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Evaluation of the long-term drift of measuring instruments and standards using time series

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Abstract **– Drift is an undesirable property of all measuring instruments and standards during their life cycle. The analysis of instrumental drift of measuring instruments and standards is important in metrology. Reliable accounting for drift plays an important role in maintaining measurement accuracy. For resistance, capacitance and inductance standards long-term drift is predictable. The analysis of drift types and the main methods of its evaluation for measuring instruments between its calibrations has been carried out. The results of evaluation of the long-term drift of inductance and capacitance standards for high-precision calibration of measuring instruments using a polynomial regression and an Exponentially Weighted Moving Average charts are presented.**

I. INTRODUCTION

Drift is an undesirable property of all measuring instruments and standards during their life cycle. It can be caused by many factors: the environment, mechanical vibrations, temperature changes, electric and magnetic fields, and so on.

Reliable accounting for drift plays an important role in maintaining measurement accuracy. Unaccounted for drift can lead to significant measurement errors. The drift uncertainty can be estimated from its history of successive calibrations. In the absence of such a history, an estimate of the order of magnitude of the calibration uncertainty can be made.

The calibrated values of many measuring instruments and standards have a predictable drift over time. To provide a statement about the measurement uncertainty, when calibrating a measuring instrument for the entire calibration interval, time drift must be taken into account. For many electrical standards times drift is predictable.

II.THE LONG-TIME DRIFT OF MEASURING INSTRUMENTS

Instrumental drift of measuring instrument (VIM, 4.21) [1] is continuous or incremental change over time in indication, due to changes in metrological properties of a measuring instrument. This drift is related neither to a change in a quantity being measured nor to a change of any recognized influence quantity. It is applicable to both the measuring instrument and the measurement standard.

Depending on the time interval used, short-term and long-term drifts are distinguished. It is rather difficult to try to accurately determine the degree of short-term drift by means of a calibration study. Long-term drift can be evaluated without any problems by successive calibrations of the measuring instrument or standard.

Calibration drift refers to the change in instrument readings over a specified period of time during normal, continuous operation. This drift is estimated by a value obtained by subtracting a known reference value from the current measured value. Time drift since the last calibration of a measuring instrument is a major contributor to the overall measurement uncertainty [2, 3].

The drift is of several main types: zero drift; span drift or sensitivity drift; zonal drift, nonlinear, power [4]. Evaluation of long-term drift is mandatory for establishing calibration intervals [5].

III.EVALUATION METHODS OF THE DRIFT OF MEASURING INSTRUMENTS

A drift (trend) is the main tendency of a certain process to change over time or a time series, which is described by various equations: linear, logarithmic, power, etc. The actual drift type is established on the basis of selection of its functional model by statistical methods or smoothing of the original time series. Data time series are used to predict a certain process or phenomenon. A drift line is a line along which the points representing data from a certain data series are located on a chart.

Drift rarely continues at the same speed and in the same direction for a long period of time. To determine the degree and nature of any drift, the measurement results are plotted on a specific time scale (days, months, years). Such an experiment captures the maximum change that can occur within a set period of time, and allows you to make the necessary correction to the measurement result. Uncorrected drift can be considered as a type A component in measurement uncertainty analysis.

The ordinary least squares (OLS) method can be used to research drift, which is one of the basic methods of regression analysis for estimating unknown parameters of regression models based on sample data. It is based on the minimization of the sum of squared deviations of the selected function from the studied data. The theoretical values are determined using a mathematical function that best represents the underlying drift of the time series. This function is called an adequate function, which is calculated by the OLS method.

The coefficient of determination is used to assess the accuracy of such a drift model

$$R^2 = \sigma_{\hat{y}}^2 / \sigma_y^2, \tag{1}$$

where $\sigma_{\hat{y}}$ and σ_y are dispersions of theoretical data obtained according to the drift model and empirical data, respectively.

The most reliable drift line is if its approximation probability value (R^2) is equal to or close to 1. The drift model is adequate for the process under study and reflects the tendency of its development over time with R^2 values close to 1.

IV.EVALUATION OF THE DRIFT OF MEASURING INSTRUMENTS BETWEEN CALIBRATIONS

In [6], instrumental drift of measuring standards or measuring instruments is distinguished. This distinguishes between systematic drift, in which the model that describes the relationship between the measured value and the “true” value changes over time, and random drift or residual biases, which appear as deviations between the model and the values obtained during calibration.

Common practice is to establish the relationship between $y(t)$ and $x(t)$, termed the calibration model, which often takes the form of a polynomial of suitable degree n (usually 1, 2 or 3):

$$y(t) = a_0 + a_1 x(t) + a_2 x^2(t) + ... + a_n x^n(t). \tag{2}$$

The OLS method is not suitable for the vast majority of calibrations, since it only makes sense if the following conditions are met [6]: there is no uncertainty associated with x (during calibration are always measurement uncertainties); the measurement uncertainty is constant across the full range of measurements (this is rarely met on calibration); there is no covariance between either the $x_i(t)$ and $y_i(t)$ (these variances are frequent on calibration). At the same time, the OLS method can be used in a number of cases to estimate the calibration intervals.

In [6], to evaluate the drift of the measuring instrument, it is proposed to calculate the deviations between two established corrections at certain points and calculate the average value and standard deviation of the resulting corrections. These characteristics represent the contribution of the instrument drift to the measurement uncertainty.

Document [7] proposes general method for optimizing and justifying the calibration intervals of measuring instruments. It takes into account the recommendations of international standards ISO 10012 [8] and ISO/IEC 17025 [3]. To optimize and justify the calibration intervals of measuring instruments, it is important to take into account the evolution of one (or more) characteristics of working standards in the laboratory, as well as the contribution of standards to the assessment of the uncertainty of measurements made under actual conditions of use. The OLS method is used for modeling of maximum instrumental drift of a calibrated measuring instrument for certain period (for example 6 years).

In [9] describes the drift algorithm for random behavior of the metrological characteristics of measuring instruments. This paper also provides useful an overview of various methods for accounting for the drift of measuring instruments. The method for calculating the drift estimate As-Found Versus As-Left is considered in more detail. It is based on the collection of appropriate samples of calibration data of the measuring instrument, their analysis to assess the statistical characteristics of the drift error. These characteristics are used to predict the drift of the measuring instrument and demonstrate the possibility of making the necessary corrections.

The method of correlation estimation of the deviation drift in time is considered in [10]. It is based on the analysis of the sample and the calculation of the standard deviation to obtain the corresponding unbiased maximum mean. If the deviation drift is greater than the unbiased maximum mean, then it is considered to have a strong time correlation. In another case, the deviation drift is considered to have no time correlation, so part of the deviation drift can be ignored when calculating the amount of drift.

A cumulative sum (CUSUM) charts to identify process disorder caused by the influence of a non-random variable is show in [11]. These charts are more sensitive to small shifts in the level of process adjustment, unlike Shewhart charts. This makes it possible detect long-term drift of metrological characteristics of measuring instruments. The peculiarity of CUSUM charts is that the decision regarding the compliance of the metrological characteristics of measuring instruments with the established requirements is made taking into account information about all the obtained results (from the first to the last inclusive). Paper does not show the consideration of measurement uncertainty during calibration when using CUSUM charts.

The issue of long-term stability of standards is covered in [12]. This issue is also mentioned in the standard IEC/ISO 17025 [5] and the guideline JCGM 100 [2]. Control charts are presented and validated with simulations and real data sets. They are tools for evaluating the statistical control of the measurement process. Autocorrelation of measurement data obtained over a long period of time has been found to limit the relevance of control charts. At the same time, time series analysis seems more acceptable than conventional control charts.

A method for accounting of time drift based on the guidance in JCGM 100 [2] is proposed in [13]. An additional measurement uncertainty component is calculated using a linear regression of measurement data. In this article, much attention is paid to estimating the measurement uncertainty of drift after calibration, and appropriate options are proposed. Three methods are proposed for reducing the full expression of measurement uncertainty to a single value of uncertainty valid over the calibration interval.

In general, the contribution of time drift to measurement error cannot be averaged over a series of measurements. This drift is usually not stable enough for precision calibrations. In [14] describes a fairly general method for effectively suppressing parasitic effects caused by slow drifts. The effectiveness of the method is illustrated by applying the obtained optimal strategies for some precision measurements.

A standardized approach to uncertainty evaluation provides the basis for fulfilling measurement requirements. An approach for estimating the uncertainty of calibration and measurement processes is shown in [15]. Assessing trueness and precision in many ways limits the ability to compare observations and evaluate changes in measurement uncertainties over time. It is important to adjust the drift estimate and specify the assumptions for users of the measurement uncertainty estimate.

V.EVALUATION OF THE DRIFT OF ELECTRICAL STANDARD FOR CALIBRATIONS

The general scheme of global metrological traceability at different measurement levels is presented in [16]. At the middle level of metrological traceability are calibration laboratories, one of the main tasks of whose is the calibration of working standards and measuring instruments [17]. Calibration laboratories of national metrological institutes carry out the most precise calibrations of working standards.

The analysis of international standards and guides on statistical methods estimation of the measurement results recommendations for those applications in laboratories is described in [18] and the use of statistical methods for evaluating measurement results is shown in [19]. The analysis of the long-term drift of standards will be limited to examples of standards of resistance, capacitance and inductance.

The methodologies for the evaluation of historical data of electrical resistance standards of 10 Ω and of 100 Ω presents in [20] to ensure precision calibration of measuring instruments. These methodologies using for improvement their metrological characteristic in relation to manufacturer’s specification and measurement uncertainty. Linear regression was applied to the obtained calibration data for a time period of 60 months (5 years) for both 10 Ω and 100 Ω resistors. The uncertainty of fitting the data to a straight line was estimated by the regression method. Estimated uncertainties of the one-year predicted resistance value are 6.4 ppm for 10 Ω and 0.0012 % for 100 Ω.

In SE “Ukrmetrteststandard” (Kyiv, Ukraine), national standards of inductance and capacitance units have been created and used for precision calibrations. These standards took part in comparisons of standards within the framework of from 2006 to 2018. Continuous measurements showed high stability of these standards over a rather long time period. Time series of measurement data for the inductance standard from 2009 to 2022, and for the capacitance standard from 2011 to 2022.

The thermostatically adjustable inductance measures P5109 (No. 424) of 10 mH and P5113 (No. 1003) of 100 mH of the inductance standard contain a built-in precision thermostat with two temperature sensors. Their instability is 10 ppm/year. The results of evaluating the long-term drift of measures of 10 mH and 100 mH of the inductance standard at 1 kHz using 3rd-order polynomial regression are show on Figs 1 and 2. In the figures, the green solid line shows the mean value for the drift, and the red dashed line shows the corresponding polynomial approximation of the drift. The specified approximations of the drift lines of the inductance measures have the probability values of R^2 equal to 0.66 and 0.78, respectively, that is, they confirm their adequacy (less than 1.00).

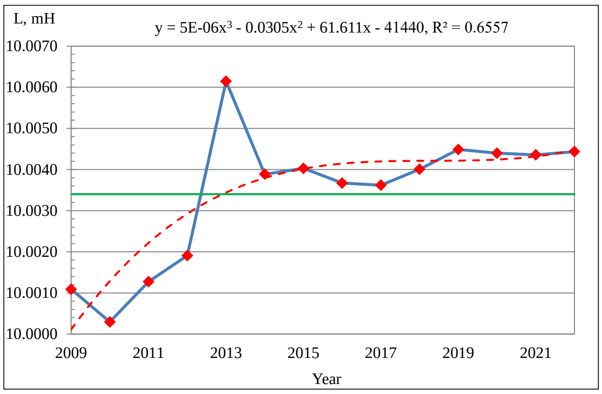

Fig. 1. Drift for 10 mH with polynomial regression.

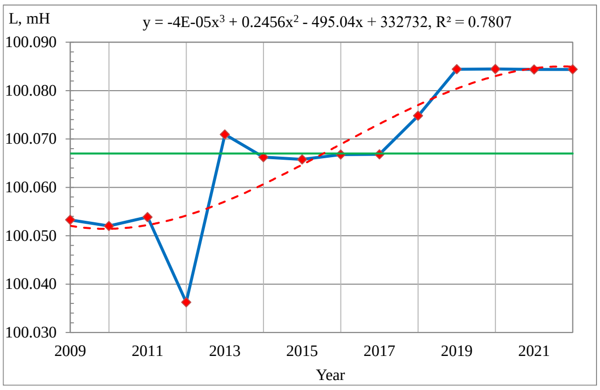

Fig. 2. Drift for 100 mH with polynomial regression

The average value of 10 mH measure from 2009 to 2022 is 10.0034, and 100 mH measure is 100.0067. The difference between the maximum and minimum values of 10 mH measure for the same time period is 0.0058, and 100 mH is 0.048. The difference between the last and first values of 10 mH measure for the same time period is 0.0033, and 10 mH measure is 0.031. The standard deviation of 100 mH measure from 2009 to 2022 is 0.0016, and 100 mH measure is 0.015.

The capacitance measures Andeen-Hagerling model AH11A of 10 pF and 100 pF are fused silica dielectric capacitors in hermetically sealed dry nitrogen filled metal containers. Their instability stability is better than 0.3 ppm/year. The results of evaluating the long-term drift of those measures using 2nd-order polynomial regression are show on Figs 3 and 4. The designations in these figures are the same as in the previous figures. The specified approximations of the drift lines of the capacitance measures have the probability values of R^2 equal to 0.13 and 0.70, respectively, that is, they confirm their adequacy (less than 1.00).

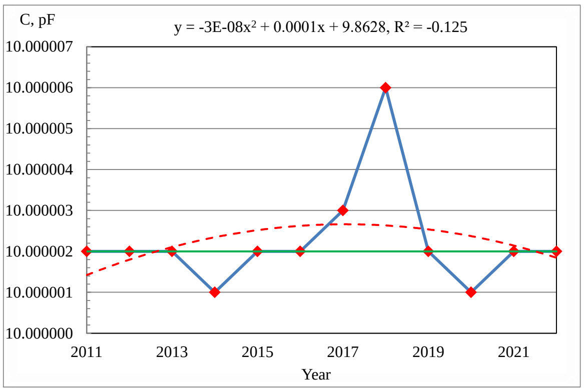

Fig. 3. Drift for 10 pF with polynomial regression

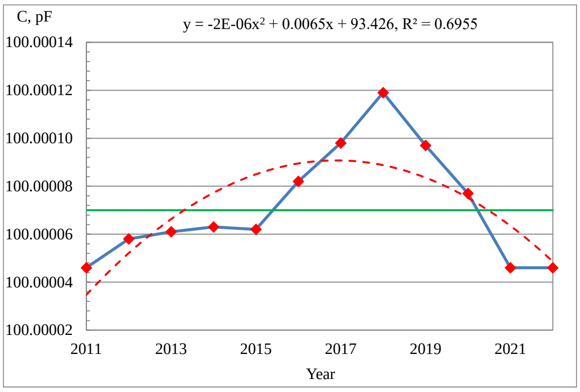

Fig. 4. Drift for 100 pF with polynomial regression.

The average value of 10 pF measure from 2011 to 2022 is 10.000005, and 100 pF measure is 100.0067. The difference between the maximum and minimum values of 10 pF measure for the same time period is 0.5 ppm, and 100 pF is 0.5 ppm. The difference between the last and first values of 10 pF measure for the same time period is 0, and 100 pF measure is 0. The standard deviation of 10 pF measure from 2011 to 2022 is 0.13 ppm, and 100 pF measure is 0.24 ppm.

Since CUSUM chart cannot be applied to data with a large number of digits after the decimal point, a Exponentially Weighted Moving Average (EWMA) chart was chosen also to analyze the long-term drift of inductance and capacitance standards. In addition, EWMA charts are applied to absolute data, not only to relative data, as applied in CUSUM charts. This is quite convenient precisely for evaluating the values of the measures under consideration.

EWMA refers to the average value of data obtained over time. The weight of the EWMA decreases exponentially for each period further into the past. Since the EWMA contains a previously calculated average, the result of the exponentially weighted moving average will be cumulative. Therefore, all received data contribute to the result, but the contribution factor is reduced when calculating the next period of EWMA. EWMA is a good tool for detecting smaller shifts in time averages bounded by a process. This allows for the analysis of long-term drift of inductance and capacitance measures.

The results of the evaluation of the long-term drift of standard inductance measurements of 10 mH and 100 mH at 1 kHz using EWMA are shown in Fig. 5 and 6. In the figures, the green solid line shows the average value of the drift (CL), and the red dashed line shows both the upper (UCL) and the lower (LCL) control limits.

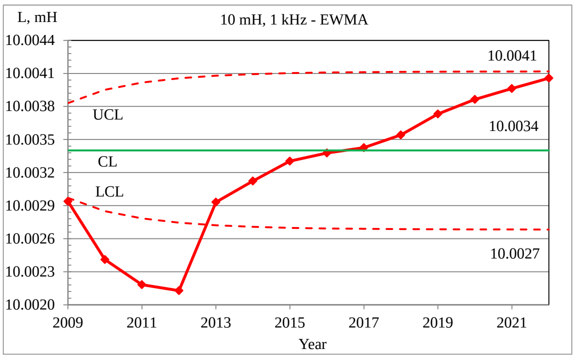

Fig. 5. Drift for 10 mH with EWMA.

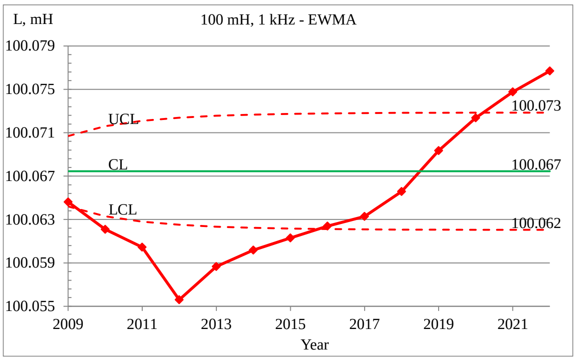

Fig. 6. Drift for 100 mH with EWMA.

The results of the evaluation of the long-term drift of standard inductance measurements of 10 pF and 100 pF using EWMA are shown in Fig. 7 and 8. The designations in these figures are the same as in the previous figures.

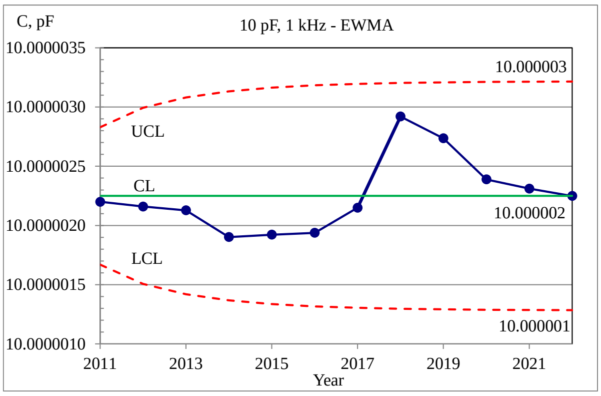

Fig. 7. Drift for 10 pF with EWMA.

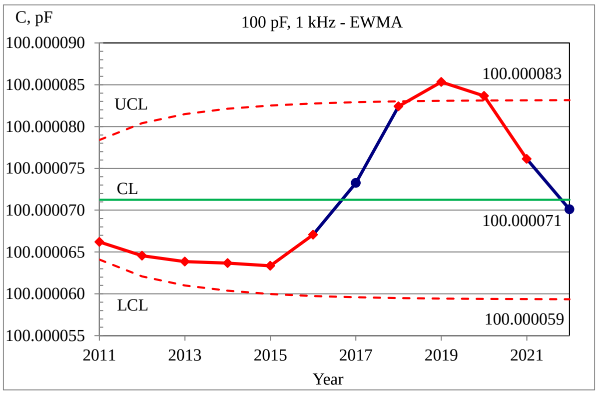

Fig. 8. Drift for 100 pF with EWMA.

VI. CONCLUSION

An analysis of the main drift assessment methods allows you to select methods for estimating the long-term drift of measuring instruments between their calibrations. To assess the drift of electrical standards for the calibration of measuring instruments, regression analysis methods are most often used. 3rd degree polynomials were sufficient to approximate the drift of the inductance standards, and 2nd degree polynomials were sufficient for the capacitance standards.

Since CUSUM chart cannot be applied to data with a large number of digits after the decimal point, a EWMA chart was chosen also to analyze the very small long-term drift of high-precision inductance and capacitance standards. Evaluation of the drift of these standards for high-precision calibration at frequency of 1 kHz using polynomial regression and EWMA charts was applied. Consistent results have been obtained.

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