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# Predictive Control Systems of Product Quality

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**Abstract**. A natural stage in the development of automated systems is their digital transformation. This process is aimed at optimizing and improving production efficiency, one of the indicators of which is the stabilization and improvement of the quality of products while reducing losses. Advanced control Systems assume the presence of predictive models, but they often cannot or are not used in operational control tasks. These models are quite widely used in the petrochemical and mechanical engineering industries, a little less in the metallurgical industry, and are almost completely absent in the coal-processing industry. Thus, the development of structures and models suitable for predictive quality management is an urgent task. Models based on the full-scale model approach and multivariate structures have shown high efficiency in such tasks. An example of one of the possible integration structures of predictive product quality analysis models is given in this article.

**Keywords**: quality, predictive control systems, digital transformation

## Introduction

Forecasting the quality of products is always given considerable attention, because it is better to prevent a defect than to state it. GOST 15467-79 defines quality forecasting as "determining the likely values of product quality indicators that can be achieved by a given time or within a given time interval" [1]. Well-known methods of predicting quality include statistical methods, neural networks, digital twins. These methods have areas of their effective application and are relevant only in some cases, and each task requires a separate study and a heuristic solution.

One of the examples of predictive quality control [2], based on the methods of machine image processing, statistical estimates, cluster analysis of connected components, the results of metallographic studies, as well as estimates of the quality of workpieces, is intended for automated verification of the planned dynamics of changes and the formation of the necessary correction of key casting parameters. The proposed assistant performs the role of an adviser and a digital model for research and experiments, but is not tied into automatic process control.

The second example also based on machine learning methods, talks about the methodology for obtaining formal models linking bitumen quality indicators with technological parameters of their production, both for classical regression equations and for formal neural networks [3]. The authors indicate that the methodology for obtaining such models is worked out on abstract dependencies, however, in the automated process control system, the use of such dependencies is impossible in a direct form, since the existing control and regulation circuits constantly influence the processes and without eliminating their effects, obtaining any adequate model is impossible both by classical identification methods and statistical methods, since it is not possible to their prerequisites are fulfilled [4].

For processes that take place in complex chains of technological units that produce physico-chemical transformations [5-7], it is especially important to evaluate and predict the output quality after each of transformations, since even a small deviation, albeit within acceptable limits at the very beginning of the chain, can lead to a large deviation at the end, leading to defect. Thus, the task of predictive quality management of processes and products [8], based on quality forecasting, arises. An example of such processes is coal enrichment processes.

## 1 Theoretical Part

In the coal enrichment industry, there is a method of long-term forecasting of the quality (ash content) of coal products [9]. This technique is designed to determine the quantitative values of the ash content of coal extracted, processed at concentrating plants and shipped (according to various brands and grades) of production associations, mines (sections) and factories for up to 25 years. The methodology is based on the apparatus of mathematical statistics and the theory of random processes, which are not suitable for forecasting in control systems [10].

The use of predictive models in management tasks is not a new approach. The American researcher R. Kalman started development such systems in the early 1960s. Nowadays, such models based on physical, chemical or empirical dependencies are one of the main elements of advanced control systems – Advanced Process Control (APC) [11].

An example of an advanced process control system from T-Soft LLC is presented in the Figure 1.

In general, the management approach with predictive models is called as "MPC". The approach involves the use of a predictive model (PM) – an explicit model of the technological process as an element of the regulator in order to compensate for the dynamics of an open object and the description of the observed and unobservable variables of the object, thereby improving the properties of a closed control system. Many well-known companies (Rockwell, Siemens, Emerson, Yokogawa/Shell, etc.) develop their MPC products, allowing them to be used both for their own equipment and for third-party equipment.

Most commercial products do not disclose the underlying principles of forecasting, and the inability to refine models and algorithms without the involvement of foreign specialists significantly limits the possibilities of their using.

Among the developments of scientists from Russia, the following examples of systems with predictive models can be distinguished – both physical [12, 13] and mathematical [14, 15]. In the mineral processing industry, an example can be given of a control system for the ore grinding complex with a ball mill [16].


**Fig 1.** – Interface of the advanced process control system

The author builds a predictive model based on a neural network that uses sensor data to indirectly control the overload of the mill with ore according to the calculated parameter of the mass of the material in the mill. In general, there are practically no competitive integrated products on the domestic market that implement the MPC approach, both for industry and for general industrial solutions.

By presenting such systems in the symbols of the theory of automatic control, in general, for a circuit consisting of a single unit and its inputs/outputs, the following SAR structure can be formed on the basis of a modified Smith SAR (figure 2). In figure 2 $Y^*$ denotes specified values of quality indicators; $\varepsilon$ – deviation of the specified values of quality indicators from the predicted ones; $\varepsilon^{\Sigma}$ – deviation taking into account the effect of regulation without taking into account the delay in the system; $U$ – controlling influence; $W$ – disturbances; $Y$ – output quality indicators; $Y^M$ – model values of quality indicators without taking into account disturbances; $\delta U^M$ – deviation of quality indicators caused by disturbances; $f^{QAS}$ – predictive quality analysis subsystem; $\Omega$ – parameters required for forecasting; $\varphi_\tau$, $\varphi_o$ – lag and object models. In this case, the extrapolation operator is a quality prediction model for a certain contour of different nature and type.

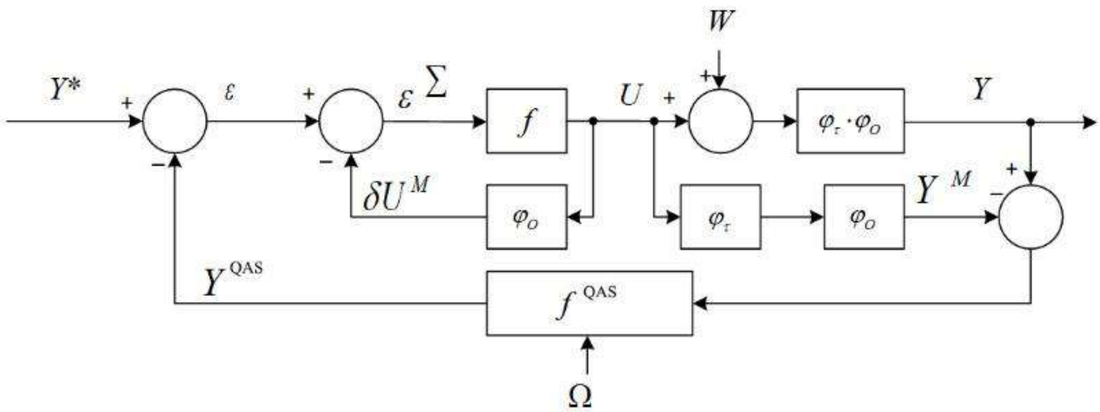


**Fig 2.** – SAR scheme with forecasting

Unlike the extrapolator in Smith's SAR, any predictive quality analysis system can be used for forecasting. It can rely on various models, methods and algorithms, and as input data it accepts not only the values of deviations of the actual output variable from the model, but also additional parameters that are somehow tied in forecasting: variables of the object and the system as a whole; inputs and outputs; system parameters that are not tied explicitly in regulation, but having an impact on quality; the properties of the input material obtained from the data of regulatory maps and/or laboratory analyses; various datasets, if the trained neural network is the basis for forecasting; etc.

To form model values of quality indicators, normative quality models can be taken as a mathematical model, obtained on the basis of "ideal" regime maps that do not take into account possible deviations in the initial quality of products and disturbances.

Integration of such predictive quality management subsystems is advisable to use both in digital adviser modes and to tie directly into automatic control and regulation if the system shows its high efficiency based on test results.

## 2 Experimental Part

In the existing control automation systems, the complexity of evaluating the effectiveness of predictive analytics systems lies in the fact that the built-in control circuits apply continuous control actions on the object to stabilize the quality. To assess the effectiveness in this case, you can use the methods of a full-scale model approach [17]. In this case, the use of the apparatus of recalculation models allows you to exclude the effects of control actions and adjust the system of predictive analysis on the object itself.

The full-scale mathematical approach for creating predictive models in control systems has proven its effectiveness and has developed historically in parallel with the MPC approach. The adaptation of its methods and algorithms for quality management is a strong alternative to systems of well-known manufacturers, since they are not rigidly tied to computer technology and can be embedded both at the level of workstations and in programmable logic controllers, which solves the problems of synchronization in time and sampling step, as well as integration with the domestic software and hardware complex automated control system.

If there are several predictive quality analytics systems, the effectiveness of each of them may depend on the situation and production conditions, then it is difficult to choose one of them as a predictor. The implementation of the multivariate mode [18] allows to choose the most effective system at the moment and implement management based on its results.

The introduction of advanced control systems has become widespread in such industries as petrochemical, machine-building. Slightly less common, but they are in demand in the metallurgy industry. The coal-processing industry often surpasses those mentioned above in terms of automation [19], however, the introduction of APC technologies is extremely rare, and at the moment it is also difficult, since few domestic manufacturers offer "boxed" solutions in this direction, and in the coal industry there are none at all.

A typical circuit for which such a system may be relevant is the enrichment of coal in a heavy-medium separator. The scheme of the section of the technological chain is shown in Figure 3. Control of this circuit is carried out by changing the density of the heavy medium by diluting the valve on water or increasing it by feeding fresh magnetite suspension.

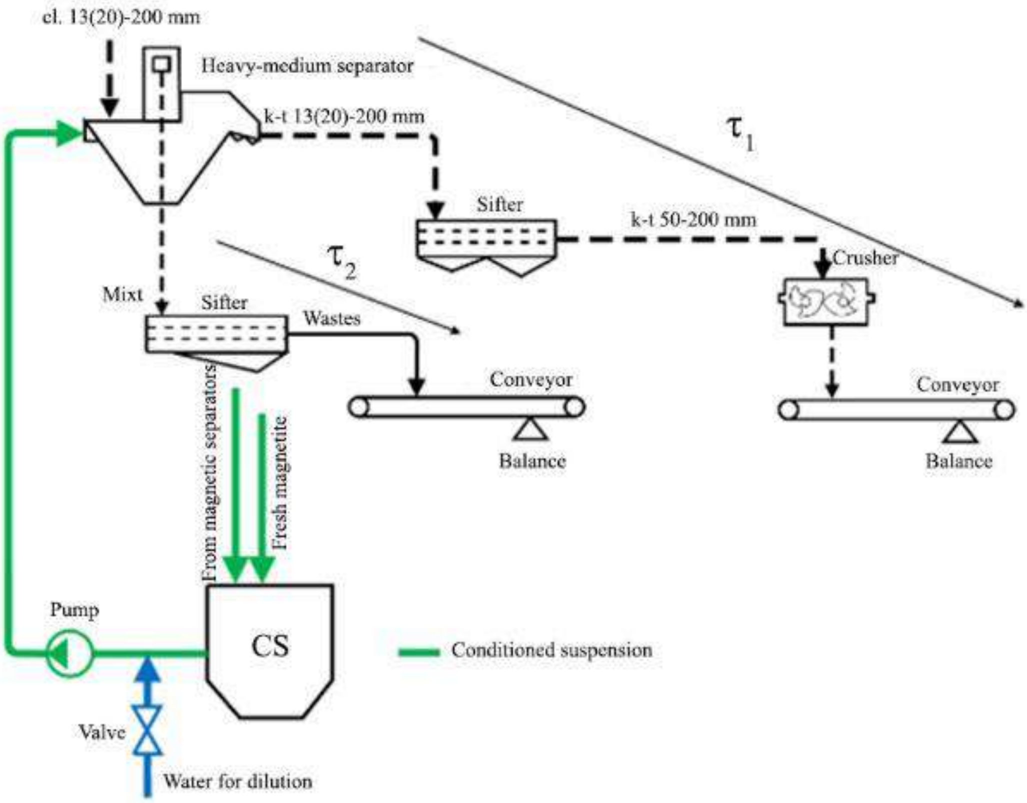


**Fig 3**. – Simplified diagram of a section of the technological chain of coal enrichment in a heavy-medium separator

As a rule, it is not accepted to equip such contours with in-line ash and moisture meters. Laboratory tests are spot-based and the delay in them can range from half an hour to several hours. It is advisable to apply an indirect assessment of the enrichment process according to the available data:

– grade and available characteristics of the formation;

– the actual value of the density of the heavy medium from the density meter;

– actual indications of coal and rock separation by conveyor scales.

The application of classical approaches to process management in this case is not effective, since the delay in the evaluation channels ($\tau_1$ and $\tau_2$) is better than the dynamics of the process. In this case, it is possible to make a model of indirect estimation and forecasting of coal quality based on the difference between the expected (normative) separation of ordinary coal from the actual one. In this case, it would be advisable to use systems with predictive models, as, for example, in figure 3.

The development of the direction of predictive quality control of coal will increase the economic efficiency of production, solving the problem of "pumping" (associated with excessive costs and wear of equipment) and defects (associated with penalties). Improving the quality of coking coal grades is a necessary condition for the development and activation of the metallurgical industry, which is necessary for the development, in turn, of the machine-building industry.

## 3 Predictive control of coal preparation

The achievable quality of coal preparation is initially determined at the stage of process chain design, when enlarged enrichment blocks are defined: enrichment with heavy media in separators and hydro cyclones, in spiral separators, in flotation machines, etc. The chains are designed flexible and switchable so that, depending on the characteristics of the input raw materials, it is possible to obtain the specified quality due to combination and sequential inclusion of units and processing units to obtain the required enrichment depth. These chains are designed to be flexible and switchable so that, depending on the characteristics of the incoming raw material, a given quality can be obtained by combining and sequentially switching on units and stages to obtain the desired depth of enrichment. In such an environment of constant switching, which is often dynamic, it is virtually impossible to build adequate enrichment models based on physicochemical patterns suitable for prediction.

In order to solve the problem of quality management, the technologists use the results of laboratory studies that combine particle size distribution and fractional analysis. So called "sieve-fractional" analysis allows to construct coal enrichment curves for each separate class in the heavy medium density grid. In this way it is possible to determine the required structure of the process chain for a given enrichment and density settings for each circuit.

An example of enrichment curves of coal grade "Zh" for +13 mm class is presented in Figure 4. The shape of the curves is rather heterogeneous and does not allow approximating the curve with acceptable accuracy. This is caused by measurement errors, heterogeneity of sampling for analysis, non-stationarity of characteristics of one and the same grade and other reasons. To construct a more accurate enrichment curve, many laboratory statistics are required to eliminate errors and minimize them to construct an adequate approximating curve.

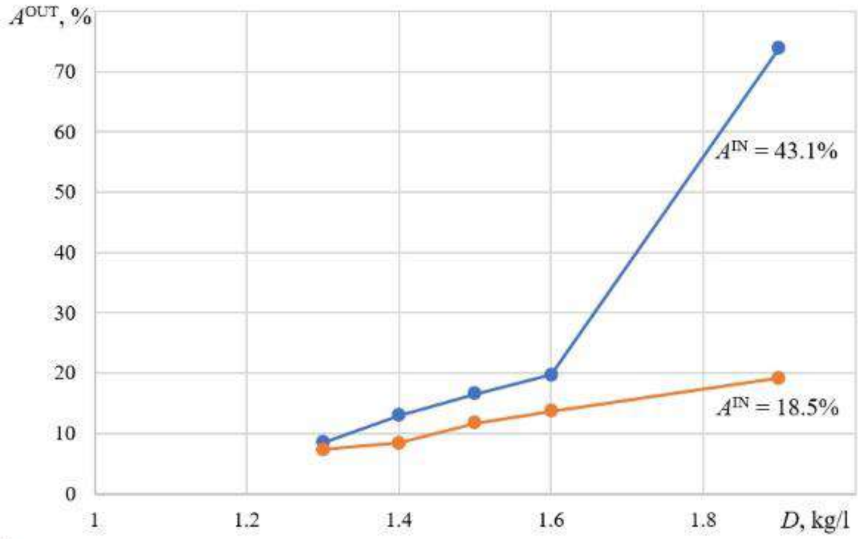


**Fig 4.** – Examples of enrichment curves

A large volume of laboratory studies allowed us to construct sufficiently accurate realizations of enrichment curves in the form of exponents with the following mathematical description:

$$A^{OUT} = a \cdot e^{b \cdot D}, \tag{1}$$

where $A^{\mathrm{OUT}}$ is the output ash content; $D$ is the density; $a$, $b$ are curve parameters.

To find the coefficients $a$ and $b$, we apply the Nelder-Meade method of search optimization by mean-modulus deviation.

Based on this expression, we obtain the solution of the equation with respect to $D$:

$$D^* = \frac{\ln\left(\frac{A^{\mathrm{OUT}*}}{a}\right)}{b},$$

where $A^{\mathrm{OUT}*}$ is the specified ash content; $D^*$ is the required density specification.

The curve of a given input ash content is determined by interpolation between neighboring curves and further approximation by expression (1). Figure 5 shows the curve for coal with input ash content of 25%. Set ash content $A^{\mathrm{OUT}*} = 17\%$, the found set density is $D^* = 1.63$ kg/l.

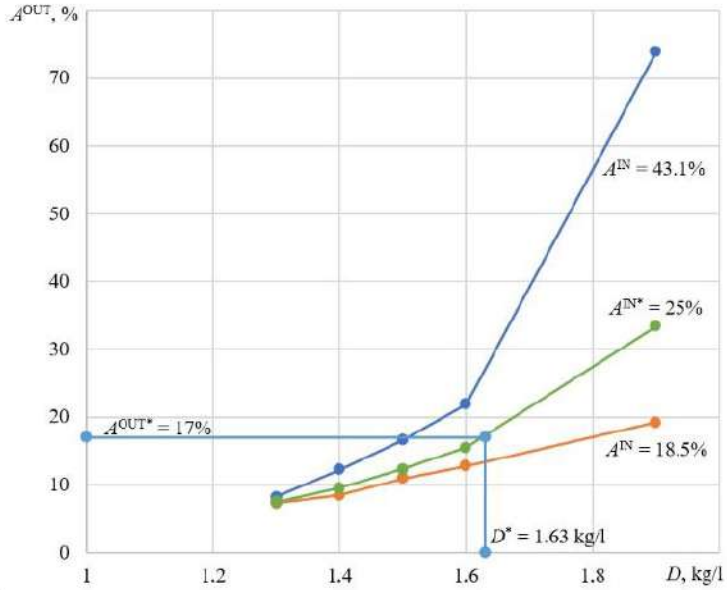


**Fig 5**. – Enrichment curves and set parameters

The proposed system works as a digital tipster in the beneficiation plant in semi-automatic mode. The technologist sets the setpoint parameters and decides whether to accept the results of the tipster or set his own. The setpoint is then transmitted by the control system to the magnetite slurry density control loop, which begins to maintain the new level.

At present, most production facilities can realize such systems only in the form of semi-automatic digital advisors. For full realization in the form of automatic predictive control systems, a serious digital transformation of all systems is required – process control systems, laboratories, warehouses, loading, etc. to integrate them into overall information space [20-23].

## 4 Conclusion

Summarizing, it is worth noting that the model of indirect assessment and forecasting of coal quality presented in the work, based on the assessment of the difference between the expected (normative) separation of ordinary coal from the actual, allows for more effective management of the quality of finished products, which further contributes to improving the position of the organization in the market and the development of the economy as a whole. In the future, the model should be improved to reduce the probability of errors.

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