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Self-Calibration of Intelligent Sensors Based on Virtual Analysis

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Abstract:

The paper considers the methods of calibration of measuring instruments using virtual analyzers. The advantages of using a virtual quality analyzer to determine the metrological condition of the measuring instrument are shown, where the main attention is paid to the accuracy of measurement. To obtain accurate calibration data, large-volume stored data is used, which is processed by a neural network model of a virtual analyzer trained with a large volume of samples. The developed self-calibration method based on the processed data of the virtual analyzer evaluates the metrological condition of the measuring instrument and generates calibration data with which the intelligent sensor performs self-calibration. The article also analyzes the trends in the development of intelligent measuring devices, in particular the functions of intelligent sensors within the framework of "Industry 4.0".

Keywords: virtual analyzers, measuring instruments, self-calibration, metrological self-control, measurement data processing, measurement accuracy.

INTRODUCTION

An integral function of intelligent sensors as metrological self-monitoring provides an opportunity to increase the reliability and reliability of measurement results through the use of active measures called "self-calibration", which increases the calibration and calibration interval while maintaining the required accuracy.

The implementation of the self-calibration function in intelligent sensors provides for the presence of a metrological self-monitoring function, since calibration is performed according to metrological control data, or such data must be entered from the outside into the sensor via a communication channel with the process control system, in turn, it is calculated in cloud systems or in automated control systems, the latter option is not acceptable according to the trend of distribution of computing load due to the intellectualization of measuring instruments, especially sensors, according to the strategy "Industry 4.0" [1].

Development and construction of intelligent sensors, implementation and use, maintenance and repair, tracking the behavior of intelligent sensors for further research, in general, the management of the life cycle of intelligent sensors implies the presence of the traceability property of sensors for data collection from the manufacturer, as well as the use of software for processing and those collected data cloud technologies, where the digital a sensor double or virtual analyzer for evaluating and predicting the metrological condition of the sensor. At the same time, data must be obtained not only from the SCADA system, but also from calibration and calibration stands, which requires the creation of special automatic calibration and calibration stands and software that support the above technologies.

REVIEW OF LITERATURE

The construction of virtual analyzers for the assessment and prediction of the metrological condition of the sensor is similar to the construction of virtual analyzers of the quality of products.

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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 [2-4].

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 [5].

The construction of virtual analyzers for assessing and predicting the metrological condition of the sensor based on the principle of the process model is not very suitable, because the model describes the course of the process and is mainly used to control the process and achieve the desired quality of the product of the technological process by easily measurable parameters, adjusting these parameters. But these models are completely useless in terms of developing and building virtual analyzers for assessing and predicting the metrological state of the sensor, since these models can be converted into knowledge for building and selecting a virtual analyzer model based on data [6].

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 [7]. In [8], the definition of the stationary state of continuous processes is discussed and a wave approach is used to solve this problem.

The considered methodologies, although they are the most common, are not the only way to develop a virtual analyzer. For example, in terminology [9] 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".

THE MAIN PART

The lost data are individual samples or a series of sets of one or more variables (i.e. measurement data), the value of which does not reflect the actual state of the physically measured quantity. The variables under consideration usually have values such as $\pm\infty$, 0.

From the point of view of the manufacturing industry, the lost data values have different reasons. The most common are sensor failure, sensor maintenance and repair, and/or temporary sensor removal. As mentioned above, manufacturing enterprises are equipped with a variety of measuring devices for monitoring and controlling the technological process, therefore, the recorded process data consists of a large number of different variables. At the same time, some sensors may fail from time to time. It should be borne in mind that some types of sensors are made in the form of mechanical devices (for example, flow velocity sensors) and therefore such measuring devices are subject to wear. Other possible causes of data loss include data transfer between sensors and databases, database errors, database access problems, and more.

Most of the methods used for data-driven virtual analyzers cannot work with lost data, so it is necessary to implement a replacement strategy. A very simple and not recommended approach, but often used in practice, is to replace the missing values with the average value of the affected

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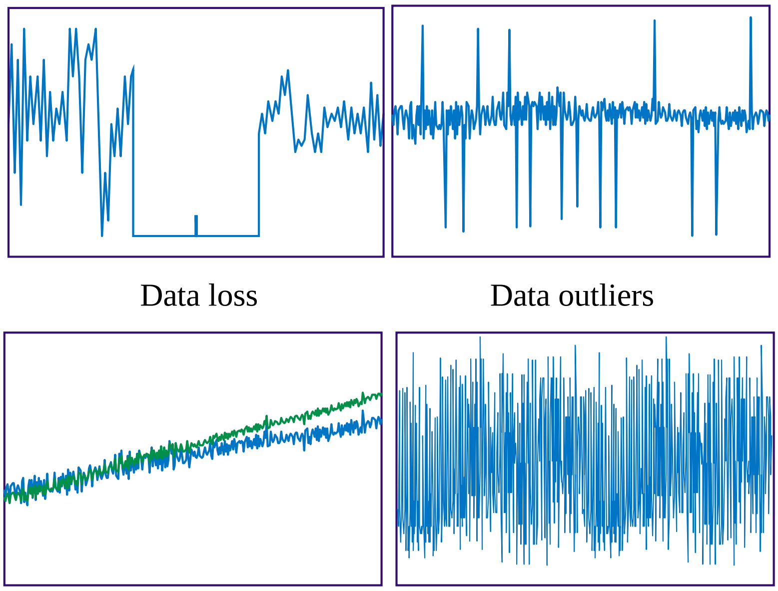
variable. Another suboptimal approach is to skip datasets consisting of variables with missing values, i.e. delete them. A more efficient approach to processing lost values takes into account multidimensional data statistics and thus restores lost values from other variables, i.e. variables whose values depend on existing variables (for example, a multi-level approach to replacing missing values). These types of approaches include detecting and eliminating sensor failures. On the other hand, two different approaches can be distinguished when working with missing values. This is: a single calculation in which the missing values are changed in one step (for example, using average values); and recalculation, these are iterative methods that are performed in several computational steps (Fig. 1).



Data loss Data outliers

Compatibility in data Noise in the data

Figure 1. General problems related to manufacturing industry data

At the initial stage, the initial data verification is performed. The purpose of this step is to get an idea of the data structure and identify specific problems that can be solved at this stage (for example, locked variables with a constant value, etc.). The next goal of this stage is to assess the complexity requirements 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 model class at this stage may be incorrect, so models and their characteristics should always be evaluated and compared with alternative models at later stages.

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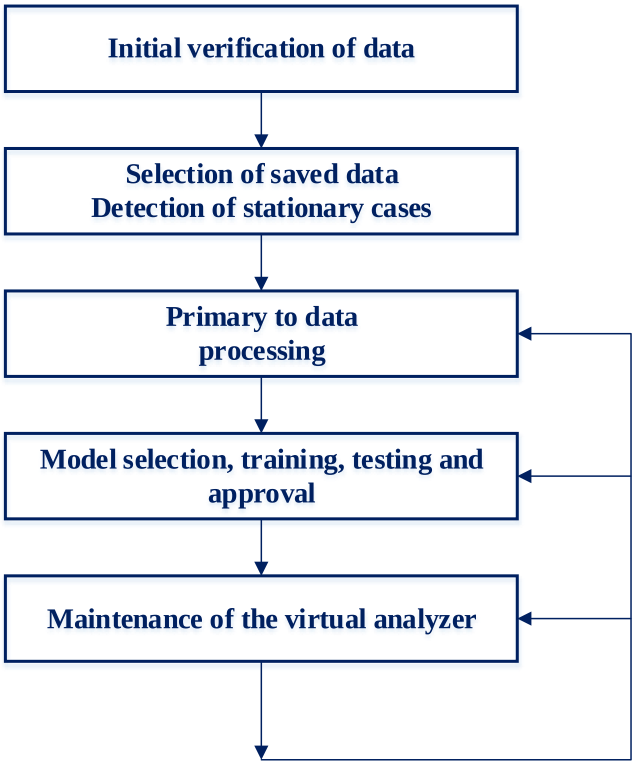

Figure 2. Methodology of development of virtual analyzers

Special attention is paid to the evaluation of the target variable. It should be checked that the output variable has sufficient variability and that it can be modeled as a whole.

Selection of stored data and identification of stationary cases. Here, the data used for training and evaluating the model is selected. Then stationary parts of the data should be identified and selected. In most cases, subsequent modeling is applicable only to the stationary state of the process. Determination of the state of a stationary process is usually carried out by human interpretation of the data.

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

Currently, there is a lot of work to be done on the primary processing of human data, as well as at the stages of model selection and verification during the development of a virtual analyzer. In general, it is necessary to collect and include a lot of information about the underlying process in the models in order to overcome the consequences of the disturbances that are present in the industry data.

In contrast to the virtual quality analyzer, the virtual metrological condition analyzer of the measuring instrument should focus on accuracy, not on speed, to obtain accurate calibration data, stored large-volume data is used, where the neural network model of the virtual analyzer, trained by a large volume of samples. At the same time, a data packet is periodically collected into the cloud, and according to this data, the virtual analyzer, albeit slowly, but with very high accuracy, gives an assessment of the metrological condition of the measuring instrument and generates calibration data, after which the intelligent sensor receives this data and calibrates itself.

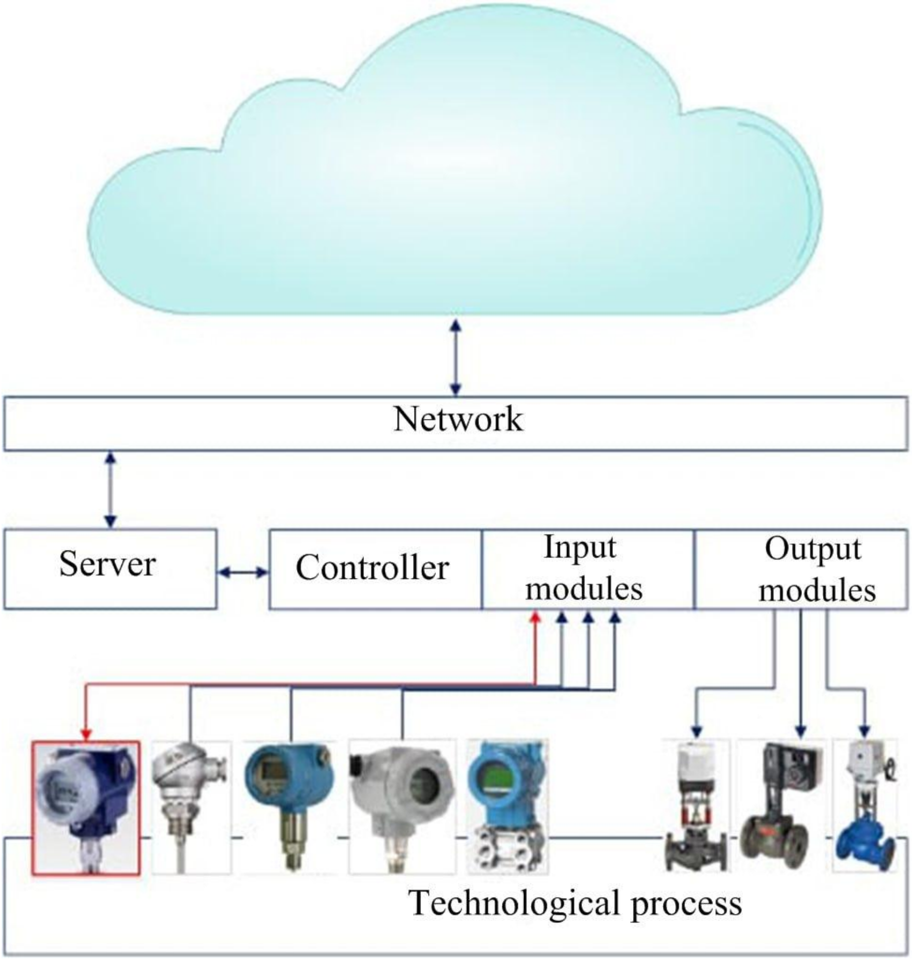

Figure 3. Application of cloud technology services to generate calibration data of an intelligent sensor

As soon as the calibration data for the smart sensor is received, depending on the method of calibration implementation (retraining of the sensor neural network, rewriting the calibration table, etc.), calibration is carried out.

CONCLUSION

In general, calibration and calibration can be combined or separated. Separation of calibration and calibration is more preferable due to the fact that this allows the sensor to self-track changes (and in case of inaccurate (or incorrect, it is unlikely) calibration, the sensor will work according to the factory calibration characteristic (according to the calibration table) until the following calibration data is obtained), and in case of large deviations from the factory calibration, give an alert for verification on a physical stand (this will be useful for further research and for the manufacturer of the smart sensor). If a neural network calibration technology is used in an intelligent sensor, then in addition it is necessary to introduce a second simpler corrective neural network trained on calibration data.

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