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VIRTUAL ANALYZERS FOR INCREASING THE INTELLIGENCE OF INDUSTRIAL PROCESS CONTROL SYSTEMS

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***Abstract**: It is shown that the development and implementation of virtual analyzers of the quality of the final industrial products is an effective tool for increasing the efficiency of industrial production. The methodology and stages of development of virtual analyzers for predicting the quality of products, monitoring non-measurable or difficult-to-measure parameters of continuous and periodic technological processes are considered, and issues of supporting and adapting a virtual analyzer during its operation without restructuring are also considered.*
***Keywords:** Virtual analyzer, Adaptation, Prediction model, Soft sensor, Online prediction.*

***Аннотация:** Саноатда тайёр маҳсулотлар сифатининг виртуал анализаторларини ишлаб чиқиш ва амалга ошириш саноат ишлаб чиқаришининг самарадорлигини оширишни ҳақиқий воситаси ҳисобланиши кўрсатилган. Маҳсулот сифатини башоратлаш, узлуксиз ва даврий технологик жараёнларнинг ўлчанмайдиган ёки қийин ўлчанадиган параметрларини назорат қилиш учун виртуал анализаторлар ишлаб чиқиш методологияси ва босқичлари, шунингдек виртуал анализаторларни фаолияти давомида адаптивлаш ва қўллаб-қуватлаш муаммолари кўриб чиқилган.*
***Таянч сўзлар:** виртуал анализатор, адаптивлаш, башоратловчи модель, дастурий датчик, онлайн башоратлаш.*

***Аннотация:** Показано, что разработка и реализация виртуальных анализаторов качества конечной промышленной продуктов является действенным инструментам повышения эффективности промышленного производстве. Рассмотрены методология и этапы разработки виртуальных анализаторов для прогнозирования качества продукции, контроля неизмеряемых или трудноизмеримых параметров непрерывных и периодических технологических процессов, а также вопросы поддержки и адаптации виртуального анализатора в процессе его эксплуатации без перестройки.*
***Ключевые слова:** виртуальный анализатор, адаптация, прогностическая модель, программный датчик, онлайн-прогнозирование.*

Introduction

At present, due to the steady growth of automation of manufacturing processes in all sectors of the economy, the increase and intensification of technological processes, there is a significant increase in the number of parameters subject to automatic control and regulation.

Technological processes of the chemical, petrochemical and oil refining industries are mainly associated with the processing of dispersed systems, suspensions, colloidal solutions, and various viscoplastic materials. Knowledge of the physico-mechanical and rheological properties of industrial products and the patterns of their changes can indicate new ways of controlling technological processes, facilitate the development of methods for monitoring and automating processes, as well as the search for constructive solutions in the design of new equipment and measuring equipment. The introduction of an automatic control system requires the selection of one or another indicator of the final product and obtaining reliable information.

One of the main parameters of physico-chemical properties that most fully characterize the quality of a whole range of liquid products of industrial production is their viscosity. By changing the viscosity value, one can judge, for example, fluctuations in density, concentration and many other indicators of the technological process. In addition, in the chemical, petrochemical, food and other industries, viscosity is often the main indicator characterizing both the quality of the technological process and the degree and readiness of the final product. Therefore, the measurement of viscosity makes it possible to make the best representation of the medium in question. If we also take into account that there is, as a rule, a well-defined relationship between the viscosity and the composition of liquids, then this circumstance makes it easy to control a large range of technological processes by measuring the viscosity. Thus, the measurement of the viscosity of liquid media is necessary both for conducting various studies in laboratory conditions, and for controlling technological processes in many industries and quality control of finished products. Despite this, such an approach to control over the quality of manufactured products and its regulation is sometimes not enough. Since the quality control of products and semi-finished products in terms of rheological characteristics, such as viscosity and density, is carried out by measuring these properties by measuring the liquid product or finished product at the outlet of the apparatus. Therefore, predicting the quality of products is necessary.

Manufacturing enterprises, as a rule, are equipped with a large number of sensors. The main purpose of sensors is to transmit data for monitoring and controlling processes. However, twenty years ago, researchers began using large amounts of data that had been measured and stored in production, creating predictive models based on this data. In the manufacturing industry, these predictive models are called virtual analyzers [1]. Other common terms for virtual analyzers in the manufacturing industry can be replaced by software sensors and virtual online analyzers.

Main part

At the general level, two different classes of virtual analyzers can be distinguished: model-based and data-based. Although there are some models of virtual analyzers based on the extended Kalman filter or adaptive observers, they are based on the first series of fundamental models of virtual analyzers [2].

The principle of the model describes the physico-chemical basis of the process. These models are mainly intended for the planning and design of industrial enterprises and therefore, as a rule, are aimed at characterizing the ideal state of processes. This is one of their disadvantages and makes it difficult to use them as the basis of virtual analyzers. Currently, data-based virtual analyzers are becoming increasingly popular as their solution [3].

Since the Model is the heart of the virtual analyzer, it is very important to choose the optimal type for its operation. There is still no single theoretical approach to this task, and therefore the type of model and its parameters are often selected individually for each specific case. The choice of the model often depends on the experience and personal desire of the developer, which may be unfavorable for the final virtual analyzer.

Despite the lack of a generally excellent approach to model selection, there are several ways to solve this problem. A possible method is to start with a simple type or structure of the model (for example, a linear regression model) and gradually increase the complexity of the model until there is a significant improvement in the performance of the model (for example, using the Student's T-test). When performing this task, it is important to evaluate the performance of the model based on independent data [4].

One of the types of virtual analyzers is focused on high-speed virtual analyzers, in which they demonstrate prediction models controlled by continuous target variables from the point of view of machine learning.

After the Virtual Analyzer is developed and put into practice, it is necessary to constantly configure and maintain it in working order. The reasons leading to a deterioration in the performance of the Virtual Analyzer are data silencing and other modifications, such a situation requires maintenance of virtual analyzers, and this is fraught with correction or rescheduling of the model.

Currently, more virtual analyzers don’t provide any automatic motions for their service. This fact, along with evidence of changes in the previously discussed data, stimulates the demand for quality control and technical services supporting virtual analyzers, which leads to significant costs for the use of virtual analyzers. Even worse, there is usually no objective measure to assess the quality of a virtual analyzer, and there is a subset based on a visual interpretation of the difference between the actual value of the target variable and its prediction, regardless of whether the model works well or not, whether the model is tied to the operator or not.

Nevertheless, there are several flexible approaches to virtual analyzers in the scientific literature. Most of these approaches are based on flexible PCA or PLS options, such as moving window PCA [5] or recursive PCA [6]. All of these methods are based on a basic component base or continuous tuning. Neural-neutral virtual analyzers often provide automatic adaptation, as indicated in [7,8]. These statements are based on the placement of new blocks in the neural structure of the model as soon as a new data state is detected. The approach, which is associated with neuro-unconventional methods, also makes it possible to adapt to local conditions. For example, data on an adaptive virtual analyzer developed within the framework of local training are presented in [9].

Despite the automated methods of adaptation of the Virtual Analyzer, the model operator still plays an important role, since knowledge and feedback about the main process determines the method of selecting the parameters of individual adaptation methods (for example, determining the length of a sliding window on the example of a sliding window method or the boundaries for installing a new one

The considered methodologies, although they are the most common, are not the only way to develop a virtual analyzer. For example, in terminology [10] an alternative methodology was developed for a virtual analyzer or logic sensor. It focuses on three different stages: 1) data collection and processing, 2) selection of impressive variables, and 3) correlation construction. These three stages correspond to "stored data selection", "data preprocessing" and "model selection, training and evaluation".

Practical part

In Figure 1, examples of variables affecting the widespread problems of industrial data that will be discussed are presented.

Lost data these are single or multiple variables (that is, measurement data) that have a value that does not reflect the actual state of the physical measured quantity, or their sequential sets. The affected variables usually have values such as ± ∞, 0.

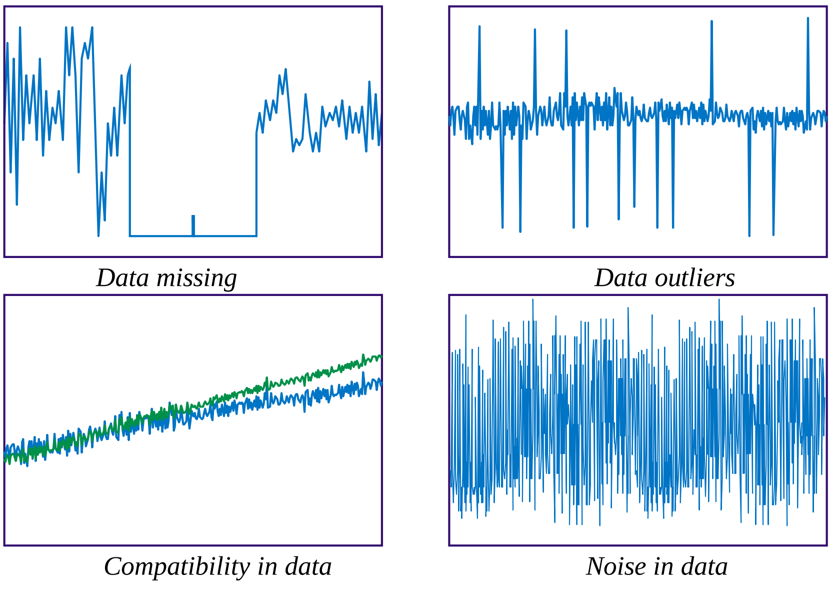

Figure 1. ***Common problems of manufacturing industry data.***

From the point of view of the manufacturing industry, the lost values have various causes. The most common are metering failure, maintenance and repair of the meter, and / or temporary removal of the meter. As mentioned above, manufacturing plants are equipped with many measuring instruments to control and manage the technological process, so the recorded data of the process consists of a large number of different variables. In this case, some sensors may fail from time to time. It should be borne in mind that some types of sensors are in the form of mechanical devices (e.g., flow velocity sensors) and therefore such measuring devices are subject to decay. Other possible causes of data loss include data transfer between sensors and databases, errors in the database, problems accessing the database, and more.

Most of the methods used for data-driven virtual analyzers cannot work with lost data, so a strategy to replace them needs to be implemented. A very simple and not recommended, but frequently used approach in practice is to replace missing values with the average value of the affected variable. Another non-optimal approach is to skip data sets consisting of variables with missing values, i.e., delete them. A more efficient approach to processing lost values takes into account multidimensional statistics of data and thus recovers lost values from others, i.e., variables whose values depend on existing variables (e.g., a multi-level approach to replacing missing values). These types of approaches involve detecting and repairing sensor failures. From another perspective, it is possible to distinguish two different approaches when working with missing values. These are: a single calculation in which the missing values are changed in one step (e.g., using average values); and recalculation, these are iterative methods that are performed in multiple computational steps.

At the initial stage, an initial verification of the data is performed. The purpose of this step is to gain an overview of the data structure and identify specific problems that can be solved at this stage (e.g., blocked variables with a constant value, etc.). The next goal of this phase is to assess the requirements for the complexity of the model. In the case of an online predictive virtual analyzer, an experienced virtual analyzer developer can make a logical decision to use a simple regression model, a more complex AKR regression model, or a nonlinear neural network to build a virtual analyzer. In some cases, the operator’s decision about the class of the model at this stage may not be correct, so the models and their performance should always be evaluated and compared with alternative models in later stages.

Particular attention is paid to the evaluation of the goal variable. It should be checked that there is sufficient variability in the output variable and that it can be modeled in general.

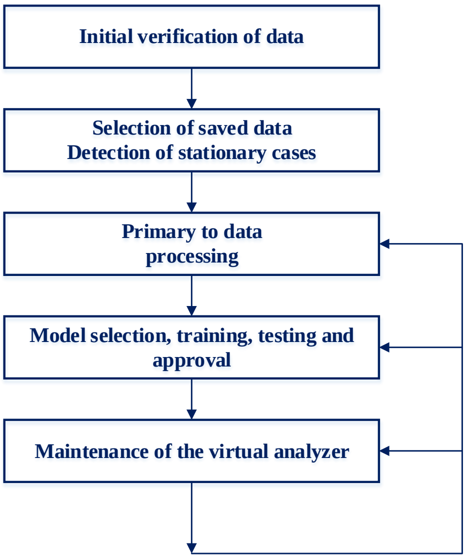

Figure 2. ***Virtual analyzer development methodology.***

Choice of stored data and finding of stationary cases. Here, the data used to train and evaluate the model are selected. Then, the stationary parts of the data must be identified and selected. In most cases, subsequent modeling will only apply to the stationary state of the process. Determining the status of a stationary process is usually done by interpreting the data by a human.

[11] discusses the determination of the steady state of continuous processes, and uses a wave-based approach to accomplish this task.

Periodic processes typically do not have stable cases, and therefore the model developer focuses more on selecting representative batches rather than identifying stable cases.

At present, a lot of work needs to be done on the initial human processing of data, as well as the model selection and verification stages during the development of the virtual analyzer. In general, a lot of information about the underlying process needs to be collected and included in the models in order to overcome the effects of the riots that are present in the industry data.

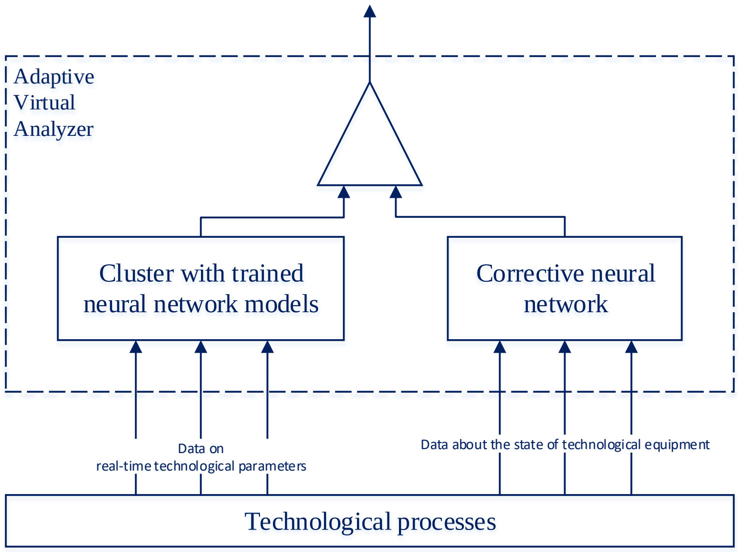

Figure 3. ***Structure of adaptive virtual analyser.***

It was noted that in manufacturing enterprises, technological processes are carried out on mechanisms and devices consisting of many mechanical and technological elements, which are constantly degraded during their operation. This can affect the process itself, for example, the flow between the two parts of the process can be reduced due to the breakdown of the mechanical pumps. Another reason for data drift may be changes in the external environment (eg, weather effects), the purity of the incoming materials, the decrease in catalyst activity, and so on. These factors not only affect the data but also the state of the process. Therefore, in case of sensor failure, the measuring devices should be recalibrated or the virtual analyzer should be adapted to the process, situation and conditions.

Over time, it is necessary to increase the reliability of its predictions by adapting virtual analyzers depending on the state of the process equipment. This can also be done through continuous and periodic retraining of the neural network model. This requires re-sorting the data to train the model. The model should also be retrained when the process equipment is repaired and restored. The following solution has been proposed to make the virtual analyzer adaptive (Figure 3).

In this case, the adaptive virtual analyzer consists of a cluster with trained neural networks and a neural network that corrects predictions. The cluster, which acts as a predictive model, consists of trained neural networks that predict product quality based on measurement data about the state of technological processes. The corrective neural network adjusts these predictions based on the state of the process equipment and the technological conditions.

Conclusion

Once the virtual analyzer is successfully launched, it can be observed that its performance gradually deteriorates. Decreases in the quality of forecast indicators are usually caused by a gradual change in the process, changes in the operating state of the process, a change in the quality of the input materials, or a breakdown of the hardware sensors. This suggests that it is almost impossible to compensate for changes by entering process data, and that the virtual analyzer must be flexible and try to compensate for the changes using some adjustment mechanisms. At present, the latter approach is a common practice.

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