuning of controller parameters. The controller parameters are determined on the basis of coefficients of the dynamic model of the control object. This is a reason, that one of the basic tasks of an efficient control is an adequate description of object dynamic model with changing parameters. It can be obtained using the fuzzy models to description of object dynamics.

There are two types of fuzzy models: Mamdani fuzzy models and Takagi-Sugeno-Kang (TSK) fuzzy models. The major difference is that Mamdani fuzzy models use only fuzzy sets whereas TSK fuzzy models use functions of input variables in the consequent of fuzzy rules. An inference method TSK is connected with rule sets which characterize fuzzy inputs and functions output. TSK model advantage is an ability to describe the complex technological processes. It makes possible a decomposition of the complex system to more simply subsystems.

The general Takagi-Sugeno-Kang (TSK) fuzzy models use M discrete-time input variables: namely $x_1(k)$, $x_2(k), \ldots$ $x_M(k)$, where k is sampling time. Input variable $x_i(k)$ is fuzzified by P_i arbitrary — shape input fuzzy sets. We denote the jth input fuzzy set for $x_i(k)$ as A_{ij} and denote its membership function as $A_{ij}(x_i)$, where $j = 1, 2, \ldots, P_i$. For M input variables $P_1 \times P_2 \times \cdots \times P_M$ different combinations of the input fuzzy sets exist and that many fuzzy rules are needed to over all the combinations. We use Ω to represent the total number of the fuzzy rules:

$$\Omega = P_1 \times P_2 \times \cdots \times P_M.$$

TSK fuzzy rules with linear rule consequent are used and the jth rule of the our general TSK models is $(1 < j <= \Omega)$:

$$\begin{gathered}\textbf{IF } x_1(k) \text{ is } A_{1j} \textbf{ AND } x_2(k) \text{ is } A_{2j} \textbf{ AND} \ldots \textbf{AND } x_M(k) \text{ is } A_{Mj} \\ \textbf{THEN } y_j(k) = a_{1j}x_j(k) + a_{2j}x_2(k) + \ldots + a_{Mj}x_M(k),\end{gathered} \tag{1}$$

where a_{ij} are coefficients of the identification models (constant gain for input variable x_i).

To combine the M membership values of the input fuzzy sets in the rule antecedent, any types of fuzzy logic AND operators may be used and different types of AND operators may be used in different rules. Input fuzzy sets A_{1j}, $A_{2j}, \ldots A_{Mj}$ is configured by some widely used components (e.g. triangular, trapezoidal or Gaussian membership functions).

The general TSK fuzzy models use the linear functions of input variables in the consequent of fuzzy rules. After defuzzification (the most popular is centroid defuzzifier), the output of the general fuzzy model is:

$$y(k) = \sum_{j=1}^{\Omega} \frac{\tau_j y_j(k)}{\sum_{j=1}^{\Omega} \tau_j}, \tag{2}$$

$$y(k) = \sum_{j=1}^{\Omega} \frac{\tau_j}{\sum_{j=1}^{\Omega} \tau_j} \left[a_{1j}x_1(k) + a_{2j}x_2(k) + \ldots + a_{Mj}x_M(k)\right]. \tag{3}$$

Using **Min**($\wedge$) for the fuzzy logic AND operator, the combined (aggregation) membership for consequent $y_j(k)$ in the jth rule is

$$\tau_j = A_{1j}(x_1) \wedge A_{2j}(x_2) \wedge \ldots \wedge A_{Mj}(x_M), \tag{4}$$

where $j = (1,\ \Omega)$.

2.2. Application of ARMAX models fuzzy expansion for the object dynamics description

The discrete transfer function of the control object is:

$$y_t = K(z^{-1})u_t, \tag{5}$$

$$y_t = \frac{B(z^{-1})}{A(z^{-1})} u_t, \tag{6}$$

$$y(k) = b_0 u(k) + \ldots + b_n u(k-n) - a_1 y(k-1) - \ldots - a_n y(k-n), \tag{7}$$

where:

y_t, u_t — observed process values, adequately, output and input,
k — sampling time,

$$A(z^{-1}) = 1 + a_1 z^{-1} + a_2 z^{-2} + \ldots + a_n z^{-n},$$

$$B(z^{-1}) = b_0 + b_1 z^{-1} + b_2 z^{-2} + \ldots + b_n z^{-n}.$$

A dynamic interpretation of TSK model we can obtained by a replacement: previous output values $y(k-1)$, $y(k-2), \ldots y(k-n)$ and a present $u(k)$ and previous input values $u(k-1)$, $u(k-2), \ldots u(k-n)$ of ARMAX model for input variables of TSK model. In this case, $y(k)$ is TSK model output.

Then the jth rule of TSK fuzzy sets have form:

$$\begin{aligned} &\textbf{IF } u(k) \text{ is } B_{j0} \textbf{ AND} \ldots \textbf{AND } u(k-n) \text{ is } B_{jn} \textbf{ AND } y(k-1) \text{ is } A_{j1} \\ &\qquad \textbf{AND} \ldots \textbf{AND } y(k-n) \text{ is } A_{jn} \\ &\textbf{THEN } y(k) = b_{j0}u(k) + \ldots + b_{jn}u(k-n) - a_{j1}y(k-1) - \ldots - a_{jn}y(k-n). \end{aligned} \tag{8}$$

3. Example of the hybrid system design for the coal flotation process control

For the hybrid system design there should be implemented the following stages:

- identification of the dynamic model of the flotation machine,
- formulation the knowledge based system (KBS),
- choice a type of discrete controller,
- tuning the controller parameters on the basis of SECS.

In order to the hybrid control of the industrial flotation process realization was carried out the identification of the flotation machine dynamic model parameters. As a structure of the dynamic model ARMAX model was chosen.

In order to carry out the identification experiment, the input-output signals of the object were determined. A dose of a collector-frother mixture was chosen as the input signal $u(k)$. The tailings ash content was chosen as the output signal $y(k)$.

The measurements were carried out in different set points of the flotation machine. The identification has been made with taking into consideration fluctuations of both the concentration and the flow intensity of the feed. Dynamic models for different average values of tailings ash content were calculated.

For simplicity of the KBS system assume, that the ancedents have two variables: measured outputs in time $y(k-1)$, $y(k-2)$. The membership functions for $y(k-1)$, $y(k-2)$ are shown in figure 4.

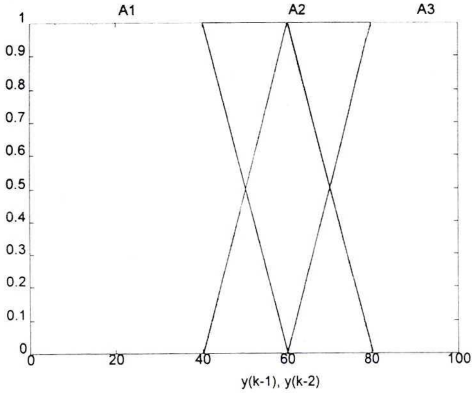

Fig. 4. The membership functions used to fuzzify $y(k-1)$, $y(k-2)$

$A1$ — the small tailings ash content,
$A2$ — the medium tailings ash content,
$A3$ — the big tailings ash content.
The total number of the fuzzy rules consists of nine rules.

1. **IF** $y(k-1)$ is A_1 **AND** $y(k-2)$ is A_1

   THEN $y(k)=b_{10}u(k)+\ldots+b_{1n}u(k-n)-a_{11}y(k-1)-\ldots-a_{1n}y(k-n)$

ALSO

2. **IF** $y(k-1)$ is A_1 **AND** $y(k-2)$ is A_2

   THEN $y(k)=b_{10}u(k)+\ldots+b_{1n}u(k-n)-a_{11}y(k-1)-\ldots-a_{1n}y(k-n)$

ALSO

3. **IF** $y(k-1)$ is A_1 **AND** $y(k-2)$ is A_3

   THEN $y(k)=b_{20}u(k)+\ldots+b_{2n}u(k-n)-a_{21}y(k-1)-\ldots-a_{2n}y(k-n)$

ALSO

4. **IF** $y(k-1)$ is A_2 **AND** $y(k-2)$ is A_1

   THEN $y(k)=b_{20}u(k)+\ldots+b_{2n}u(k-n)-a_{21}y(k-1)-\ldots-a_{2n}y(k-n)$

ALSO

5. **IF** $y(k-1)$ is A_2 **AND** $y(k-2)$ is A_2

   THEN $y(k)=b_{20}u(k)+\ldots+b_{2n}u(k-n)-a_{21}y(k-1)-\ldots-a_{2n}y(k-n)$

ALSO

6. **IF** $y(k-1)$ is A_2 **AND** $y(k-2)$ is A_3

   THEN $y(k)=b_{20}u(k)+\ldots+b_{2n}u(k-n)-a_{21}y(k-1)-\ldots-a_{2n}y(k-n)$

ALSO

7. **IF** $y(k-1)$ is A_3 **AND** $y(k-2)$ is A_1

   THEN $y(k)=b_{20}u(k)+\ldots+b_{2n}u(k-n)-a_{i1}y(k-1)-\ldots-a_{2n}y(k-n)$

ALSO

8. **IF** $y(k-1)$ is A_3 **AND** $y(k-2)$ is A_2

   THEN $y(k)=b_{30}u(k)+\ldots+b_{3n}u(k-n)-a_{31}y(k-1)-\ldots-a_{3n}y(k-n)$

ALSO

9. **IF** $y(k-1)$ is A_3 **AND** $y(k-2)$ is A_3

$$\textbf{THEN}\ \ y(k)=b_{30}u(k)+\ldots+b_{3n}u(k-n)-a_{31}y(k-1)-\ldots-a_{3n}y(k-n) \tag{9}$$

Number of the dynamic model structures has been limited to three, considering the changes character of the output. On the basis of SECS, having couple of measurements data $y(k-1)$, $y(k-2)$ we can obtain a structure and coefficients of the dynamic models.

3.1. Case studies

In this section we use two examples to demonstrate how to determine the dynamic model $y(k)$ for time k using measurements data in time $k-1$, $k-2$: $y(k-1)$, $y(k-2)$.

I.

The gauge of tailings ash content shown:

$y(k-1) = 50\,[\%]$,
$y(k-2) = 70\,[\%]$.

Min ($\wedge$) fuzzy logic AND operator is used in the rules and the centroid defuzzier is employed for defuzzification.

The dynamic model parameters according to formulas (2–4) have form:
$\tau_1 = (0.5 \wedge 0) = 0$, $\tau_2 = (0.5 \wedge 0.5) = 0.5$, $\tau_3 = (0.5 \wedge 0.5) = 0.5$, $\tau_4 = (0.5 \wedge 0) = 0$, $\tau_5 = (0.5 \wedge 0.5) = 0.5$, $\tau_6 = (0.5 \wedge 0.5) = 0.5$, $\tau_7 = (0 \wedge 0) = 0$, $\tau_8 = (0 \wedge 0.5) = 0$, $\tau_9 = (0 \wedge 0) = 0$

$$b_0 = \frac{\tau_2 b_{10}}{\sum_{j=1}^{m}\tau_j} + \frac{\tau_3 b_{20}}{\sum_{j=1}^{m}\tau_j} + \frac{\tau_5 b_{20}}{\sum_{j=1}^{m}\tau_j} + \frac{\tau_6 b_{20}}{\sum_{j=1}^{m}\tau_j} = \frac{0.5b_{10}+0.5b_{20}+0.5b_{20}+0.5b_{20}}{2} = 0.25b_{10}+0.75b_{20}, \tag{10}$$

$$b_n = \frac{\tau_2 b_{1n}}{\sum_{j=1}^{m}\tau_j} + \frac{\tau_3 b_{2n}}{\sum_{j=1}^{m}\tau_j} + \frac{\tau_5 b_{2n}}{\sum_{j=1}^{m}\tau_j} + \frac{\tau_6 b_{2n}}{\sum_{j=1}^{m}\tau_j} = \frac{0.5b_{1n}+0.5b_{2n}+0.5b_{2n}+0.5b_{2n}}{2} = 0.25b_{1n}+0.75b_{2n}, \tag{11}$$

$$a_1 = \frac{\tau_2 a_{11}}{\sum_{j=1}^{m}\tau_j} + \frac{\tau_3 a_{21}}{\sum_{j=1}^{m}\tau_j} + \frac{\tau_5 a_{21}}{\sum_{j=1}^{m}\tau_j} + \frac{\tau_6 a_{21}}{\sum_{j=1}^{m}\tau_j} = \frac{0.5a_{11}+0.5a_{21}+0.5a_{21}+0.5a_{21}}{2} = 0.25a_{11}+0.75a_{21}, \tag{12}$$

$$a_n = \frac{\tau_2 a_{1n}}{\sum_{j=1}^{m}\tau_j} + \frac{\tau_3 a_{2n}}{\sum_{j=1}^{m}\tau_j} + \frac{\tau_5 a_{2n}}{\sum_{j=1}^{m}\tau_j} + \frac{\tau_6 a_{2n}}{\sum_{j=1}^{m}\tau_j} = \frac{0.5a_{1n}+0.5a_{2n}+0.5a_{2n}+0.5a_{2n}}{2} = 0.25a_{1n}+0.75a_{2n}, \tag{13}$$

$$y_I(k) = b_0 u(k) + \ldots + b_n u(k-n) - a_1 y(k-1) - \ldots - a_n y(k-n). \tag{14}$$

II.

The gauge of tailings ash content shown:

$y(k-1) = 40\,[\%]$,
$y(k-2) = 80\,[\%]$.

The dynamic model parameters according to formulas (2–4) have form:

$\tau_1 = (1 \wedge 0) = 0,\ \tau_2 = (1 \wedge 0) = 0,\ \tau_3 = (1 \wedge 1) = 1,\ \tau_4 = (0.5 \wedge 0) = 0,\ \tau_5 = (0 \wedge 0) = 0,$
$\tau_6 = (0 \wedge 1) = 0,\ \tau_7 = (0 \wedge 0) = 0,\ \tau_8 = (0 \wedge 0) = 0,\ \tau_9 = (0 \wedge 1) = 0$

$$b_0 = \frac{\tau_3 b_{20}}{\sum_{j=1}^{m} \tau_j} = \frac{1 b_{20}}{1} = b_{20}, \tag{15}$$

$$b_n = \frac{\tau_2 b_{2n}}{\sum_{j=1}^{m} \tau_j} = \frac{1 b_{2n}}{1} = b_{2n}, \tag{16}$$

$$a_1 = \frac{\tau_2 b_{21}}{\sum_{j=1}^{m} \tau_j} = \frac{1 a_{21}}{1} = a_{21}, \tag{17}$$

$$a_n = \frac{\tau_2 a_{2n}}{\sum_{j=1}^{m} \tau_j} = \frac{1 a_{2n}}{1} = a_{2n}, \tag{18}$$

$$y_{II}(k) = b_0 u(k) + \ldots + b_n u(k-n) - a_1 y(k-1) - \ldots - a_n y(k-n). \tag{19}$$

The parameters of the discrete controller can be tuned using the parameters of the above discrete dynamic model. Tuning rules of the discrete controller parameters, based on dynamic model parameters, have been presented in other works (Kalinowski & Kaula, 1997), (Kaula, 1997).

3.2. Discussion

In the general case, for any couple of consecutive measurements we can assign a structure and coefficient values of the dynamic models (F_i). For a chosen input space we can present the models (F_i) in the form of a survey table. For example, discretizing the data of the tailings ash content in sampling period 5% (in brackets 25%–95%), we can present used models in table 1. Please note, that the choice of the membership function shape (figure 4) limited the models number (F_i) from 225 (all combinations data $y(k)$) to 81. KBS assumption about limitations of set rules from 9 to 3 structure (with regard to set points: small, medium, big — tailings ash content), additionally limited models to 16 (table 2). The weight coefficient of respective models have been shown in table 3.

For comparison the weight coefficients of models from above examples are adequate for models $F4$ and $F5$.

It was noticed that this way of models presenting it can be an valuable tool for simplification of the control algorithm designing.

TABLE 1

The survey table of the possible forms of the flotation machine dynamic model. The fuzzy sets space discretize in sampling period 5%

$y(k-1)$ / $y(k-2)$	25 [%]	30 [%]	35 [%]	40 [%]	45 [%]	50 [%]	55 [%]	60 [%]	65 [%]	70 [%]	75 [%]	80 [%]	85 [%]	90 [%]	95 [%]
25[%]	F1	F1	F1	F1	F2	F3	F4	F5	F6	F7	F8	F9	F9	F9	F9
30[%]	F1	F1	F1	F1	F2	F3	F4	F5	F6	F7	F8	F9	F9	F9	F9
35[%]	F1	F1	F1	F1	F2	F3	F4	F5	F6	F7	F8	F9	F9	F9	F9
40[%]	F1	F1	F1	F1	F2	F3	F4	F5	F6	F7	F8	F9	F9	F9	F9
45[%]	F10	F10	F10	F10	F11	F12	F13	F14	F15	F16	F17	F18	F18	F18	F18
50[%]	F19	F19	F19	F19	F20	F21	F22	F23	F24	F25	F26	F27	F27	F27	F27
55[%]	F28	F28	F28	F28	F29	F30	F31	F32	F33	F34	F35	F36	F36	F36	F36
60[%]	F37	F37	F37	F37	F38	F39	F40	F41	F42	F43	F44	F45	F45	F45	F45
65[%]	F46	F46	F46	F46	F47	F48	F49	F50	F51	F52	F53	F54	F54	F54	F54
70[%]	F55	F55	F55	F55	F56	F57	F58	F59	F60	F61	F62	F63	F63	F63	F63
75[%]	F64	F64	F63	F64	F65	F66	F67	F68	F69	F70	F71	F72	F72	F72	F72
80[%]	F73	F73	F73	F73	F74	F75	F76	F77	F78	F79	F80	F81	F81	F81	F81
85[%]	F73	F73	F73	F73	F74	F75	F76	F77	F78	F79	F80	F81	F81	F81	F81
90[%]	F73	F73	F73	F73	F74	F75	F76	F77	F78	F79	F80	F81	F81	F81	F81
95[%]	F73	F73	F73	F73	F74	F75	F76	F77	F78	F79	F80	F81	F81	F81	F81

TABLE 2

The survey table of the possible forms of the flotation machine dynamic model. The consequent limitations taking into consideration

$y(k-1)$ / $y(k-2)$	25 [%]	30 [%]	35 [%]	40 [%]	45 [%]	50 [%]	55 [%]	60 [%]	65 [%]	70 [%]	75 [%]	80 [%]	85 [%]	90 [%]	95 [%]
25[%]	F1	F1	F1	F1	F2	F3	F4	F5	F5	F5	F5	F5	F5	F5	F5
30[%]	F1	F1	F1	F1	F2	F3	F4	F5	F5	F5	F5	F5	F5	F5	F5
35[%]	F1	F1	F1	F1	F2	F3	F4	F5	F5	F5	F5	F5	F5	F5	F5
40[%]	F1	F1	F1	F1	F2	F3	F4	F5	F5	F5	F5	F5	F5	F5	F5
45[%]	F1	F1	F1	F1	F11	F3	F13	F5	F15	F15	F15	F18	F18	F18	F18
50[%]	F1	F1	F1	F1	F11	F3	F13	F5	F15	F18	F26	F27	F27	F27	F27
55[%]	F1	F1	F1	F1	F11	F3	F13	F5	F15	F26	F27	F27	F27	F27	F27
60[%]	F1	F1	F1	F1	F2	F3	F4	F5	F18	F27	F36	F45	F45	F45	F45
65[%]	F2	F2	F2	F2	F3	F13	F49	F5	F26	F27	F53	F45	F45	F45	F45
70[%]	F3	F3	F3	F3	F13	F4	F49	F5	F11	F27	F13	F45	F45	F45	F45
75[%]	F4	F4	F3	F4	F49	F49	F49	F5	F26	F27	F53	F45	F45	F45	F45
80[%]	F5	F5	F5	F5	F5	F5	F5	F5	F18	F27	F36	F45	F45	F45	F45
85[%]	F5	F5	F5	F5	F5	F5	F5	F5	F18	F27	F36	F45	F45	F45	F45
90[%]	F5	F5	F5	F5	F5	F5	F5	F5	F18	F27	F36	F45	F45	F45	F45
95[%]	F5	F5	F5	F5	F5	F5	F5	F5	F18	F27	F36	F45	F45	F45	F45

TABLE 3

The weight of the particular structures use in dynamic models

	Model structure 1	Model structure 2	Model structure 3
F1	1	0	0
F2	0.75	0.25	0
F3	0.5	0.5	0
F4	0.25	0.75	0
F5	0	1	0
F11	2/3	1/3	0
F13	1/3	2/3	0
F15	0	5/6	1/6
F18	0	0.75	0.25
F25	0	0.75	0.25
F26	0	2/3	1/3
F27	0	0.5	0.5
F36	0	0.25	0.75
F45	0	0	1
F49	1/6	5/6	0
F53	0	1/3	2/3

3.3. Simulation example

There have been obtained three dynamic models (for three different working points) of the flotation machine, based on carried out identification of the industrial object (table 4).

TABLE 4

The average values of the output

Model	$A_{0\_av}[\%]$
$A1$	51,32
$A2$	61,17
$A3$	79,44

The time courses of input and output signals, used to determine particular model parameters are shown in figures 5–7. The polynomial coefficient values of ARMAX models have been given in tables 5–7. According to assumption announced in section 3 the parameters of these models are used in the SECS structures.

— Model $A1$

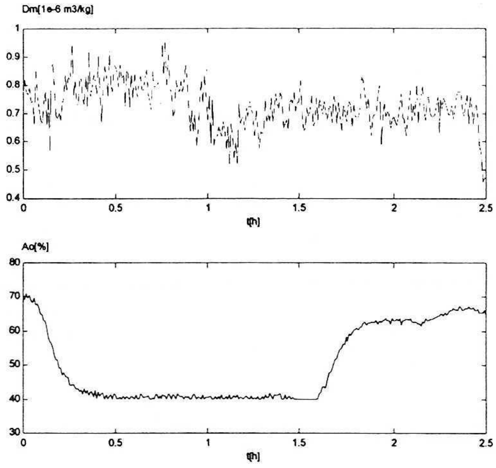

Fig. 5. The measurement data of input $D_m(t)$ and output $A_0(t)$ values for model $A1$

TABLE 5

ARMAX 25 parameters for model $A1$

Polynomial	1	z^{-1}	z^{-2}	z^{-3}	z^{-4}	z^{-5}	z^{-6}
$A(z^{-1})$	1	-1.7701	0.7705				
$B(z^{-1})$	0	0	0	0	0	-0.5087	0.4094

— Model $A2$

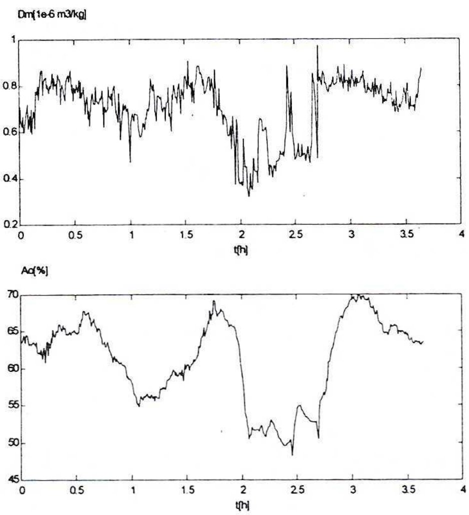

Fig. 6. The measurement data of input $D_m(t)$ and output $A_0(t)$ values for model $A2$

TABLE 6

ARMAX 25 parameters for model $A2$

Polynomial	1	z^{-1}	z^{-2}	z^{-3}	z^{-4}	z^{-5}	z^{-6}
$A(z^{-1})$	1	−1.869	0.8728				
$B(z^{-1})$	0	0	0	0	0	0.2059	−0.1892

— Model $A3$

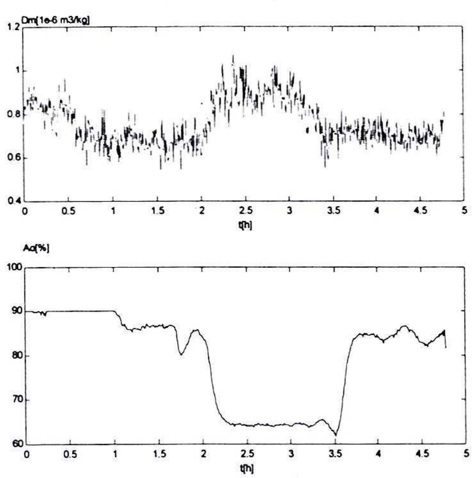

Fig. 7. The measurement data of input $D_m(t)$ and output $A_0(t)$ values for model $A3$

TABLE 7

ARMAX 24 parameters for model $A3$

Polynomial	1	z^{-1}	z^{-2}	z^{-3}	z^{-4}	z^{-5}	z^{-6}
$A(z^{-1})$	1	−1.9101	0.9109				
$B(z^{-1})$	0	0	0	0	−0.1866	0.1694	

The output value of the dynamic model $y_m(k)$

TABLE 8

$y_m(k) = B_4 * u(k-4) + B_5 * u(k-5) + B_6 * u(k-6) - A_1 * y_p(k-1) - A_2 * y_p(k-2)$
$B_4 = ((-0.1866)*(\tau_8+\tau_9))/\tau$ $B_5 = ((-0.5087)*(\tau_1+\tau_2)+(0.2059)*(\tau_3+\tau_4+\tau_5+\tau_6+\tau_7)+(0.1694)*(\tau_8+\tau_9))/\tau$ $B_6 = ((0.4094)*(\tau_1+\tau_2)+(-0.1892)*(\tau_3+\tau_4+\tau_5+\tau_6+\tau_7))/\tau$ $A_1 = ((-1.7701)*(\tau_1+\tau_2)+(-1.869)*(\tau_3+\tau_4+\tau_5+\tau_6+\tau_7)+(-1.9101)*(\tau_8+\tau_9))/\tau$ $A_2 = ((0.7705)*(\tau_1+\tau_2)+(0.8728)*(\tau_3+\tau_4+\tau_5+\tau_6+\tau_7)+(0.9109)*(\tau_8+\tau_9))/\tau$
$\tau = \tau_1+\tau_2+\tau_3+\tau_4+\tau_5+\tau_6+\tau_7+\tau_8+\tau_9$

In order to estimate of fitting grade of the dynamic model to changes in the object dynamics, there has been carried out a comparative analysis. For the comparative analysis, there have been chosen the measurement data with a wide range of the output fluctuations (figure 8).

The parameters of the flotation machine dynamic model have been calculated on the basis of SECS. The output values of the dynamic model y_m in time k have been calculated on the basis of previous output values y_p and input values u of the object (table 8).

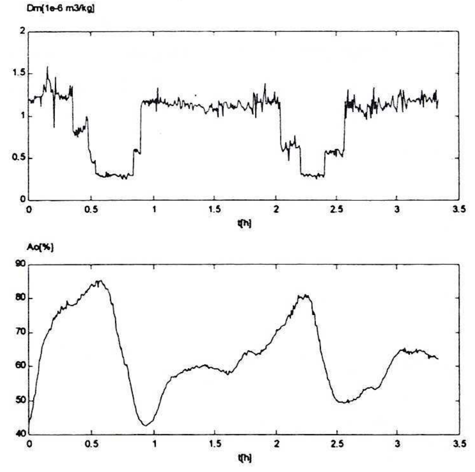

Fig. 8. The measurement data of input $D_m(t)$ and output $A_0(t)$ values used in the comparative analysis

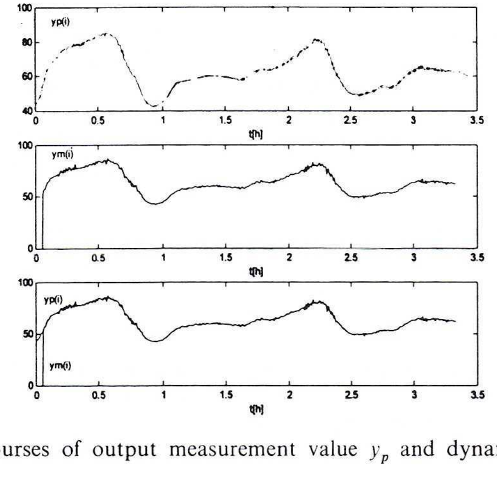

Fig. 9. The time courses of output measurement value y_p and dynamic model value y_m

The time courses of the output measurement value y_p and output y_m calculated by the parameters of the dynamic models are shown in figure 9. It can be observed significant compatibility for the output measurement output value y_p and the output model value y_m.

4. Conclusions

1. Verification of the idea of the hybrid control system should be carried out on the basis of the discrete control algorithms with regard to qualitative and quantitative criteria of the coal flotation process.

2. In order to obtain the knowledge based system about a controlled plant, regardless of the choice of a control type, there is necessary the dynamic model identification of the coal flotation process in a wide range considering:
   - change of the flotation machine set point,
   - influence of the operating variables on the output,
   - influence of process disturbances.

3. The selection of membership function is an important element of the hybrid system design.

4. Taking more variables number in KBS into consideration can causes the better system dynamics description, but it also significantly increases the number of rules and the same it increases time needed to the control signals tuning.

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