Modernization of an Integrated Calibration System for Aeronautical Instrumentation with Automated Orthogonal-Distance-Regression Model Selection

Luis Antonio Marin de Oliveira[1], Marina Gonçalves Moreira[2] e Marcos R. O. A. Maximo[1]
[1]Instituto Tecnológico de Aeronáutica, São José dos Campos/SP - Brazil
[2]Instituto de Pesquisas e Ensaios em Voo, São José dos Campos/SP - Brazil

***Abstract*— Before flight-test campaigns, aircraft instrumentation must be calibrated for reliable measurements. At the studied laboratory, this process is fragmented across the legacy SALEV 1.0 system (Visual Basic, unsupported since 2008), spreadsheets, and MATLAB routines, limiting traceability and leaving uncertainty analysis dependent on non-integrated tools. This paper proposes SALEV 2.0, a unified platform with a Flutter/Dart front-end and a Python/Flask back-end over an SQLite database, featuring real-time IENA-protocol acquisition over UDP, a foreign-key standards-versioning scheme for traceability, and uncertainty analysis compliant with EA-4/02, targeted for native implementation. The analytical layer performs Orthogonal Distance Regression with polynomial-degree recommendation assisted by an F-test and cross-validated via an adapted PRESS statistic, compared against ordinary least squares. Results from real calibration data demonstrate workflow centralization and assess the automated criteria as decision support for the operator. The proposed platform establishes a more traceable and extensible foundation for aeronautical instrumentation calibration.**

***Keywords*— Calibration, Orthogonal Distance Regression, Model Selection.**

I. Introduction

Before any flight-test campaign, the instrumentation installed on the aircraft must be calibrated to guarantee the reliability of the acquired measurements [1], [2]. In the calibration laboratory studied here, the embedded data acquisition system (DAS), an Acra KAM-500, conditions, samples and quantizes the transducer signals, which are represented numerically and dimensionlessly in *counts*. Calibration relates these counts to the physical quantities expressed in engineering units (E.U.), determining the coefficients of the fitting curve as well as the parameters needed to express measurement uncertainty.

The process currently in use is fragmented across multiple platforms: Microsoft Excel, MATLAB and the Flight Test Laboratory Automation System (SALEV) 1.0 [3], [4]. SALEV 1.0 was developed in Microsoft Visual Basic, a technology whose official support ended in 2008. This fragmentation hinders the traceability of information, increases processing and validation time, and requires manual data transfer between applications. There is, therefore, a need to consolidate acquisition, processing, calibration and storage into a single platform. Modern flight-test calibration systems have been migrating from local-file models to web architectures integrated with SQL databases, which improve data management and the technicians' workflow [5], [6].

This work proposes SALEV 2.0, structured around three contributions: (i) a unified software architecture with a Flutter/Dart front-end and a Python/Flask back-end over an SQLite relational database, including a standards-versioning scheme for historical metrological traceability; (ii) real-time acquisition of IENA-protocol packets over UDP, validated on a physical bench; and (iii) an analytical layer that performs polynomial regression with automated, operator-assisting degree recommendation. This paper focuses on the system and, in particular, on the comparison between Orthogonal Distance Regression (ODR) and Ordinary Least Squares (OLS) and on the automated, cross-validated selection of the polynomial degree.

The remainder of this work is organized as follows. Section II presents the theoretical background needed to understand this work, covering the OLS, WLS and ODR estimators, the F-test used for degree selection, and the PRESS-based cross-validation adapted to the orthogonal-distance model. Section III describes the development of the SALEV 2.0 system, including its software architecture, the real-time communication with the DAS, and the data layer designed for metrological traceability. Section IV details the methodology of the analytical layer applied to the calibration data. Section V presents and discusses the results obtained from real calibration data. Finally, Section VI concludes this work and outlines directions for future work.

II. Theoretical Background

This section briefly reviews the statistical foundations underlying the analytical layer of SALEV 2.0: the polynomial regression estimators (OLS, WLS and ODR), the F-test used for automated degree selection, the PRESS-based cross-validation adapted to the orthogonal-distance model, and the expected properties of the fit residuals.

A. Polynomial Regression: OLS, WLS and ODR

Let the dependent variable y relate to an independent variable x through a polynomial of degree p,

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \cdots + \beta_p x_i^p + \epsilon_i, \qquad (1)$$

with $p+1$ parameters to be estimated and ϵ_i a measurement error. The OLS estimator minimizes the sum of squared vertical residuals under the assumption of homoscedasticity,

Luis A. M. de Oliveira, marin@ita.br; Marina G. Moreira, moreiramgm@fab.mil.br; Marcos R. O. A. Maximo, mmaximo@ita.br.

i.e. constant error variance [7]. In real aeronautical calibrations this assumption is frequently violated, since the precision varies along the measurement range, yielding heteroscedasticity. Under heteroscedasticity, OLS coefficient estimates remain unbiased, but are no longer of minimum variance among linear unbiased estimators. Weighting each observation by the inverse of its variance (Weighted Least Squares, WLS) restores this efficiency property when the weights correctly reflect the true error variances, so that levels with larger dispersion exert proportionally less influence on the final curve [7], [8]. In this work, the per-level weights are estimated directly from the sample variance of the counts collected at each setpoint; their reliability therefore depends on the number of raw samples acquired per level. Each level is sampled at 32 Hz for approximately 20 s, yielding on the order of 6×10^2 raw samples per direction (ascending or descending), which was found sufficient for stable variance estimates in the well-behaved transducers but becomes a limiting factor for parameters with few distinct calibration levels, such as NR_LO (see Section V-A).

Metrologically, the counts produced by the DAS are themselves subject to acquisition noise, so the independent variable is not error-free. ODR generalizes least squares to this errors-in-variables setting: instead of vertical residuals, it minimizes the weighted squared orthogonal distance from each point to the curve,

$$\min_{\beta} \sum_{i=1}^{n} \Big[w_{x,i}\, \delta_i^2 + w_{y,i} \big(y_i - f(x_i + \delta_i; \beta) \big)^2 \Big], \qquad (2)$$

where δ_i is the horizontal adjustment of the i-th point and the weights $w_{x,i}$ and $w_{y,i}$ are the inverses of the variances of the counts (per level) and of the engineering-unit uncertainty, respectively. OLS is recovered as the limiting case in which the independent variable carries no error. Under the assumption that both measurement errors are Gaussian, ODR is the maximum-likelihood estimator (MLE) of β for this errors-in-variables model [9]: minimizing (2) is equivalent to maximizing the joint likelihood of the observed counts and engineering-unit values given the latent, error-free curve. This is what makes it meaningful to reuse likelihood-based selection criteria, such as the F-test described next, on ODR fits.

B. Degree Selection by the Partial F-test

The partial F-test compares two nested models to assess whether adding terms produces a statistically significant improvement, avoiding both underfitting and overfitting [7], [10]. For a reduced model of degree q and a full model of degree $q + r$, under the null hypothesis that the added coefficients are jointly zero,

$$F = \frac{(\mathrm{RSS}_{\mathrm{red}} - \mathrm{RSS}_{\mathrm{full}})/r}{\mathrm{RSS}_{\mathrm{full}}/(n-k)}, \qquad (3)$$

where n is the number of observations and k the number of coefficients of the full model. When applied to ODR fits, $\mathrm{RSS}_{\mathrm{red}}$ and $\mathrm{RSS}_{\mathrm{full}}$ are taken as the minimized weighted sums of squared orthogonal distances of (2) for the reduced and full models, respectively, rather than ordinary vertical residuals. The procedure is incremental: starting from degree 1, each model is compared with the next degree, and the additional term is accepted whenever the associated p-value is below the significance level ($\alpha = 0.05$), selecting the smallest sufficient degree.

On the validity of the F-test for ODR. Because ODR is the Gaussian MLE of the errors-in-variables model [9], comparing weighted orthogonal-distance sums of squares via (3) is a natural extension of the classical likelihood-ratio argument behind the OLS F-test. However, unlike OLS, the ODR fit is an *implicit, nonlinear* estimation problem – the latent abscissa $x_i + \delta_i$ is estimated jointly with β – so the classical result that (3) follows an exact $F_{r,n-k}$ distribution does not carry over exactly. The test is therefore used here as an asymptotic approximation, whose accuracy depends on the model's intrinsic and parameter-effects curvature being small [11], [12], on the assumed per-level weights being close to the true variances, and on the compared models being nested. For these reasons, the F-test-recommended degree is treated as decision support for the operator – on the same standing as the PRESS-based check described next – rather than as an automatic, final replacement for the operator's judgment; the final degree used for a given parameter remains a choice made by the technician, as reflected in Table II.

C. Validation by the PRESS Statistic for ODR

The F-test is an in-sample criterion. To validate its recommendation with an out-of-sample criterion, the Predicted Residual Sum of Squares (PRESS) [7] is adapted to the orthogonal-distance model. Each calibration setpoint is left out, the curve is refitted on the remaining setpoints, and the squared orthogonal distance of the omitted point to that curve is accumulated,

$$\mathrm{PRESS}_{\mathrm{ODR}} = \sum_{i=1}^{n} d_i^2\big(\hat{\beta}_{(i)}\big), \qquad (4)$$

where $\hat{\beta}_{(i)}$ is the ODR fit obtained without setpoint i and d_i^2 is the weighted squared orthogonal distance defined in (2). Because the ascending and descending cycles revisit the same setpoints, the omission is performed per *level* (leave-one-level-out): both readings of a setpoint are removed together, preventing an identical companion reading from remaining in the training set and producing an optimistic estimate. A polynomial of degree d has $d + 1$ coefficients, so each leave-one-level-out fit is over-determined only if the number of distinct setpoints L satisfies $d \leq L - 3$; this bound is used as a ceiling on the candidate degrees, which removes degenerate quasi-interpolating fits. Like the F-test, PRESS is used here as a decision-support signal for the operator rather than a fully autonomous selector.

D. Residual Properties

For an adequate fit, the residuals are expected to behave as independent, identically distributed noise with zero mean, and their sample standard deviation should be of the same order of magnitude as the estimated signal noise [7]. Systematic curvature or periodic oscillation in the residual plot indicates underfitting, signalling that the chosen degree does not capture the structure of the data; conversely, for an adequate model the variation in the residual dispersion reflects only the physical properties of the noise.

III. System Development

This section describes the implementation of SALEV 2.0: the overall software architecture and front-end/back-end technology stack, the real-time communication with the DAS over the IENA/UDP protocol, and the relational data layer designed to support metrological traceability.

A. Architecture

The back-end was developed in Python with a Flask application server and an SQLite relational database that stores calibration information, system parameters and acquisition records. Flask manages service initialization, communication routes, the Create–Read–Update–Delete (CRUD) operations and the processing of the implemented calculations. The front-end was built with the Flutter framework and the Dart language as a single-page application (SPA), providing a single multiplatform graphical interface. The widget-based structure of Flutter composes each screen from small, reusable and independently testable components, which favours code organization, interface consistency and maintainability; as an SPA, navigation between the calibration steps updates the relevant widgets reactively, without full page reloads, yielding a fluid user experience that speeds up the calibration workflow and reduces operational errors. Dynamic dropdown menus query server routes to obtain data directly from the database, mitigating typing errors during the selection of transducers and reference standards. Fig. 1 shows the calibration screen with the automatically recommended best degree highlighted.

B. Communication with the DAS

Data acquisition from the Acra KAM-500 is performed over the network. The DAS transmits IENA-protocol packets, composed of a header, a binary payload (16-bit words) and a tail, whose field positions are parameterized by XML files [13]. Transport uses UDP [14] rather than the connection-oriented TCP [15], because the lower processing overhead and latency of UDP are well suited to real-time, continuous data streaming where small losses are tolerable [16]. A continuous UDP socket listens for and unpacks the packets, which are then queued and stored, respecting the offset configured in the XML parameterization. Bench tests with the KAM-500 hardware confirmed the integration.

C. Data Layer and Traceability

Metrological traceability requires that measurement results be traceable to the International System of Units through an unbroken, documented chain of calibrations [17]. In the previous structure, the reference standard of a parameter was stored as a single text field. In SALEV 2.0, this field was replaced by a foreign key referencing a dedicated *Standard* table, allowing the creation of new versions of recalibrated standards instead of overwriting standards with database dependencies. This guarantees that the uncertainty calculations of past measurements remain reproducible, fulfilling the traceability requirements. Uncertainty analysis for the calibrated parameters is currently performed outside SALEV 2.0, using dedicated spreadsheets that already comply with the EA-4/02 guideline [18]. What has not yet been implemented is the *native* execution of this analysis within SALEV 2.0 itself: the same EA-4/02-compliant procedure is to be reproduced inside the platform, so that the uncertainty budget can be computed natively, without depending on external, multi-platform tools, as discussed in Section VI. The current relational schema, with the dedicated tables connected through foreign keys, is shown in Fig. 2.

IV. Methodology of the Analytical Layer

Real calibration data acquired from the aircraft were processed by a routine that, for each parameter, separates the acquisition matrix into ascending and descending cycles and, for hysteresis treatment, groups them into a single calibration curve, since the systems that consume the coefficients require a single relation between counts and engineering units [19]. For each setpoint, spurious samples are filtered and the variance of the counts is computed; its inverse defines the weights, so that unstable levels are down-weighted and the fidelity of the curve at the more stable levels is protected.

Because the counts carry per-level acquisition noise, the fitting is performed with ODR (weighting both axes), and OLS is computed as a baseline. While the counts (independent variable) receive a per-level weight obtained from the measured variance, the engineering-unit uncertainty (dependent variable) was taken as the largest range uncertainty among the calibration ranges and assumed identical for all points, so that the corresponding weight w_y is constant along the curve. For each parameter, polynomials of degree 1 to 5 are fitted; the degree recommended to the operator is selected automatically by the incremental F-test of (3), bounded by the number of distinct setpoints ($d \leq L - 3$), and cross-validated against the minimization of the orthogonal-distance PRESS of (4). Both criteria serve as decision support: the routine surfaces a recommended degree and its cross-validation status, but the operator retains the final choice, as is standard practice in the laboratory. The routine was implemented in Python, and the same logic was incorporated into the native software.

V. Results and Discussion

This section reports the results obtained by applying the analytical layer to real calibration data: it compares ODR and OLS in terms of residual standard deviation and PRESS, evaluates the agreement between the F-test and PRESS-based degree recommendations against the historical technician's choice, and discusses the limitations observed for parameters with few calibration levels or non-polynomial behavior.

A. Calibration Dataset

The results reported below are drawn from real calibration campaigns performed on transducers installed in military-application aircraft. The parameters listed in Tables I and II are representative examples chosen to illustrate well-behaved and noisy cases, not the totality of the available data; SALEV maintains an extensive historical calibration database spanning multiple aircraft and several years of campaigns, of which the present routine was validated against a subset.

For each calibration level (setpoint), the DAS samples the transducer output at 32 Hz for approximately 20 s, yielding on the order of 6×10^2 raw samples per ascending or descending direction. For each level, the acquisition routine stores the individual sampled points, their mean value, the

Fig. 1. SALEV 2.0 calibration page: polynomial fits, residual plot and coefficient/standard-deviation tables, with the F-test-recommended degree highlighted.

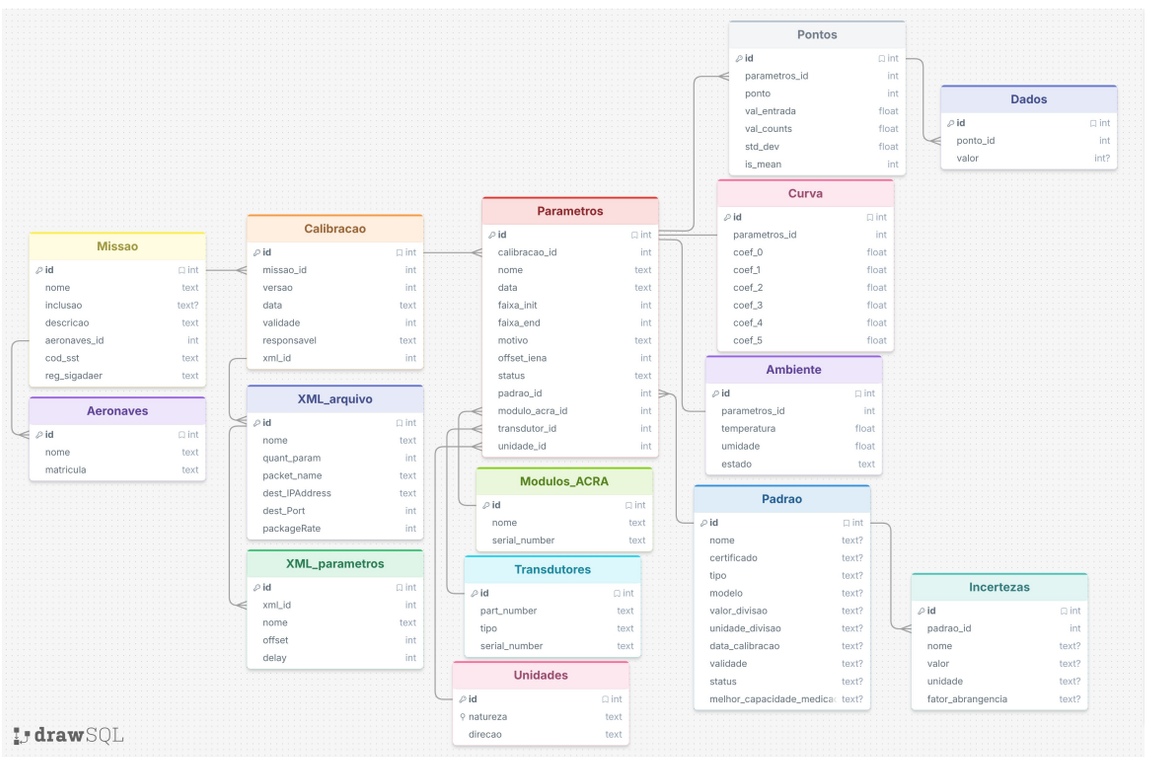

Fig. 2. Relational database schema of SALEV 2.0, with calibration, parameter, standard, curve and uncertainty tables linked by foreign keys.

sample count, and, for historical parameters, the polynomial degree previously selected by the operator. In this context, the operator is the aircraft flight-test technician responsible for the parameter, familiar with the behavior of its calibration curves across previous campaigns; the technician's historical degree choice is therefore adopted in this study as a reference value, analogous to a ground truth, against which the automated F-test and PRESS-based recommendations are compared in Table II

The number and distribution of calibration levels directly affect both the degree ceiling $d \leq L - 3$ and the reliability of the leave-one-level-out PRESS. Parameters with many, well-distributed levels (e.g. DN, PB1, QB1, with $L = 15$) admit a wider range of candidate degrees and yield a smoother PRESS profile across degrees, whereas parameters sampled at few levels (e.g. NR_LO, $L = 6$) are simultaneously more constrained in candidate degree and more prone to an erratic PRESS profile when a boundary level is omitted, as discussed below. This sampling-dependent behavior reinforces the role of the F-test and PRESS as decision-support signals rather than a fully autonomous substitute for the operator's judgment, and motivates the more robust, small-sample-aware criterion suggested as future work in Section VI.

TABLE I

ODR VS. OLS PER DEGREE (COUNTS): RESIDUAL STD. DEV. AND PRESS

Param.	Deg.	Std.Res. (ODR)	PRESS (ODR)	Std.Res. (OLS)	PRESS (OLS)
DN	1	0.2991	325.68	0.2991	325.68
DN	2	0.1224	75.37	0.1224	75.37
DN	3	0.0768	26.75	0.0768	26.75
DN	4	0.0675	26.02	0.0675	26.01
DN	5	0.0668	49.71	0.0668	49.68
NR_LO	1	5.6487	1974.68	5.6386	1925.87
NR_LO	2	0.7382	75.28	0.7297	84.78
NR_LO	3	0.2370	46.31	0.2339	47.41
NR_LO	4†	0.0024	0.10	0.0024	0.10
NR_LO	5†	0.0000	0.92	0.0000	0.92

† Degrees above the ceiling $d \leq L - 3$ for NR_LO ($L = 6$); excluded.

B. ODR vs. OLS Comparison and Degree Selection

The pipeline was applied to real calibration parameters. Table I reports, for two representative parameters, the residual standard deviation (Std. Res.) and PRESS of both ODR and OLS for each degree. Parameter DN, with 15 distinct setpoints, is typical of the well-behaved transducers; NR_LO, with only 6 distinct setpoints, is the noisiest case.

Two observations follow. First, for the well-behaved parameters, ODR and OLS produce virtually identical residual standard deviations and PRESS values (for DN they coincide to four significant figures). This indicates that the acquisition noise in the counts is small relative to the fitting residuals, so the two formulations agree numerically; ODR is nonetheless the metrologically rigorous choice, since the counts genuinely carry error, and a divergence between ODR and OLS would itself signal a non-negligible x-uncertainty. Second, for the noisier parameter NR_LO the orthogonal-distance PRESS of ODR is consistently lower than that of OLS at the selected degrees (e.g. 46.31 against 47.41 at degree 3, and 75.28 against 84.78 at degree 2), confirming that accounting for the error in the independent variable yields a modestly better out-of-sample behavior exactly when it matters.

For NR_LO the raw acquisition contains 11 readings, but the ascending and descending cycles revisit the same six setpoints, so the number of distinct levels is $L = 6$. A fifth-degree polynomial (six coefficients) would interpolate the six levels and drive the in-sample residual to zero (Table I), which is a symptom of overfitting rather than of a good fit. The degree ceiling $d \leq L - 3$ restricts the candidates to degrees 1–3 and, together with the leave-one-level-out PRESS, leads the recommendation to degree 3, in agreement with the technician's choice as a reference.

Table II summarizes, for the polynomial parameters, the degree recommended by the F-test, the degree that minimizes the orthogonal-distance PRESS (within the ceiling), and the historical technician's choice reference. The two automatic criteria coincide for the majority of the parameters and differ by at most one degree in all but one case. The divergences occur where the PRESS profile is erratic across degrees, a known effect of the leave-one-level-out scheme when a curve extreme is removed and the prediction becomes an extrapolation; PRESS is therefore used as a corroborating criterion (read together with the elbow of the curve), not as a replacement for the F-test. The agreement between two criteria of different nature, in-sample (likelihood-based) and out-of-sample (prediction-based), strengthens the confidence in the recommendation offered to the operator, while the divergent cases flag the parameters that deserve closer inspection.

TABLE II

RECOMMENDED POLYNOMIAL DEGREE BY CRITERION

Param.	L	F-test	PRESS-min	Technician
ALFAG	15	2	5	2
BETAG	15	4	4	2
DDMP	12	2	2	2
DL	14	5	5	3
DM	15	3	4	3
DN	15	4	4	3
NR_LO	6	3	3	3
PB1	15	2	3	2
QB1	15	4	5	3

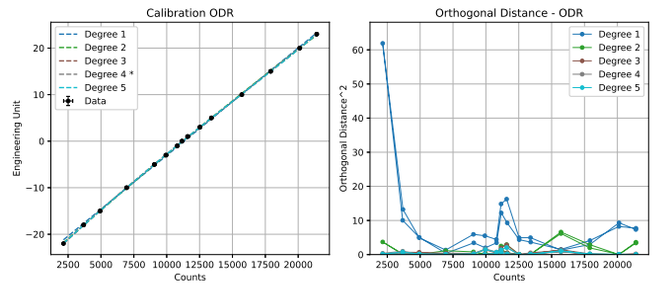

Fig. 3. ODR fits of degree 1 to 5 (counts vs. engineering units) and the respective squared orthogonal distances for parameter DN.

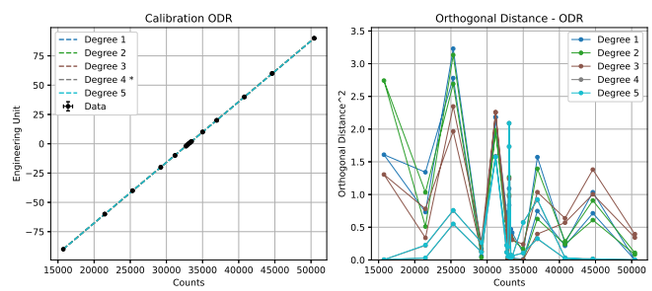

Fig. 4. ODR fits of degree 1 to 5 (counts vs. engineering units) and the respective squared orthogonal distances for parameter BETAG.

Figs. 3 and 4 illustrate, for two representative parameters, the five polynomial fits superimposed on the data and the corresponding squared orthogonal distances per degree, which support the visual diagnosis of the residual structure.

Finally, one of the analyzed parameters exhibited an apparently asymptotic, non-polynomial response: no polynomial degree was able to represent its behavior adequately, and its residuals retained a systematic pattern. The adequate modelling of such transducers requires a different, nonlinear approach and care with error-distribution distortions under naive linearization [20]; this is left as future work and is outside the scope of the present comparison.

VI. Conclusion

This work presented the modernization of the calibration system into the unified SALEV 2.0 platform, centralizing in a single application functions previously distributed across SALEV 1.0, MATLAB and spreadsheets. The relational reorganization of the database, with the foreign-key standards-versioning scheme, provides the historical traceability required by calibration standards, and the IENA/UDP integration enables real-time reception of packets from the DAS, validated on a physical bench. In the analytical layer, the polynomial

degree is recommended automatically by the F-test and cross-validated against the minimization of an orthogonal-distance PRESS computed by leave-one-level-out, with the candidate degrees bounded by the number of distinct setpoints; both criteria are provided as decision support, with the operator retaining final selection authority, as evidenced by the historical technician references in Table II. The comparison between ODR and OLS on real data shows that the two are numerically close for the well-behaved transducers, where the counts noise is small, while ODR is the rigorous formulation – the maximum-likelihood estimator under measurement error in both axes – and yields a better out-of-sample behavior for the noisier parameter. The agreement between the in-sample and out-of-sample criteria corroborates the automated recommendation, and the divergent cases identify parameters for inspection.

The F-test, while a convenient and already-validated in-sample criterion, is only an asymptotic approximation when applied to ODR fits, since the underlying estimation problem is implicit and nonlinear; its accuracy is expected to degrade for parameters with few distinct calibration levels and higher model curvature. As a more robust next step, future work will investigate small-sample-corrected information criteria – in particular the corrected Akaike Information Criterion, AICc [21] – computed directly from the ODR likelihood. Unlike the F-test, AICc does not require the compared models to be nested, which would allow the same criterion to be applied uniformly across the polynomial transducers and the asymptotic, non-polynomial transducer identified above. Additional future work includes the native implementation of a nonlinear model for transducers with asymptotic response and the native, in-software implementation of the uncertainty analysis: this analysis is already performed today, outside SALEV 2.0, in compliance with the EA-4/02 guideline, and future work will reproduce the same procedure natively within the platform, removing the current dependence on external, multi-platform tools.

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