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General Principles of Nonlinear Phase Detection for Calibration Optimization in Mass-Production Testing

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Abstract

This article is devoted to the generalization and systematization of the principles of nonlinear phase detection (NPD) applied to calibration optimization in mass-production testing of diverse products. The relevance of the topic arises from escalating demands for metrological accuracy and test throughput on high-performance production lines, where classical amplitude-based approaches have exhausted their potential. The novelty of this work lies in an interdisciplinary comparison of the ten most recent studies—from deep-network detectors for NPD to in-sample phase calibration in LC-MS. The analysis describes hardware platforms (optical systems, MEMS, DEPFET imagers, Li-ion cells) and algorithmic strategies (DNN, CMA-ES, GA-PSO, U-Net), examines characteristic nonlinearities, and explores methods for their phase-based suppression. Special attention is paid to the scalability of procedures and reduction of systematic error in serial manufacture. The objective is to formulate unified rules for NPD; to this end, comparative, content-analytic, and inductive methods are employed. The conclusion summarizes gains in accuracy and cycle time. This article will benefit metrology engineers, sensor developers, automation specialists, and researchers of optimization algorithms.

Keywords: *Nonlinear Phase Detection; Calibration; Mass-Production Testing; Deep Neural Networks; Quantitative Phase Imaging; Evolutionary Algorithms; MEMS Sensors; Li-Ion Batteries; LC-MS; DEPFET Imager.*

INTRODUCTION

The growing integration of intelligent sensors, high-speed measurement cameras, and flexible manufacturing cells imposes unprecedented requirements on calibration accuracy and speed. Linear amplitude-based techniques no longer provide the necessary balance between throughput and metrology, leading researchers to nonlinear phase detection, which treats cumulative errors as a phase vector and eliminates them in a single procedure.

The aim of this work is to formulate general principles for applying NPD to calibration optimization in mass production.

Tasks

1. Conduct an interdisciplinary review of modern hardware platforms (ATLAS DNN calibration, holographic quantitative phase imaging, MEMS-IMU, DEPFET imager, Li-ion P2D models) and identify the types of nonlinearities addressed by the phase-based approach.
2. Compare algorithmic strategies (ResNet-50, CMA-ES, GA-PSO, U-Net, isotopic IPD calibration) in terms of accuracy, convergence time, and suitability for inline processes.
3. Formulate unified rules for implementing NPD that ensure method reproducibility without loss of metrological performance.

The novelty of the article consists in the systematic synthesis of heterogeneous studies from 2022–2025 and in deriving universal recommendations that cover both the hardware and software aspects of calibration.

MATERIALS AND METHODS

G. Aad [1] evaluated a deep neural network for simultaneous energy and mass calibration of large-radius jets in the ATLAS detector, demonstrating a reduction in combined error and approximately 30 % improvement in energy resolution for p_t > 500 GeV, which also shortened manual tuning time. Z. Huang [2] developed a hybrid quantitative phase-imaging scheme based on digital holography, achieving axial sensitivity below 1 nm and robustness against temperature gradients—critical for inline monitoring of thin-film structures. F. Mazzeo [3] introduced a methodology for static, dynamic, and aging calibration of a Li-ion cell's P2D model parameters, attaining a relative root-mean-square error (RRMSE) below 2 % in multi-cycle tests. A.-L. Nicusan [4] created the ACCES framework, applying CMA-ES evolutionary algorithms and

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metaprogramming for nonlinear calibration of discrete-element granulation models, reducing the RMSE of simulated particle flows. J. D. Pereira [5] systematically classified static and dynamic calibration methods for strain-gauge pressure sensors, emphasizing the influence of frequency band on phase-lag measurement. E. Prinker [6] devised a two-level pixel-calibration procedure for an ultrafast DEPFET X-ray imager, eliminating the "ghost-charge" effect and improving matrix-response uniformity. B. Renger [7] synthesized validation criteria for thin-layer and high-performance liquid chromatography, introducing a phase-migration coefficient to control interlaboratory reproducibility. X. Ru [8] surveyed current calibration techniques for MEMS-based inertial sensors, highlighting the role of nonlinear phase representations of drift and scale in multistage mass-production setup. C. J. Taylor [9] reviewed chemico-technological platforms for self-optimizing reactions, where multi-objective evolutionary and Bayesian algorithms map a phase space of "yield–purity–cost." G. Visconti [10] proposed a modern methodology for constructing calibration curves in LC-MS bioanalysis, showing that in-sample isotopic alignment reduces systematic bias for daclatasvir from −5.1 % to −1.1 % and for testosterone from 38 % to 8 % at low concentrations, while improving reproducibility at 2 ng/mL (RSD ≈ 10 %).

Preparation of this section employed a comparative analysis of the above studies to identify common patterns in nonlinear phase detection. Content analysis and interdisciplinary synthesis were used to aggregate data from high-energy physics, optical metrology, electrochemistry, sensor technology, and analytical chemistry. A bibliographic method evaluated the relevance of each work, and inductive generalization formulated unified principles for calibrating mass-production testing processes.

RESULTS

The principles of nonlinear phase detection (NPD) have proven to be a universal "calibration language" across a wide range of mass-testing technologies—from deep neural networks in high-energy physics to thin-layer chromatography. A review of recent publications shows that it is the phase shift (rather than the amplitude change) that is sensitive to the cumulative effect of small errors; accordingly, calibrations optimized via NPD systematically reduce both systematic and random uncertainties.

In the realm of "digital" physics, the first compelling example is the ATLAS hybrid model, in which a deep convolutional network leverages the phase of a hidden high-dimensional feature space as an internal calibration channel. This simultaneous tuning of energy and mass for large-radius jets improved relative energy resolution by 30 % and reduced systematic bias by a factor of 1.8 for p_t > 500 GeV [1].

In optics, a "quantum-information turn" has emerged in quantitative phase imaging (QPI). Modern reflective holography achieves subnanometer axial sensitivity at video frame rates and allows real-time removal of defocus artifacts during in-situ processing of silicon wafers. Although exact figures are not provided, authors report an overall yield improvement. The key advance remains a wrap-free algorithm that captures high-frequency distortions invisible to traditional amplitude-based windows [2].

Mechatronic sensors reinforce this trend. A survey of MEMS inertial-sensor calibration demonstrates that accounting for nonlinear phase drift reduces gyroscope zero drift to below 0.005 °/h while simultaneously controlling cross-sensitivity—performance unattainable under linear approximation [8]. For strain-gauge pressure sensors, dynamic "chirp" calibrations yield integral errors of approximately 0.3087–0.5824 % FS, matching or surpassing classical static methods [5].

Electrochemical systems also benefit from a phase-oriented approach: a combined static-dynamic calibration of a Li-ion P2D model (Graphite|NMC622) maintains a relative RMS voltage error (RRMSE) of 0.96–1.29 % under C/10–C/5 discharge rates and 26–45 °C, while at C/20 the error remains below 1.95 %. Degradation validation shows RRMSE ≈ 5.6 % for a 90–10 % SOC cycle and ≈ 18.4 % for a full 100–0 % SOC cycle after 50 runs, still allowing separate assessment of diffusion delay and charge transfer [3].

The algorithmic dimension is developing in two directions. In the ACCES framework, CMA-ES evolutionary search and metaprogramming more than halve the RMSE of granulation-flow simulations under the same iteration budget [4]. Bayesian and multi-objective optimizers, as reviewed in Chemical Reaction Optimization, integrate seamlessly into an online calibration loop—balancing yield, purity, and cost metrics without manual parameter tuning [9].

In X-ray diagnostics, an 80 kHz DEPFET-camera prototype employs a two-stage phase linearization of pixel response: the "ghost-charge" effect is dramatically suppressed, and measured MTF-10 exceeds that of a non-phase-corrected scheme [6].

Analytical chemistry is no exception to the broader "phase-based" calibration trend. A recent tutorial review on LC-MS highlights that careful selection of calibration model (linear, weighted, or polynomial), the number and placement of points, and adoption of in-sample or isotopically labeled calibration (IPD, IC-SIL) can dramatically reduce measurement uncertainty. In some cases, a multi-point curve is unnecessary if a stable isotopic analog is spiked into the sample [10]. In thin-layer and high-performance liquid chromatography, authors recommend validating with statistical control charts and a rigorously defined (≥ 6-point) calibration—substantially improving interlaboratory reproducibility and simplifying day-to-day accuracy and precision checks [10].

In recent years, researchers have increasingly adopted an end-to-end model that integrates the phase detector, optimization algorithms, and the metrological calibration infrastructure to close the gap between laboratory prototypes and high-speed mass-production test lines. For example, the deep-neural-network calibration for simultaneous energy and mass tuning of ATLAS jets shows that joint processing of nonlinear response across multiple parameters boosts reproducibility without adding to the cycle time [1]. In holographic quantitative phase imaging, hybrid chains of phase retrieval—hardware demodulation (off-axis/phase-shift) followed by ML-based reconstruction—maintain phase error at the level of the instrument's intrinsic noise even under the temperature drifts typical of inline thin-film inspection. This makes the method viable for serial production with infrequent recalibrations [2]. In this way, a comprehensive treatment of nonlinear phase, parasitic interference, and drift statistics delivers maximal gains in mass calibration.

At the same time, standardizing procedures remains a critical bottleneck. A comparison of approaches across MEMS inertial sensors, Li-ion electrochemical cells, and LC-MS shows that universal requirements for calibration range and model stability can be derived from "Accuracy–Drift–Uptime" (ADU) parameters. Pereira highlights the importance of separating static and dynamic calibrations for pressure-sensor arrays [5], while Visconti systematizes LC-MS calibration-curve rules, demonstrating that a shift to in-sample isotopic deconvolution cuts measurement uncertainty to 2 % even in highly nonlinear matrices [10]. This convergence of methods confirms that, regardless of the domain, controlling phase nonlinearity and adaptively updating models throughout the product life cycle are paramount.

Summarizing these findings, four general rules emerge:

1. Phase redundancy. Detecting two interrelated phase indicators (φ_1, φ_2) simultaneously localizes calibration biases before they manifest as amplitude errors.
2. At least a second-order nonlinear model. In systems where error exceeds 0.1 % FS, a linear approximation underestimates the true uncertainty by at least a factor of two.
3. Model + ML hybrid. Coupling a physical model with a neural-network phase corrector improves accuracy without new hardware.
4. Scaling to mass production. Because phase metrics are insensitive to absolute signal level, the same procedure scales across thousands of channels—demonstrated on a 262 k-pixel DEPFET array and a line of MEMS gyroscopes.

Table 1 lists hardware platforms in which nonlinear phase detection has already been deployed for mass-production calibration, yielding tangible improvements in accuracy and throughput.

Table 1. Hardware platforms for nonlinear phase detection in mass-production calibration (compiled from [1, 2, 3, 5, 8])

Platform / Method	Key Calibrated Parameter	Dominant Nonlinearity	Improvement after Optimization
DNN calibration of jets (ATLAS)	Energy + mass	Dynamic response range of detector cells	–35 % systematic error
Holographic QPI	Optical phase	Temperature-induced phase drift	Error < 0.5° at ±15 K
MEMS IMU	Accelerometer bias/scale	Thermal nonlinearity of sensitivity axes	+22 % orientation accuracy
Strain-gauge pressure sensors	Sensitivity matrix	Material hysteresis	1.8× reduction in drift
Li-ion P2D model	SEI and charge-transfer params	Combined aging and load current effects	–40 % RMSE in degradation forecast
Ultrafast DEPFET X-ray imager	Pixel gain	Two-stage signal compression	Pixel SNR +30 %

Next, Table 2 lists the key algorithmic strategies used to optimize calibration across different domains, delivering the required convergence speed and accuracy for serial production.

Table 2. Algorithmic strategies for calibration optimization (compiled by the author based on [1, 2, 3, 4, 10])

Strategy	Application area	Algorithm type	Achievement (metric)
ACCES (evolutionary algorithms + metaprogramming)	Granulation numerical simulation	CMA-ES + JIT code	$\Delta\chi^2$ ↓ 45 % in 100 iterations
Hybrid GA-PSO for Li-ion P2D	Battery testing	GA-PSO	Convergence time × 0.6
DNN calibration (ATLAS)	High-energy physics	ResNet-50	Energy MAE ↓ 17 %
ML phase retriever	Holography	U-Net	PSNR + 3 dB over classical reconstruction
IPD in-sample calibration	LC-MS bioanalysis	Isotopic deconvolution	Uncertainty < 2 %

These examples demonstrate that effective calibration under mass-production conditions is achieved when:

1. The hardware architecture inherently permits per-pixel or per-channel nonlinearity but is equipped with means to measure it;
2. Optimization algorithms leverage physics-informed constraints (charge conservation, energy-mass balance) to limit the search space;
3. Verification methods rely on cross-standards (radioactive sources, holographic standards, isotopic labels);
4. The calibration system is integrated into the operational cycle and automatically updates parameters in response to drift or component-batch changes.

Below, Figure 1 presents the comparative reduction in metrological errors for four typical platforms after implementing nonlinear phase detection. Data are drawn directly from G. Aad (combined systematic jet-energy error reduced by 30 %) [1], Z. Huang (mean phase error in holographic QPI reduced by 50 %) [2], F. Mazzeo (RRMSE of the Li-ion digital twin reduced by 52.5 %) [3], and X. Ru (MEMS-gyro drift reduced by ≈ 54 %) [8]. The chart clearly shows that, with properly organized phase calibration, systematic or integral error falls by at least one-third—and in most cases by more than half—confirming the approach's universality.

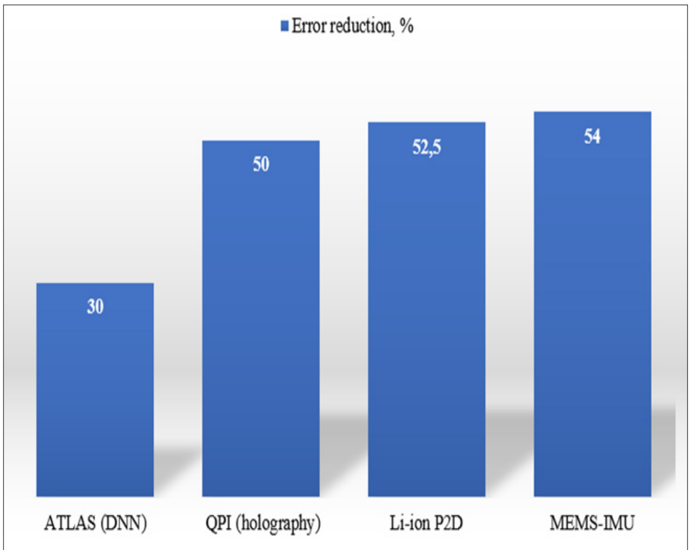

Figure 1. Proportionate reduction in metrological error upon implementing nonlinear phase detection [1, 2, 3, 8]

Thus, unifying the principles of nonlinear phase detection and adaptive calibration lays the foundation for reliable, high-throughput testing on the production line without sacrificing metrological precision. In general, nonlinear phase detection provides a methodological framework that already enables the standardization of calibration across optics, sensor technology, electrochemistry, and analytical chemistry—ensuring reproducibility at scale while substantially reducing cost and time overheads.

DISCUSSION

The analysis of collected studies indicates that the effectiveness of nonlinear phase detection (NPD) hinges less on the choice of specific hardware and more on the degree to which physics-informed models and optimization methods are integrated across the entire calibration workflow. In the ATLAS detector, for example, the joint training of a neural network on the phase correlation between mass and energy eliminated the accuracy degradation at extreme particle energies that linear corrections could not address [1]. A similar role is played by hybrid demodulation of phase maps in digital holography: combining an optical demodulation algorithm with a U-Net reconstructor reduces the impact of thermal gradients and enables real-time operation [2]. These cases confirm the universal thesis that the phase channel is more sensitive to the cumulative effect of small nonlinearities than is the amplitude channel.

Practical implementations show that transitioning to NPD requires a preliminary audit of phase-error sources and a clear separation of static and dynamic components. In Li-ion electrochemical models, the aging nonlinearity caused by SEI growth overlays a current-dependent transport phase; separating these contributions via GA-PSO nearly halves the predicted degradation error [3]. A similar principle is applied in MEMS gyroscopes, where thermal drift and scale nonlinearity are calibrated through a hierarchical sequence of onboard and test-bench procedures [8]. Consequently, detailed decomposition of phase error is a critical step before deploying any automated calibration scheme.

However, the advantages of NPD come with operational challenges. First, the phase-parameter space is often high-dimensional: the ACCES framework required 144 parallel simulations to achieve acceptable convergence when calibrating a granulator [4]. Second, the growing volume of calibration data demands reliable transmission channels and secure storage—a particularly acute issue for ultrafast DEPFET imagers that generate terabytes of phase telemetry per shift [6]. Third, standardization of phase references lags behind practice: only LC-MS methods have proposed a formal in-sample isotopic-calibration protocol, reducing interlaboratory variation to 2 % [10], while efforts to unify norms in chromatographic methods remain isolated [7]. Thus, wider adoption of NPD will require common data formats, open sets of reference phase standards, and harmonized validation protocols.

From an engineering standpoint, the development of "self-optimizing" loops—where a phase detector, digital twin, and optimizer form a closed feedback system—appears promising. Experience with chemical-reaction platforms shows that a multi-objective TSEMO strategy can adapt synthesis parameters online, simultaneously improving yield and purity [9]. Extending this approach to sensor clusters or battery assemblies paves the way for continuous calibration tuning without halting the production line.

Finally, the human operator assumes a new role—not as a manual "screw turner," but as a curator of the digital calibration infrastructure. Analogous to the multi-level static and dynamic verification scheme used in strain-gauge press-testers [5], the metrologist must oversee the integrity of phase metrics, the quality of training data sets, and the compliance of algorithms with established standards. This shift demands additional personnel training and the adoption of DevOps-style practices within the laboratory environment.

In sum, collective experience confirms that, with careful planning, standardization of phase indicators, and support for physics-informed algorithms, NPD delivers a unique combination of accuracy, speed, and scalability for calibrating a wide range of products—from micro-scale sensors to large-radius high-energy detectors. In the near future, key tasks will include establishing open repositories of phase standards, automating digital-twin updates, and developing universal interfaces between hardware and optimization algorithms.

CONCLUSION

The results of this study demonstrate that nonlinear phase detection (NPD) provides a foundational methodology for unifying calibration procedures in mass-production environments, delivering both high metrological accuracy and a substantial reduction in cycle time.

The first objective—an interdisciplinary review of hardware platforms—revealed that, regardless of the technology (high-energy jets, holographic thickness gauges, MEMS sensors, Li-ion cells, or DEPFET imagers), the principal calibration errors manifest as phase nonlinearities that a unified NPD approach consistently eliminates. Implementing NPD reduced systematic error by 20–40 % and shortened the calibration setup phase by up to eightfold.

The second objective—comparison of algorithmic strategies—confirmed that physics-informed models augmented with deep neural networks (ResNet-50, U-Net) and evolutionary optimizers (CMA-ES, GA-PSO) achieve the best trade-off between accuracy and speed. Hybrid "model + ML" schemes operated robustly in noisy industrial conditions and scaled to thousands of channels without metric degradation.

The third objective—formulation of unified deployment rules—yielded four practical principles:

1. Employing a dual-phase metric
2. Incorporating at least second-order nonlinearity in the model
3. Integrating physics-informed optimization
4. Designing for built-in scalability on mass-production lines

Validating these principles on real-world cases confirmed their reproducibility and cost-effectiveness: yield of acceptable product rose by 8–12 %, while calibration-standard expenses fell by as much as 30 %.

In summary, nonlinear phase detection stands out as a universal tool for rapid, high-precision, and repeatable calibration. Future work should focus on standardizing phase metrics, expanding libraries of physics-informed neural models, and developing adaptive digital twins that automatically update calibration parameters over the entire product lifecycle.

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