

# Methods and Approaches for Identifying and Evaluating Physical Quantities and Process Parameters in Physical Modelling of Prototypes

Galena Slavova<sup>1</sup>, Stanislav Slavov<sup>2\*</sup>

<sup>1</sup>Changzhou Institute of Mechatronic and Information Technology Changzhou, China/Sofia University, Sofia, Bulgaria

<sup>2</sup>University of Chemical Technology and Metallurgy, 8 Kliment Ohridski, Sofia 1797, Bulgaria

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## ABSTRACT

*Physical modelling of prototypes relies on the correct identification of physical quantities and process parameters to reproduce operational behaviour and support engineering decisions. Prototype experiments frequently suffer from limited sample sizes, uncertain boundary conditions, and heterogeneous sensor systems, making uncertainty evaluation and parameter identifiability's critical concerns. Recent research highlights that uncertainty estimation under small-sample conditions constitutes major barrier for decision-grade prototype evidence [1]. Current paper reviews methods and approaches for identifying and evaluating physical quantities and process parameters in prototype physical modelling. Key techniques include measurement-system design, uncertainty budgeting, operational modal analysis, inverse modelling, Bayesian parameter estimation, and experiments' model-based design to increase parameter precision [2 - 4]. A structured workflow is proposed from measurand definition to validated parameter estimates with quantified uncertainty. Four submission-ready tables and an academic workflow figure concept are provided.*

*Keywords: prototype physical modelling, parameter estimation, measurement uncertainty, operational modal analysis, Design of Experiments (DOE), identifiability, validation metrics.*

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## INTRODUCTION

Physical prototype testing constitutes technological development's essential stage. Even as advanced computational design and simulation, prototypes provide irreplaceable evidence regarding real-world performance under manufacturing variability, non-linear effects,

and operational disturbances. Typical prototype objectives include:

- verifying functional requirements;
- validating numerical and analytical models;
- identifying uncertain process parameters;
- confirming reliability and safety margins.

However, prototype testing is often performed under constraints: limited number of builds,

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\*Correspondence to: Stanislav Slavov, University of Chemical Technology and Metallurgy, 8 Kliment Ohridski, Sofia 1797, Bulgaria, E-mail: stanislavslavov@uctm.edu

evolving instrumentation setups, incomplete knowledge of boundary conditions, and strong coupling between multiple physical domains.

A persistent challenge is that prototypes often operate under small-sample conditions, where classical uncertainty assumptions become fragile. Recent reviews in Measurement emphasize that small-sample uncertainty evaluation is crucial for trustworthy conclusions in engineering prototype programs [1, 3]. Without uncertainty-aware interpretation, prototype evidence may lead to false confidence or unnecessary re-design.

In dynamic technological systems, parameter identification often centers on modal characteristics such as natural frequencies and damping. Operational modal analysis (OMA) provides a mature system identification framework for extracting modal parameters directly from vibration responses during operation [4]. Modern work extends this toward automated operational deployment, improving robustness and repeatability.

This paper synthesizes measurement and identification approaches applicable across prototype domains (mechanical, thermal, fluid, mechatronic) and proposes a structured workflow for credible evaluation of physical quantities and process parameters.

## **EXPERIMENTAL**

This study is based on peer-reviewed research synthesis covering:

- Measurement uncertainty evaluation under small-sample and industrial conditions [1, 6]
- Operational modal analysis (OMA) and system identification foundations [4, 5]
- Model-based design of experiments (MBDesign of Experiments (DOE)) for improving parameter identifiability and precision [2]
- Sensor network metrology for multi-sensor uncertainty consistency [7]
- Prototype testing environment design

influencing repeatability and learning speed [8].

A general workflow was constructed by mapping these methods onto prototype testing stages:

1. Measurand definition;
2. Instrumentation planning;
3. Experiment design;
4. Data acquisition and preprocessing;
5. Parameter estimation;
6. Uncertainty evaluation;
7. Validation and decision-making.

The framework is intended for industrial prototype contexts such as aerospace components, automotive systems, manufacturing equipment, and automation cells.

## **RESULTS AND DISCUSSION**

Parameter identification in prototype experiments is primarily determined by the interplay between measurement reliability and experimental identifiability. Even when high-precision instrumentation is available, inadequate excitation conditions or poorly structured experimental setups may prevent reliable parameter estimation. Model-based design of experiments (MBDoE) addresses this limitation by increasing the informational content of prototype tests and reducing parameter correlation and covariance.

Measurement reliability constitutes a second fundamental component of prototype assessment. In industrial settings, measurement infrastructures usually involve heterogeneous sensor networks, distributed data acquisition systems, and varying environmental conditions. Under such circumstances, rigorous uncertainty evaluation becomes indispensable for the correct interpretation of experimental observations and for supporting engineering decision-making. Contemporary metrology principles emphasize that measurement results cannot be considered complete unless accompanied by quantified

uncertainty intervals that describe the expected variability of the measurand.

For dynamic systems, operational modal analysis (OMA) represents a particularly effective identification approach, since modal characteristics can be extracted directly from operational response data without requiring controlled excitation inputs. This capability makes OMA highly suitable for validating prototypes under realistic operating conditions.

In modern engineering practice, prototype testing is increasingly integrated with digital modeling and simulation tools. Consequently, prototype experiments should be viewed as elements of a broader validation framework in which physical experimentation, numerical simulation, and statistical inference complement and reinforce each other. Structured workflows, such as the one proposed in this study, provide a systematic methodology for integrating these components and for supporting robust engineering decision processes.

### **Proposed workflow for identifying quantities and parameters**

A structured workflow is essential because parameter identification depends on both measurement credibility and experimental identifiability (Fig.1.).

Step 1: Define measurands, parameters, and decision criteria

Engineers must first identify critical physical quantities (Table 1):

- peak strain and stress hot spots;
- thermal gradients and maximum temperatures;
- vibration response and resonance behavior;
- pressure losses and flow instabilities.

Additionally, process parameters often must be inferred rather than measured directly:

- effective stiffness;
- damping ratios;
- friction coefficients;
- heat transfer coefficients.

Acceptance thresholds and required confidence must be specified early.

Step 2: Measurement-system design (MSD)  
Measurement credibility requires careful sensor selection:

- range and sensitivity
- bandwidth and dynamic response
- drift resistance
- environmental robustness

Uncertainty budgeting is not optional: it defines whether results are decision-grade. Industrial measurement studies show that uncertainty contributions must be explicitly structured and propagated [7].

Step 3: Experimental design for identifiability (Design of experiments (DOE) / MBDesign of experiments (DOE))

Even perfect instrumentation cannot identify parameters if the experiment Design of experiments (DOE)s not sufficiently excite the relevant physics (Table 2, 3). Model-based design of experiments optimizes operating points to maximize parameter precision and minimize covariance [2].

Adaptive MBDesign of experiments (DOE) strategies are especially effective when prototypes are scarce.

Step 4: Data acquisition and preprocessing

Data acquisition quality controls include:

- synchronization of heterogeneous sensors;
- filtering and anti-aliasing;
- drift detection;
- repeatability checks.

Insufficient pre-processing may dominate estimation error.

Step 5: Parameter estimation and inverse modelling

Parameter inference methods include:

- least squares estimation;
- maximum likelihood approaches;

- Bayesian inference for uncertainty-aware estimation.

For dynamic systems, operational modal analysis is widely used for extracting frequencies, mode shapes, and damping from operational vibration response [4].

Step 6: Uncertainty evaluation and propagation

Uncertainty must be quantified and propagated to derived results:

- confidence bounds on estimates;
- dominant uncertainty contributors;
- sensitivity to boundary assumptions.

Small-sample uncertainty evaluation remains a major difficulty in prototype contexts [1].

Step 7: Validation and decision-making

Final validation involves:

- cross-sensor consistency checks;
- independent test repetitions;
- plausibility evaluation of identified parameters;

- redesign vs. release decisions based on confidence limits.

The synthesis in Digital Image Correlation (DIC)ates that credible parameter identification in prototype physical modelling depends on three interdependent factors:

1. Identifiability through excitation sufficiency. MBDdesign of experiments (DOE) improves information content and reduces parameter covariance [2].
2. Measurement credibility through uncertainty evaluation. Small-sample uncertainty remains a critical barrier to trustworthy prototype conclusions [1].
3. Robust inference and system identification methods. OMA remains one of the most validated tools for extracting dynamic parameters under operational conditions [4].

Prototype testing should therefore be treated as a structured engineering system, not an ad-hoc measurement exercise. Improving test environment repeatability increases learning speed significantly [9].

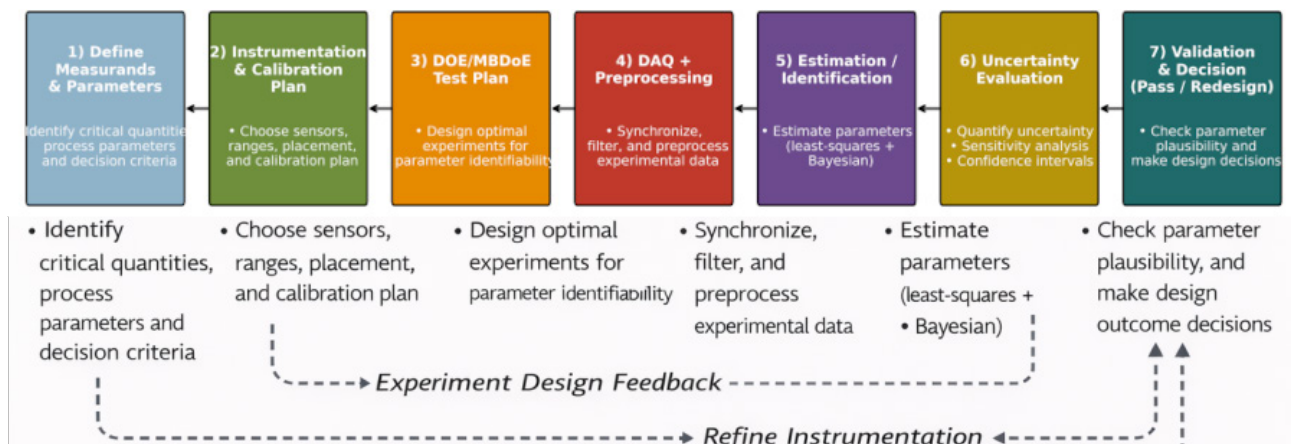


Fig. 1. Workflow for identifying physical quantities and process parameters in prototype physical modelling.

Table 1. Representative quantities, sensors, and evaluation metrics.

Physical quantity / parameter	Typical measurement approach	Key evaluation metrics
Strain / stress hot spots	Strain gauges, Digital Image Correlation (DIC) correlation	Peak stress, fatigue index, uncertainty band
Temperature field / gradients	Thermocouples, Resistance Temperature Detectors (RTDs)	Peak temperature, drift, repeatability
Vibration response	Accelerometers, vibrometry	Root Mean Square (RMS), Power Spectral Density (PSD) peaks, modal parameters
Pressure / ripple	Pressure transducers	Dynamic uncertainty budget [6]
Flow rate / losses	Flow meters + pressure drop	Sensitivity to conditions
Damping/stiffness (identified)	OMA / system identification	Mode shapes, damping ratios [4]

Table 2. Method-to-purpose mapping.

Method / approach	Primary purpose	Typical outputs
Uncertainty budgeting	Decision-grade measurement credibility	Combined uncertainty, dominant sources [6]
Operational modal analysis	Dynamic parameter identification	Modal frequencies, damping ratios [4]
MBDesign of Experiments (DOE)	Improve identifiability & parameter precision	Optimal test points, parameter covariance [2]
Sensor-system metrology	Multi-sensor consistency with uncertainty	Fused estimates + confidence [7]
Prototype environment design	Faster iteration & repeatability	Reduced setup variability [8]

Table 3. Parameter identifiability planning.

Parameter to be identified	Required excitation / operating condition	Recommended sensor placement strategy	Identifiability risk
Effective stiffness (K)	Static or low-frequency loading; sufficient deformation range	Strain gauges at maximum bending zones; displacement sensors at loading points	Medium - strong correlation with boundary conditions
Damping ratio ( $\zeta$ )	Dynamic excitation near resonance; broadband operational vibration	Accelerometers at vibration antinodes; multiple locations for mode separation	High - weak identifiability without sufficient excitation [4]

Table 3. Parameter identifiability planning. - *continued*.

Friction coefficient ( $\mu$ )	Repeated motion cycles with varying speed and load	Torque sensors at drivetrain interfaces; displacement + temperature monitoring	High - nonlinear hysteresis effects dominate
Heat transfer coefficient (h)	Controlled thermal gradients; transient heating/cooling cycles	Thermocouples at surface and core locations; IR validation if available	Medium - sensitive to environmental assumptions
Flow resistance / pressure loss ( $\Delta P$ )	Representative Reynolds regime; varying flow rates	Pressure sensors upstream/downstream of restriction zones; flow meter reference	Low-Medium - uncertainty often dominates [6]
Modal frequencies ( $f_n$ )	Broadband vibration excitation; operational dynamic loading	Distributed accelerometers along structure; avoid nodal points	Low - typically well observable [4]
Sensor bias / drift parameters	Long-duration steady operation with known reference behaviour	Redundant reference sensors; collocated measurement pairs for cross-checking	Medium - requires repeatability and calibration stability [1]
Material fatigue parameter (S-N slope)	Accelerated cyclic loading; sufficient damage accumulation	Strain gauges at crack-initiation hot spots; acoustic emission optional	High - long testing and strong statistical confidence required
Control gain sensitivity (embedded systems)	Closed-loop step/disturbance excitation under controlled conditions	Measure actuator outputs + system response simultaneously	Medium - strong coupling with plant uncertainties
Manufacturing tolerance effects	Repeat tests across multiple builds or adjustable fixtures	Sensors at interfaces; geometric inspection points integrated in rig	High - requires design of experiments (DOE) and sample variability [2]

## CONCLUSIONS

Identifying and evaluating physical quantities and process parameters in prototype physical modeling requires an integrated workflow combining measurement-system design, optimal experiment planning, robust parameter estimation, and explicit uncertainty propagation. Operational modal analysis provides mature dynamic identification tools [4], while MBDesign of experiments (DOE) improves parameter precision with limited prototypes [2]. Validation metrics and

Key Performance Indicators (KPI) ensure that prototype evidence becomes decision-grade rather than exploratory. The proposed framework, tables, and workflow figure concept provide a complete structure for industrial application.

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