# Test for non-linearity concerning linear calibrated chemical measurements 

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#### Abstract

Linear calibrated chemical measurements are based on the assumption of linearity. Due to influences of matrices at real samples the condition of linearity can be violated. Therefore, a profound examination has to attach much importance on the linearity of calibration. However, different procedures have been applied for this purpose in literature. In order to examine linear calibration for non-linearity, a recently presented procedure is compared with conventional techniques. The associated statistical models and estimations are represented. The applicability of the different procedures is demonstrated in some practical examples, the determination of arsenic in surface water samples taken from different sites in abandoned mining areas in central Germany. Recommendations for using the indicators and tests of non-linearity are given.


Keywords Linear calibration • Non-linearity

## Introduction

In the international standard ISO 11843 [1] procedures are presented for the computation of the critical value of the response variable, the critical value of the net state variable, and the minimum detectable value of the net state variable.

[^0]The calibration model used is based on the assumption that the calibration function is linear and that the standard deviation is linearly dependent on the net state variable and is given by
$Y_{i j}=b_{0}+b_{1} x_{i}+\varepsilon_{i j}$,
where $x_{i}$ : is the symbol for the net state variable in state $i ; \varepsilon_{i j}$ : are random variables which describe the random component of sampling, preparation and measurement error.

It is assumed that the $\varepsilon_{i j}$ are independent and normally distributed with expectation zero and variance $V\left(\varepsilon_{i j}\right)=\sigma^{2}\left(x_{i}\right)$.

The well-known estimates for the weighted linear regression (WLSR) [2] are calculated from the $N=I * J$ data pairs of the calibration data set $\left\{x_{i}, y_{i j}\right\}$, where $i=1, \ldots, I$ and $j=1, \ldots, J$, respectively.

For this study the weights are estimated by $w_{i}=$ $1 / \sigma^{2}\left(x_{i}\right):=1 / s_{i}^{2}$, where $s_{i}$ symbolizes the standard deviation of the repeated measurements of response $y$ at $x_{i}$.
For the regression coefficients $\hat{b}_{1}=$ $\frac{\sum w_{i} \sum w_{i} x_{i} y_{i j}-\sum w_{i} x_{i} \sum w_{i} y_{i j}}{\sum w_{i} \sum w_{i} x_{i}^{2}-\left(\sum w_{i} x_{i}\right)^{2}}$ and $\hat{b}_{0}=\bar{y}-\hat{b}_{1} \bar{x}$ are used, where $\bar{x}=\sum w_{i} x_{i} / \sum w_{i} ; \quad \bar{y}=\sum w_{i} y_{i} / \sum w_{i}$ and the predicted value of the regression line at position $i$ is given by $\hat{y}_{i}=\hat{b}_{0}+\hat{b}_{1} x_{i}$.

## Test for non-linearity

The correctness of the model and the goodness of fit have to be checked with the help of the residual plot belonging to the residuals

$$
\begin{equation*}
e_{i j}=\sqrt{w_{i}}\left(y_{i j}-\hat{y}_{i}\right) \tag{2}
\end{equation*}
$$

Table 1 Main components of the water samples under investigation

|  | Cospuden recultivated <br> mining lake water <br> Ex. 1 | Kulkwitz Recultivated <br> mining lake water <br> Ex. 2 | Luppe river <br> water <br> Ex. 3 | Pleisse river <br> water <br> Ex. 4 | RL 111 mining <br> lake water <br> Ex. 5 | Schwel-Vollert mining <br> lake water <br> Ex. 6 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Analyte | Concentration (mg/L) |  |  |  |  |  |
| Na | 47 | 74 | 117 | 60 | 7 | 19 |
| K | 8 | 16 | 30 | 10 | 3 | 6 |
| Ca | 325 | 352 | 140 | 138 | 206 | 225 |
| Mg | 78 | 43 | 37 | 35 | 27 | 49 |
| Fe | $<0.1$ | $<0.1$ | 0.9 | 5 | 130 | $<0.1$ |
| $\mathrm{NO}_{3}{ }^{-}$ | 3 | 3 | 27 | 63 | 1 | $<1$ |
| $\mathrm{Cl}^{-}$ | 73 | 175 | 170 | 98 | 8 | 610 |
| $\mathrm{SO}_{4}{ }^{2-}$ | 1050 | 910 | 350 | 315 | 1150 | 82 |

By visual inspection of the residual plot, deviations of linearity, normality and variance homogeneity, and also that of outliers are recognized.

With the help of the Durbin-Watson test it can be checked for a sequential dependence in which each error (and so residual) is correlated with those before and after it in the sequence. The test focuses specifically on the differences between successive residuals on the base of the Durbin-Watson statistic
$D=\sum_{u=2}^{N}\left(e_{u}-e_{u-1}\right)^{2} / \sum_{u=2}^{N} e_{u}^{2}$.
For $D$ was shown [2], that

- $0 \leq D \leq 4$ always
- If successive residuals are positively serially correlated, $D$ will be near 0
- If successive residuals are negatively serially correlated, $D$ will be near 4
- The distribution of $D$ is symmetric about 2

The residual standard deviation of the regression
$s_{e}:=\hat{\sigma}=\sqrt{\sum_{i, j}\left(y_{i j}-\hat{y}_{i}\right)^{2} /(N-p)}$
is an estimate of the variance of the measurements (pure experimental error), if the model is correct.

That means, that for $p=2$ (linear calibration function), a comparatively large value of $s_{e}$ can indicate weak nonlinearity. Likewise, for $p=2$ a small value of the coefficient of determination of the regression
$R^{2}=1-\sum_{i, j}\left(y_{i j}-\hat{y}_{i}\right)^{2} / \sum\left(y_{i j}-\bar{y}\right)^{2}$,
which represents the part of the variance that is explained by regression (this quantity is equal to the square of the correla-

Table 2 Experimental parameters for the determination of arsenic

| ICP spectrometer | CIROS, Spectro A.I. |
| :--- | :--- |
| Wavelength | 189.042 nm (background |
|  | corrected) |
| Power | 1.4 kW |
| Nebulizer | Cross flow |
| Uptake rate | $1.9 \mathrm{~mL} \mathrm{~min}^{-1}$ |
| Ar Gas flow | Aerosol gas $\left(0.9 \mathrm{~L} \mathrm{~min}^{-1}\right)$ |
|  | Cooling gas $(14 \mathrm{~L} \mathrm{~min}$ |
|  | Auxilliary gas $\left(0.8 \mathrm{~L} \mathrm{~min}^{-1}\right)$ |

tion coefficient), can indicate weak non-linearity. However, a possible misuse of this indicator must be avoided (see for instance [3, 4, 8]).

The suitability of regression model should be proven by a special statistical lack-of-fit-test [5], which is based on analysis of variance (ANOVA). In this way the residual sum of squares of regression is separated into two components: the sum of squares due to lack of fit (LOF) and the pure "error" sum of squares (PE)

$$
\begin{align*}
\sum_{i, j} w_{i}\left(y_{i j}-\hat{y}_{i}\right)^{2}= & \sum_{i} J w_{i}\left(\bar{y}_{i}-\hat{y}_{i}\right)^{2} \\
& +\sum_{i, j} w_{i}\left(y_{i, j}-\bar{y}_{i}\right)^{2} \tag{6}
\end{align*}
$$

The following $F$-test is based on the means of the deviation squares concerned, $M S_{\mathrm{LOF}}=\sum_{i} J w_{i}\left(\bar{y}_{i}-\hat{y}_{i}\right)^{2} /(I-2)$ and $M S_{\mathrm{PE}}=\sum_{i, j} w_{i}\left(y_{i, j}-\bar{y}_{i}\right)^{2} /(N-I)$. The hypothesis $H_{0}$ (regression model is suitable) is examined by means of the test value $F_{\text {test }}=M S_{\mathrm{LOF}} / M S_{\mathrm{PE}}$, which is compared with the corresponding value of the $F$-distribution with $I-2$ and $N-I$ degrees of freedom at the significance level $\alpha$. For $F_{\text {test }}>F_{a ; I-2 ; N-I} H_{0}$ is rejected, i.e. a non-linearity referring to the calibration model (1) is indicated.

Further possibilities for testing for non-linearity results from application of the polynomial calibration model of

Table 3 Calibration data sets for the calibration experiments for measurement of the arsenic content of six water (concentrations and responses are denotes by $x$ and $y$, respectively). Ex example

| Calibration level (standard <br> addition) $\left(\mathrm{mg} \mathrm{L}^{-1}\right)$ | Cospuden recultivated <br> mining lake water <br> Ex. 1 | Kulkwitz recultivated <br> Mining lake water <br> Ex. 2 | Luppe <br> river water <br> Ex. 3 | Pleisse <br> river water <br> Ex. 4 | RL 111 mining <br> lake water <br> Ex. 5 | Schwel-Vollert <br> mining lake water <br> Ex. 6 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| $x$ | $y$ | $y$ | $y$ | $y$ | $y$ | $y$ |
| 0.0 | -43 | -89 | -119 | -36 | -14 | 21 |
| 0.0 | -59 | 31 | -36 | 31 | -44 | 21 |
| 0.0 | -92 | 10 | -80 | -70 | -48 | -63 |
| 0.0 | -31 | -17 | -18 | -17 | -63 | 9 |
| 0.5 | 1,436 | 1,340 | 1,329 | 1,283 | 1,313 | 1,222 |
| 0.5 | 1,386 | 1,352 | 1,280 | 1,211 | 1,243 | 1,226 |
| 0.5 | 1,376 | 928 | 1,376 | 1,406 | 1,270 | 1,367 |
| 0.5 | 1,396 | 909 | 1,278 | 1,307 | 1,307 | 1,299 |
| 2.0 | 5,527 | 5,152 | 5,029 | 5,212 | 4,804 | 4,773 |
| 2.0 | 5,429 | 5,493 | 5,177 | 5,040 | 4,891 | 4,785 |
| 2.0 | 5,179 | 5,520 | 4,959 | 5,072 | 4,831 | 5,203 |
| 2.0 | 5,377 | 5,370 | 4,933 | 5,124 | 4,896 | 5,120 |
| 5.0 | 13,554 | 12,720 | 12,749 | 12,911 | 12,350 | 12,661 |
| 5.0 | 13,848 | 13,206 | 12,985 | 12,708 | 12,406 | 12,808 |
| 5.0 | 13,940 | 13,133 | 13,315 | 13,466 | 12,735 | 13,063 |
| 5.0 | 13,185 | 13,566 | 13,389 | 13,148 | 12,663 | 13,144 |
| 10.0 | 26,080 | 25,560 | 25,460 | 25,649 | 24,833 | 24,575 |
| 10.0 | 27,439 | 25,258 | 25,292 | 24,970 | 25,180 | 25,000 |
| 10.0 | 27,500 | 25,960 | 2,109 | 25,981 | 25,101 | 24,648 |
| 10.0 | 25,768 | 26,394 | 25,579 | 25,340 | 25,296 | 24,660 |

degree $p-1 \geq 2$
$Y_{i j}=b_{0}+\sum_{l=1}^{p-1} b_{l} x^{l}+\varepsilon_{i j}$.

By means of Mandel's fitting test [6], it can be determined as to whether the residual variances, resulting from the linear and the quadratic calibration function, significantly differ. The hypothesis $H_{0}$ (no significant difference between the residual variances) is examined by means of the test value
$F_{\text {test }}=\left((N-2) s_{e, 2}^{2}-(N-3) s_{e, 3}^{2}\right) / s_{e, 3}^{2}$.
This is compared with the corresponding value of the $F$ distribution with 1 and $N-3$ degrees of freedom at the significance level $\alpha$. For $F_{\text {test }}>F_{a ; 1 ; N-3} H_{0}$ is rejected. Therefore, the calibration problem is fitted better by a quadratic function than by the linear one. Thus, an indication of non-linearity of the calibration function is obtained.

Recently, another non-linearity test based on the model (7), created by Mark and Workman [7], was suggested. To avoid correlations between the various powers of X , a transformation of the original variable X is accomplished in the following manner

$$
\begin{equation*}
x_{1}:=x \quad \text { and } \quad x_{l}:=\left(x-z_{l}\right)^{l} \tag{9}
\end{equation*}
$$

resulting in the multiple linear regression model
$Y_{i j}=b_{0}+\sum_{l=1}^{p-1} b_{l} x_{l}+\varepsilon_{i j}$.
Evaluation of non-linearity of the calibration is reduced on testing the statistical significance of each of the coefficients.

The condition
$\operatorname{Cov}\left(x, x_{l}\right)=0$
gives equations solvable for $z_{l}$.
To improve the representation, in the following the abbreviation
$H_{l}=\sum x^{l}(x-\bar{x})$
is used.
For $l=2$ one obtains
$\sum(x-\bar{x})\left(x-z_{2}\right)^{2}=0$
$\sum x^{2}(x-\bar{x})-2 z_{2} \sum x(x-\bar{x})=0$
$z_{2}=H_{2} / 2 H_{1}$.
Table 4 Results for variance homogeneity tests refer to the calibration experiments of the examples represented in Table 3. Ex example

| Test quantity | Cospuden recultivated mining lake water Ex. 1 | Kulkwitz recultivated mining lake water Ex. 2 | Luppe river water <br> Ex. 3 | Pleisse river water Ex. 4 | RL 111 mining lake water Ex. 5 | Schwel-Vollert mining <br> lake water <br> Ex. 6 | Critical value of thecorresponding distribution |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $F$-test |  |  |  |  |  |  |  |
| $S_{i \text { min }}^{2}$ | 691.667 | 2,738.250 | 2,059.583 | 1,776.667 | 421.583 | 1,632.000 |  |
| $S_{i}^{2}$ max | 813,023.250 | 24,3201.333 | 124,528.667 | 186,387.333 | 38,693.667 | 50,082.000 | $F_{J-1 ; J-1 ; 1-\alpha / 2}=15.4$ |
| $F_{\text {test }}=S_{i \text { max }}^{2} / S_{i \text { min }}^{2}$ | 1,175.45 | 88.82 | 60.46 | 104.91 | 91.78 | 30.69 |  |
|  | Significant | Significant | Significant | Significant | Significant | Significant |  |
| Barlett-test |  |  |  |  |  |  |  |
| $X_{\text {test }}^{2}=(1 / c)^{*}$ | 114.2 | 100.8 | 92.5 | 96.7 | 82.4 | 86.8 | $X_{I-1 ; 1-\alpha / 2}^{2}=11.1$ |
| $\sum\left[(J-1) \ln \left(S_{W}^{2} / S_{i}^{2}\right)\right]$ | Significant | Significant | Significant | Significant | Significant | Significant VH violated (weak) |  |
|  | VH violated (strong) |  |  |  |  |  |  |

Table 5 Results for non-linearity indicators and tests refer to the calibration experiments of example 1 represented in Table 3. non-lin non-linearity; Ex example

|  | Cospuden recultivated mining lake water Ex. 1 | Kulkwitz recultivated mining lake water Ex. 2 | Luppe river water Ex. 3 | Pleisse river water <br> Ex. 4 | RL 111 mining lake water Ex. 5 | Schwel-Vollert mining <br> lake water <br> Ex. 6 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Non-linearity indicators and tests | Results |  |  |  |  |  |
| Coefficient of determination | 0.997995 | 0.998811 | 0.999108 | 0.999417 | 0.999492 | 0.999522 |
| Residual standard deviation | 1.461 | 1.128 | 1.289 | 1.017 | 1.794 | 1.427 |
| Visual inspection of residuals | Some indication of non-lin | Little indication non-lin | Little indication non-lin | No indication non-lin | Little indication non-lin | Little indication non-lin |
| Test for serial correlation of residuals (Durbin-Watson) | Test is inconclusive | No non-lin | No non-lin | No non-lin | No non-lin | No non-lin |
| $F$-test: Lack of fit | Non-lin | No non-lin | Non-lin | No non-lin | Non-lin | Non-lin |
| Mandel's fitting test | Non-lin | Non-lin | No non-lin | No non-lin | No non-lin | Non-lin |
| Test for non-linearity <br> (Mark/Workman) (With $p=4$ : <br> Significance of $b_{2}$ or $b_{3}$ ) | Non-lin | Non-lin | No non-lin | No non-lin | No non-lin | Non-lin |



Fig. 1 a Regression line of the WLS-regression to the calibration of example 1. b Residuals of the WLS-regression to the calibration of example 1
$l=3$ yields
$\sum(x-\bar{x})\left(x-z_{2}\right)^{3}=0$

$$
\begin{align*}
& \sum x^{3}(x-\bar{x})-3 z_{3} \sum x^{2}(x-\bar{x}) \\
& \quad+3 z^{2} \sum x(x-\bar{x})=0  \tag{17}\\
& z_{3}=  \tag{18}\\
& H_{2} / 2 H_{1} \pm \sqrt{H_{2}^{2}-(4 / 3) H_{1} H_{3} / 2 H_{1}} .
\end{align*}
$$

However, it can be proved that for the radicand
$H_{2}^{2}-(4 / 3) H_{1} H_{3} \leq 0$


Fig. 2 a Regression line of the WLS-regression to the calibration of example 4. b Residuals of the WLS-regression to the calibration of example 4
is valid, i.e., for $z_{3}$ only the real solution
$z_{3}=H_{2} / 2 H_{1}$
can be achieved and the correlation between $x$ and $\left(x-z_{3}\right)^{3}$ has a minimum value, however Eq. (11) is not completely fulfilled. Equations (17), (18) and (20) differ slightly from the results of Mark/Workman [7], because the equation [A14] given in the authors' paper [7] is not completely correct.

In the following the hypothesis $H_{0}$ ( $b_{l}$ not significant) is examined by means of the test value
$t_{l, \text { test }}=b_{l} / s_{b l}$,
which is compared with the corresponding value of the $t$-distribution with $N-p$ degrees of freedom at the signifi-

Table 6 Results for non-linearity indicators and tests refer to the calibration experiment of Example 1 (taken from the corresponding MS Excel spreadsheet)

cance level $\alpha$. For $t_{\text {test }}>t_{1-a / 2 ; N-1} H_{0}$ is rejected. Thus, an indicator for non-linearity of the calibration function is obtained.

The partial $F$-statistic with 1 and $v$ degrees of freedom is exactly equal to the square of the $t$-statistic with $v$ degrees of freedom obtained from Eq. (21) (see reference [2])
$F_{1, d f, 1-\alpha}=\left\{t_{d f, 1-\alpha / 2}\right\}^{2} ;$
therefore, the tail probability to the test value $t_{2 \text {,test }}$ of the quadratic regression coefficient is identical with the corresponding probability to Eq. (8).

The aim of the present work is both to investigate the dependence of matrix influence on the linearity of calibration and to compare the novel non-linearity test [7] with the conventional non-linearity tests represented above by means of practical examples.

## Experimental

An environmentally important task is the determination of arsenic in surface water samples, e.g. in areas influenced by mining activities. Depending on the sampling site, the effects of different matrices with different strengths can occur. These can affect the calibration. For this study, water samples were collected from several lakes in abandoned lignite mining areas and two rivers, which pass through a mining region in Germany. For the determination of arsenic ICP atomic emission spectrometry, a relatively less sensitive analytical technique for this task, was chosen. For the determination of arsenic, an ICP atomic emission spectrometer CIROS (Spectro A.I.) with pneumatic nebulization (cross-flow) was used. The samples are distinctly different concerning their matrix composition (Table 1). The experimental parameters are given in Table 2.

For each sample a calibration was done based on standard addition ( $0,0.5,2,5,10 \mathrm{mg} \mathrm{L}^{-1}$ of arsenic) in four parallel runs. The designed calibration experiments for the comparison of the non-linearity tests represented above are compiled in Table 3. A preceding examination of variance homogeneity with all examples resulted in this condition being violated (see Table 4). Therefore weighted linear regression models for the calibration were used.

## Results and discussion

The results concerning all calibration experiments are compiled in Table 5. Despite significant differences in the sample composition concerning the matrix elements, the sensitivity of the calibration (not discussed here) was not an influence in the calibration range. As shown by the data for the different natural water samples, we found different results in testing the linearity of the calibrations despite the facts that the calibrations are based on a standard addition procedure and the use of a less sensitive ICP atomic emission spectrometry technique for the determination of arsenic. This indicates that the linearity of the calibration is influenced by the varying matrices.

One can see that all tests in the case of strong nonlinearity (example 1, see Figs. 1a,b, example 6) indicate "non-linearity", although the calibration was only done in a calibration range of 1.5 orders of magnitude in concentration. That means that the calibrations of examples 1 and 6
have to be examined. In the case of strong linearity (example 4, see Figs. 2a,b), all tests indicate "no non-linearity". More difficult to judge are the cases characterized by a weak nonlinearity (examples 2, 3, and 5). In these cases, the result of the Mandels fitting test is preferred, because this test gives a special result, i.e., that a quadratic calibration function is more suitable as a linear function.

For the non-linearity test [7] and the model with $p-1=2$, it is shown that the Mandels fitting test yields the same tail probability 0.012840 (see Table 6), demonstrating the validity of Eq. (22). The test for serial correlation of residuals is proved as being a little sensitive in the treated cases of linear calibration. This test is ineffective in our case of calibration data, which are typically chemical measurements ( $I=5$ calibration levels, $J=4$ replicates). Also, the residual standard deviation of the regression and the coefficient of determination can not be used in the treated cases as an indicator for non-linearity.

## Conclusion

From the results shown one must conclude that an appropriate statistic examination of the linearity is necessary, working with samples characterized by a strong matrix load. The residual plot absolutely has to be checked. Moreover, the lack-of-fit test (based on replications) and above all the Mandels fitting test are proven as being efficient tools for the detection of non-linearity.

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