

Kinematic Calibration and Positioning-Error Compensation of Industrial and SCARA Robots: A Comprehensive Review

P. Kalyan Babu¹ SK. Sabbir² R. Raju³ Dr. T. Haritha⁴

⁴Professor

^{1,2,3,4}Department of Mechanical Engineering

^{1,2,3,4}Dr RVR NRI Institute of Technology Deemed to Be University, Pothavarappadu (V), Agiripalli(M), Eluru, Andhra Pradesh, India

Abstract — Absolute positioning accuracy decides whether an industrial robot can be programmed offline and trusted in assembly, machining, inspection, and wafer handling, yet most robots are repeatable to a fraction of what they are accurate. This review examines 100 studies, from the 1980s foundations of robot calibration to articles published in 2026, with attention to serial, SCARA, parallel, and hybrid architectures. The literature is organised into six themes: error sources and kinematic error models (modified Denavit–Hartenberg, complete and parametrically continuous, product-of-exponentials, and arm-signature formulations); measurement systems and calibration procedures (laser trackers, interferometers, vision, double ball bars, constraint-based and self-calibration); parameter identification and measurement-configuration optimisation (observability indices, least-squares and Kalman-type estimators); non-geometric errors, namely joint and link compliance and stiffness modelling; calibration of SCARA, parallel, and over-constrained mechanisms; and data-driven compensation with neural networks, deep belief networks, and hybrid model-plus-learning schemes. A final theme links accuracy to dynamics and control. The review finds a clear shift from purely geometric models toward combined geometric, compliance, and learned corrections, and from laboratory metrology toward robot-mounted and vision-based, in-situ calibration. Key gaps include SCARA-specific non-geometric models, limited cross-robot benchmarks, thermal and wear drift, reduced-dataset learning with guaranteed accuracy, and the lack of standard reporting protocols. The paper closes with recommendations for load-aware, self-updating, and verifiable calibration.

Keywords: Robot Calibration, Positioning Accuracy, SCARA Robot, Kinematic Error Model, Stiffness Modelling, Error Compensation, Neural Networks, Hand-Eye Calibration

I. INTRODUCTION

An industrial robot is repeatable long before it is accurate. Repeatability, the ability to return to a taught point, is set largely by the drives and encoders, whereas absolute accuracy, the ability to reach a commanded pose in the workspace, also depends on how well the controller's kinematic model matches the real mechanism. When tasks are programmed offline from a CAD model, or when a part must be located without a teaching step, the gap between the two decides whether the process works. Early industrial studies of calibration methods and results established accuracy, repeatability, and calibration as separate concepts and showed that calibration is the route to closing the gap [1], [82]. Overviews followed in the 1980s and 1990s [2], [12], and the field has since grown into a large body of work on

error modelling, measurement, identification, and compensation.

Three developments drive the present review. First, measurement has changed. Early calibration relied on theodolites and dedicated fixtures, whereas recent studies use laser trackers, interferometers, double ball bars, stereo and monocular vision, and sensors mounted on the robot itself [21], [25], [28], [40], [41], [46], [49]. Second, models have widened. Purely geometric error models are now routinely extended with joint and link compliance, base deformation, and other non-geometric effects, because heavy-duty and machining robots are limited by compliance, not by link-length errors [22], [37], [39], [43], [62]. Third, learning-based methods have become a common route to compensating whatever the physical model leaves behind [32], [33], [50], [90], [91], [100], and a recent survey organises this data-driven strand [92].

SCARA robots occupy a special place in this picture. Their planar structure, light links, and high speed make them dominant in electronics assembly and wafer handling, but also make them sensitive to joint-angle and link-length errors, because the horizontal position error is a direct function of the two revolute joints. SCARA-specific work exists on condition-number-based calibration [10], stereo-camera compensation [17], positioning-accuracy measurement [18], [47], [48], automatic vision-based calibration for wafer inspection [51], and hand-eye calibration [95], yet it is scattered across journals and often treated as a special case of general serial-arm calibration. The same fragmentation affects the links between calibration and the dynamics and control of SCARA and related mechanisms [55]–[57], [86], [87].

This review brings these strands together. Its contributions are:

- Unified treatment of error sources, kinematic and non-kinematic error models, measurement, identification, and compensation in one framework [1]–[15], [22]–[25].
- Model-family comparison of Denavit–Hartenberg-based, complete-and-parametrically-continuous, product-of-exponentials, and signature-based formulations [3]–[5], [13], [23], [74], [77], [78].
- Measurement-system comparison across laser tracking, interferometry, vision, ball bars, sensorised linkages, and constraint-based self-calibration [21], [24], [25], [46], [49], [52]–[54], [80], [96].
- Identification and experiment design, including observability indices and estimator choice [8], [11], [27], [35], [61], [75], [76], [79].
- Compliance and stiffness modelling, from joint-compliance models to elastostatic calibration [22], [37], [44], [45], [62]–[65], [84].

- Architecture-wise coverage of SCARA, serial, parallel, and over-constrained robots [10], [47], [48], [67]–[72], [97], [99].
- Data-driven compensation, including neural, deep, and hybrid methods [19], [20], [32]–[36], [50], [89]–[93], [100].
- Gaps and directions for load-aware, self-updating, and verifiable calibration.

A map of how the review is organised is given in Fig. 1, and the generic calibration workflow that the later sections follow is summarised in Fig. 2.

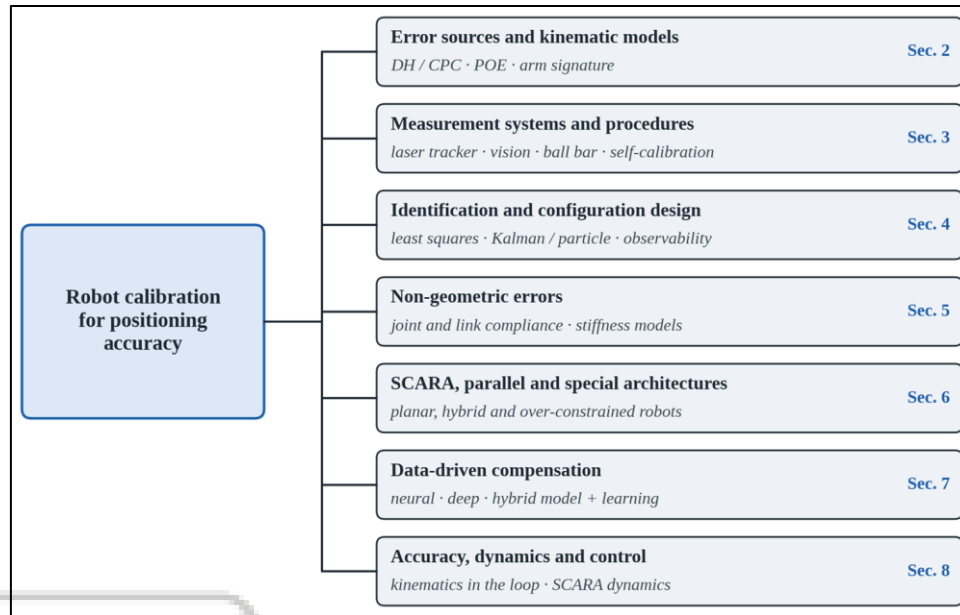


Fig. 1: Organisation of the review: the seven technical themes and the sections that cover them. Section 9 closes with gaps and directions.

II. ERROR SOURCES AND KINEMATIC ERROR MODELS

Calibration begins with a model of how the real robot differs from the nominal one. This section reviews the error sources,

the parameterisations used to describe geometry, and the accuracy measures against which methods are compared. The calibration workflow that links the following sections is shown in Fig. 2.

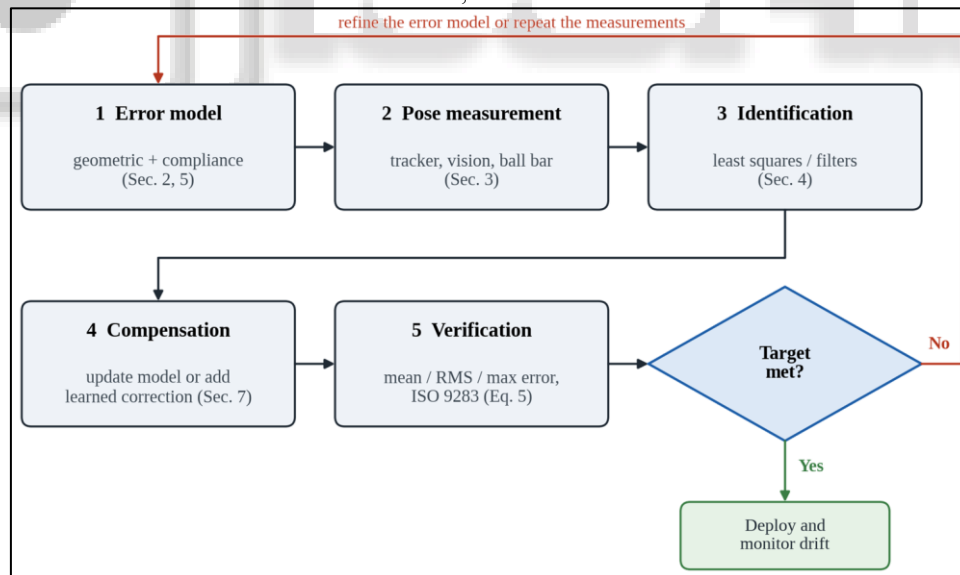


Fig. 2: Generic robot calibration workflow: error modelling, pose measurement, parameter identification, compensation and verification, with a loop back when the accuracy target is not met.

A. Error Sources

Robot positioning errors are conventionally split into geometric and non-geometric groups. Geometric errors come from manufacturing and assembly tolerances in link lengths, joint offsets, and axis alignment, and an early analysis traced end-effector error to such parameters for robots with all rotary joints [3]. Broderick and Wampler showed how

manufacturing errors can be determined and corrected [5], and Veitschegger and Wu linked robot accuracy to the kinematic structure [81]. Non-geometric errors include joint and link compliance, gear and transmission effects, backlash, and base deformation, and several studies model them explicitly because geometric calibration alone leaves residual error [14], [15], [30], [39]. Whitney and Rourke separated

accuracy, repeatability, and calibration as distinct concepts in an industrial setting [82], and an assessment of the positioning performance of an industrial robot illustrates how accuracy is evaluated in practice [31]. Overviews of calibration and of the accuracy of manipulation-robot models organise these sources [2], [12].

B. Kinematic Parameterisations

The Denavit–Hartenberg (DH) convention describes the nominal robot, but it becomes singular when two consecutive joint axes are parallel or nearly so, so error models usually use a modified form. The complete and parametrically continuous (CPC) model adds a rotation about the second axis for such cases, giving a link transform of the form

$${}^{i-1}T_i = \text{Rot}(z, \theta_i) \text{Trans}(z, d_i) \text{Trans}(x, a_i) \text{Rot}(x, \alpha_i) \text{Rot}(y, \beta_i) \quad (1)$$

and its error-model-based calibration is documented in [13]. The forward kinematics of an n -joint arm is the product of the link transforms,

$$T(q, \phi) = \prod_{i=1}^n {}^{i-1}T_i(q_i, \phi_i) \quad (2)$$

where q collects the joint values and ϕ the kinematic parameters. Product-of-exponentials (POE) formulations avoid frame-assignment ambiguity by describing each joint with a screw axis ξ_i :

$$T(q) = e^{[\xi_1]q_1} e^{[\xi_2]q_2} \dots e^{[\xi_n]q_n} T(0) \quad (3)$$

This yields a parametrically continuous model that has been used for serial-robot calibration [23], and a local variant treats each joint's screw in its own frame [74]. The arm-signature approach identifies parameters of a signature model from measurements within an assembly environment

[77], and its statistical performance has been evaluated [78]. Perturbation methods linearise the effect of small parameter changes on pose [4], and a modelling reference covers identification and control of robots more broadly [85]. A study comparing model-based and modelless calibration, with fuzzy interpolation as the modelless route, shows that geometry-free alternatives exist where the model is incomplete [83].

C. Linear Error Model and Accuracy Measures

Whatever the parameterisation, most methods linearise the pose error about the nominal parameters:

$$\Delta p = J_\phi(q) \Delta \phi \quad (4)$$

with Δp the pose error and J_ϕ the identification Jacobian. Rank deficiency of J_ϕ reveals parameters that cannot be separated, and the mapping from this rank problem to measurement design is treated in Section 4 [6], [7]. Accuracy is typically reported with the mean, root-mean-square, and maximum position error over a set of test poses. The widely used ISO 9283 definitions give the positional accuracy as the distance between the commanded point and the barycentre of the attained points,

$$AP = \sqrt{(\bar{x} - x_c)^2 + (\bar{y} - y_c)^2 + (\bar{z} - z_c)^2} \quad (5)$$

and repeatability as $RP = \bar{l} + 3S_l$, with $\bar{l}$ the mean distance of attained points from their barycentre and S_l its standard deviation. Duellen and Schroer reported calibration methods and results for industrial robots [9], and Judd and Knasinski reported a calibration technique with experimental verification [6]. Fig. 3 illustrates accuracy (AP) and repeatability (RP) before and after calibration.

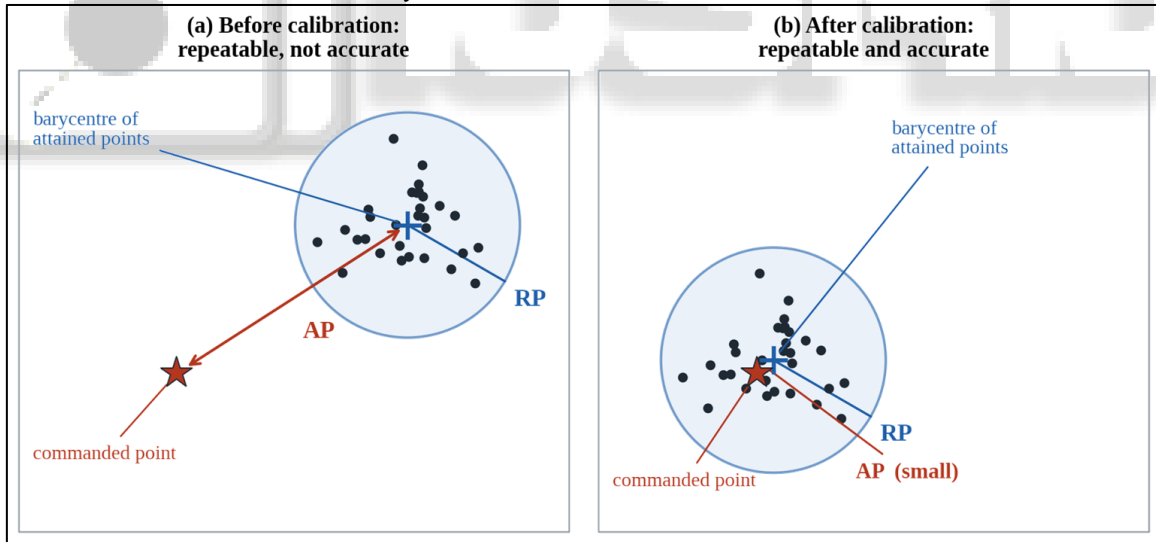


Fig. 3: Illustration of ISO 9283 positional accuracy (AP) and repeatability (RP): (a) a repeatable but inaccurate robot before calibration; (b) the same scatter centred on the commanded point after calibration.

Aspect	Main idea	Strength	Limitation	Refs.
DH / CPC models	Four- or five-parameter link description	Familiar; CPC handles parallel axes	Frame-assignment dependent	[3], [13], [81]
POE / local POE	Screw-axis product	Parametrically continuous	Less familiar to practitioners	[23], [74]
Arm signature	Signature-model identification	Suited to assembly environment	Model-specific	[77], [78]
Perturbation	Linearised effects of parameter change	Simple identification	Valid for small errors	[4], [5]

Modelless	Interpolation without geometry	No model needed	Needs dense measurements	[83]
Concepts and overviews	Accuracy vs repeatability vs calibration	Common vocabulary	Largely qualitative	[1], [2], [12], [82]

Table I: Error Sources and Modelling Approaches

Geometric models remain the foundation, and the main open issues are consistent parameterisation across robot types, standard accuracy reporting, and the treatment of errors that depend on load and pose.

III. MEASUREMENT SYSTEMS AND CALIBRATION PROCEDURES

Calibration is only as good as its measurements. This section reviews the instruments used, the quantities they provide, and the procedures that reduce the need for expensive equipment.

A. Laser Trackers and Interferometry

A laser tracker measures the three-dimensional position of a reflector with high accuracy over a large volume, and absolute calibration of an industrial arm with a tracker is a well-documented example [25]. Laser-based kinematic calibration using differential kinematics has been demonstrated for a robot manipulator [24], and tracker measurements combined with nonlinear least squares have also been used for calibration [98]. Interferometry offers higher resolution for single axes: a laser interferometry-based technique estimates positioning errors for accuracy improvement [21], and an open-loop tracking interferometer has been used to map bidirectional angular positioning deviation of rotary axes in a SCARA-type robot [47]. These instruments provide the reference but are costly and demand careful set-up, which motivates alternatives.

B. Vision-Based Measurement

Cameras make calibration cheaper and allow on-line operation. A three-dimensional vision-based measurement system with a single camera has been used for calibration [16], a kinematic calibration method uses autonomous visual measurement [28], and a vision-based framework addresses calibration of industrial manipulators [40]. For SCARA robots, a stereo-camera 3D error model compensates positioning error [17], and a fully automatic vision-based calibration has been applied to wafer inspection scheduling [51]. Robot-mounted sensing and local calibration aim at

high-accuracy manufacturing where only a region of the workspace matters [41], and self-alignment of on-board sensors addresses the sensor's own placement [29]. Vision-based approaches trade measurement accuracy for convenience, and their errors depend on camera calibration, lighting, and target detection.

C. Mechanical Gauges, Linkages, and Pose Measurement

Mechanical instruments reduce cost. A double ball bar provides distance measurements that identify kinematic parameters [49], and a sensorised spatial linkage supports full-pose measurement for kinematic calibration [46]. Measurement of positioning accuracy specific to SCARA robots has been addressed [18], and a system for measuring the end-effector of a six-axis welding robot has been developed [58]. Adaptive real-time estimation of end-effector position and orientation from precise position measurements offers a route to on-line pose knowledge [59], and a two-step calibration based on complete pose measurement was verified on a heavy-duty robot [42]. Partial pose measurements, designed with design of experiments, achieve calibration with less instrumentation [26]. Assessing positioning performance in this way fixes the baseline against which calibration is judged [31].

D. Constraint-Based and Self-Calibration

Constraint methods replace external measurement with a physical constraint. Bennett, Hollerbach and Geiger used a single precision constraint for autonomous calibration [80], and Zhong and Lewis proposed a new method for autonomous robot calibration [96]. More recently, spherical constraints support self-calibration of the end-effector [53], and variable pose constraints with vision allow self-calibration of industrial robots [54]. Fast re-calibration for industrial arms addresses the need to repeat calibration when conditions change [52]. These methods reduce setup cost and enable calibration on the shop floor, but they typically calibrate fewer parameters than tracker-based methods. Typical set-ups for these methods are sketched in Fig. 4.

System	Quantity measured	Strength	Limitation	Refs.
Laser tracker	3D position	Accurate over large volume	Costly; set-up	[24], [25], [98]
Interferometer	Axis displacement	High resolution	Single-axis; set-up	[21], [47]
Camera / stereo vision	Image-based pose	Low cost; on-line	Camera and target errors	[16], [17], [28], [40], [51]
Robot-mounted sensing	Local pose	In-situ; local accuracy	Limited volume	[29], [41], [59]
Ball bar / linkage	Distance; full pose	Inexpensive	Limited coverage	[46], [49]
Pose-based methods	Full or partial pose	Fewer instruments	Needs careful design	[26], [42], [58]
Constraint / self-calibration	Constraint residual	Shop-floor use	Fewer parameters	[52]–[54], [80], [96]

Table II: Measurement Systems for Robot Calibration

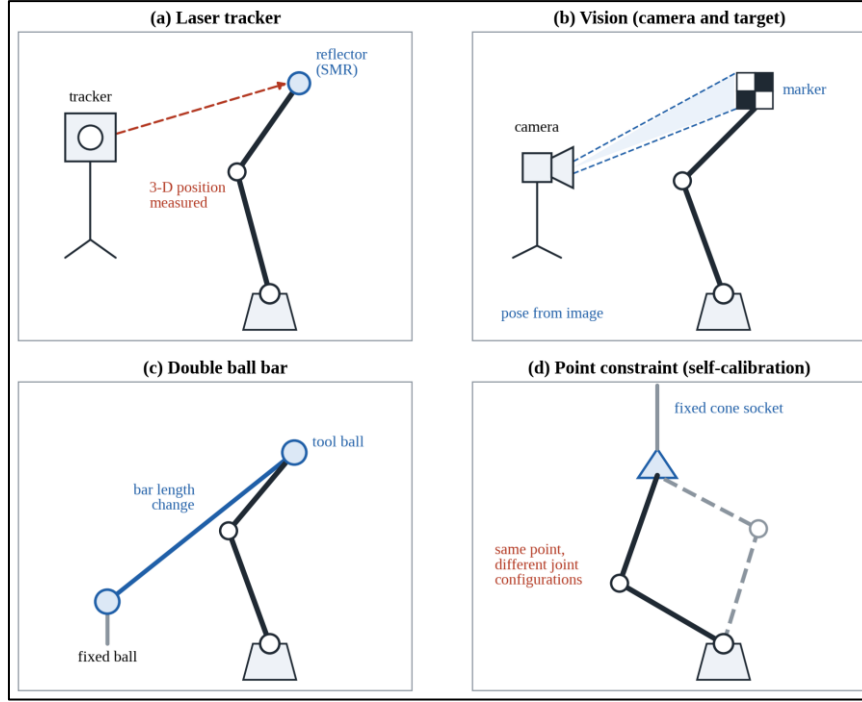


Fig. 4. Schematic measurement set-ups for robot calibration: (a) laser tracker with a reflector on the tool; (b) camera viewing a marker; (c) double ball bar between a fixed and a tool-mounted ball; (d) point constraint reached in different joint configurations.

Open issues include uncertainty budgets for vision-based methods, calibration volumes that match the working region, and standard procedures for comparing instruments on the same robot.

IV. PARAMETER IDENTIFICATION AND MEASUREMENT-CONFIGURATION DESIGN

With a model and measurements in hand, the kinematic parameters are estimated by minimising the discrepancy between measured and predicted poses. The quality of the result depends on the estimator and on which poses are measured.

A. Least-Squares Identification

Given N measured poses p_k^m at joint vectors q_k , the parameters are found from

$$\hat{\phi} = \underset{\phi}{\operatorname{argmin}} \sum_{k=1}^N \|p_k^m - f(q_k, \phi)\|^2 \quad (6)$$

and the problem is usually solved by iterating a damped Gauss–Newton or Levenberg–Marquardt step,

$$\Delta\phi = (J_\phi^T J_\phi + \lambda I)^{-1} J_\phi^T e \quad (7)$$

where e stacks the pose residuals. Early calibration work formulated this identification for general robots [6], [7], and a statistical view of the estimation was given by Driels and Pathre [76]. Computationally efficient and robust calibration methodologies have been developed and applied to industrial robots [27], and structural-parameter identification has been developed for six-DOF industrial robots [73]. When the identification Jacobian is poorly conditioned, regularisation or parameter elimination is needed; a six-DOF hybrid robot calibration addresses multicollinearity in the identification Jacobian explicitly [72].

B. Recursive and Filter-Based Estimators

Batch least squares uses all measurements at once, whereas filter-based estimators update the parameters as data arrive. Treating the parameter vector as a slowly varying state,

$$\phi_{k+1} = \phi_k + w_k, \quad z_k = h(q_k, \phi_k) + v_k \quad (8)$$

an extended Kalman filter updates the estimate with gain $K_k = P_k H_k^T (H_k P_k H_k^T + R)^{-1}$, and a particle filter replaces the Gaussian assumption with sampled hypotheses. A calibration method combining the extended Kalman and particle filter algorithms has been reported for robotic kinematic parameters [35]. Filter-based identification suits recalibration during operation, which matters when parameters drift, and it connects to the fast re-calibration problem discussed in Section 3 [52].

C. Measurement Configurations and Observability

The choice of calibration poses strongly affects the identified parameters and the final accuracy. Observability indices summarise the identification Jacobian through its singular values $\sigma_1 \geq \dots \geq \sigma_L$. Borm and Meng proposed an index based on the geometric mean of the singular values,

$$O_1 = \frac{(\sigma_1 \sigma_2 \dots \sigma_L)^{1/L}}{\sqrt{m}} \quad (9)$$

with m the number of measurements [8], while condition-number-based indices use $O_2 = \sigma_L/\sigma_1$ and related forms [75]. Driels discussed optimal measurement configurations for calibration [79], and Joubair and Bonev compared the efficiency of five observability indices on a robot [11]. Wu et al. combined enhanced partial pose measurements with design of experiments [26], and Zhang et al. used enhanced error models with measurement-configuration optimisation for industrial robots [61]. A related application-oriented idea selects poses and forces for elastostatic calibration [45], and Driels and Pathre studied the

significance of observation strategy on parameter estimation [75]. Together these show that well-chosen poses can reduce the number of measurements needed for a given accuracy, and that conclusions about index quality are partly robot-dependent.

D. Calibration for Process-Specific Accuracy

Not every task needs global accuracy. Schneider et al. improved robotic machining accuracy through experimental

error investigation and modular compensation [60], showing that error sources can be addressed one at a time for a given process. Local calibration, as in robot-mounted sensing [41], follows the same logic of targeting accuracy where it is needed.

Topic	Key idea	Strength	Limitation	Refs.
Batch least squares	Minimise pose residuals	Simple; well understood	Sensitive to poor conditioning	[6], [7], [27], [73], [76]
Regularisation / elimination	Handle multicollinearity	Stable estimates	May hide parameters	[72]
EKF / particle filter	Recursive parameter estimate	Suits on-line use	Tuning; noise models	[35], [52]
Observability indices	Singular-value measures	Guides pose selection	Index choice robot-dependent	[8], [11], [75], [79]
Design of experiments	Planned partial or full poses	Fewer measurements	Design effort	[26], [45], [61]
Process-specific compensation	Target error sources for a task	Practical gains	Narrow validity	[41], [60]

Table III: Identification and Experiment-Design Methods

Open issues include a common benchmark for observability indices, estimator choices that remain valid under drift, and calibration poses that are feasible in cluttered cells.

V. NON-GEOMETRIC ERRORS: COMPLIANCE AND STIFFNESS

After geometric calibration, residual error is dominated by effects that link-length and offset parameters cannot represent. This section reviews compliance and stiffness models and the calibration methods built on them.

A. Why Compliance Matters

Gravity, payload, and process forces deflect joints and links, and the resulting end-effector error varies with pose and load. Jang, Kim and Kwak calibrated geometric and non-geometric errors of an industrial robot together [14], and Gong, Yuan and Ni identified and compensated nongeometric errors by inverse calibration [15]. Khalil and Besnard extended geometric calibration to robots with flexible joints and links [22], and Lightcap et al. improved the positioning accuracy of a PA10-6CE robot by adding flexibility to geometric calibration [30]. For rigid-link robots with elastic joints, the effect of a wrench w on the pose error can be written through the joint compliance K_{θ}^{-1} :

$$\Delta p_c = J(q) K_{\theta}^{-1} J^T(q) w \quad (10)$$

and the total error combines geometric and compliance terms:

$$\Delta p = J_{\phi}(q) \Delta \phi + J(q) K_{\theta}^{-1} J^T(q) w \quad (11)$$

so identifying ϕ and the stiffness parameters together is the goal of compliance calibration.

B. Stiffness Modelling

Stiffness modelling of industrial robots with geometric and compliance errors was developed by Klimchik, Pashkevich

and Chablat [62], who also proposed optimal calibration of robotic manipulators using stiffness and geometric models [63]. Pashkevich, Klimchik and Chablat enhanced stiffness modelling of manipulators with passive joints [64], and Pashkevich, Chablat and Merlet analysed the stiffness of overconstrained parallel manipulators [65]. Alici and Shirinzadeh presented enhanced stiffness modelling, identification, and verification for robot manipulators [84]. For a high-accuracy patient positioning system, geometric and elastic errors were calibrated together [66]. These works make explicit that stiffness and geometry should be identified in one framework rather than sequentially.

C. Application-Oriented Compliance Calibration

Recent studies extend compliance calibration to specific difficulties. A screw-based kinematic calibration handles joint compliance with circular-point analysis [37]. Ryu and Moon calibrated geometric and non-geometric parameters of an industrial manipulator for improved positioning accuracy [38]. Ma et al. considered non-kinematic and weak rigid base errors in industrial robot error compensation [39], and Wang et al. calibrated both kinematic and non-kinematic parameters of a 7R six-DOF robot with a non-spherical wrist [43]. Ye, Wu and Huang calibrated an over-constrained robot with geometric error and internal deformation [44]. Application-oriented selection of poses and forces for elastostatic calibration aligns the calibration load cases with the intended task [45]. In a related vein, the modular compensation approach for machining separates error sources by their physical origin [60].

Approach	Focus	Strength	Limitation	Refs.
Combined geometric and non-geometric	Joint identification	Fewer residual errors	More parameters	[14], [15], [38]

Flexible joints and links	Elastic model in calibration	Captures deflection	Needs load data	[22], [30], [66]
Stiffness modelling	Compliance matrices	Physically based	Model complexity	[62]–[65], [84]
Joint compliance with screw methods	Circular-point analysis	Handles joint compliance	Specialised formulation	[37]
Base and special structures	Weak base, non-spherical wrist, over-constrained	Task-specific accuracy	Case-specific	[39], [43], [44]
Load-aware calibration	Select poses and forces	Matches task loads	Needs force application	[45], [60]

Table IV: Compliance and Non-Geometric Error Methods

Open issues include load-dependent stiffness identification that stays valid across payloads, efficient force application during calibration, and models that cover backlash and transmission errors alongside compliance.

VI. SCARA, PARALLEL, AND SPECIAL ARCHITECTURES

The general methods above apply to all robots, but architecture changes which errors dominate and which measurements are practical.

A. SCARA Robots

For a planar two-link SCARA arm, joint-angle errors $\delta\theta_i$ and link-length errors δl_i map directly to horizontal position error. Differentiating the planar kinematics gives The geometry of these errors is sketched in Fig. 5.

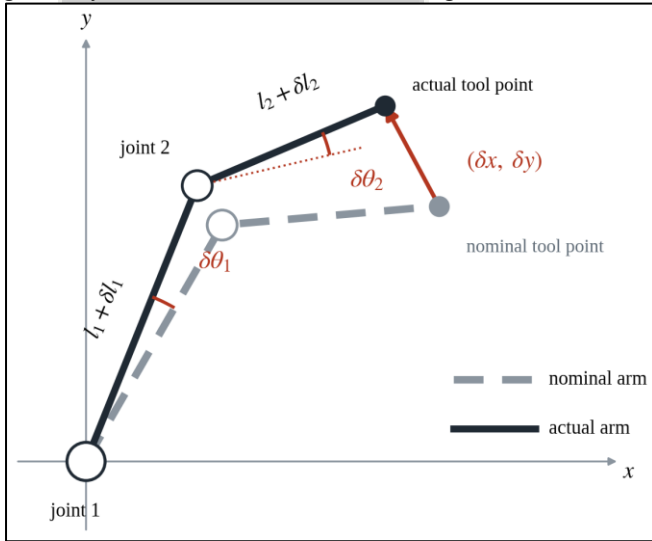


Fig. 5: Planar two-link SCARA arm: joint-angle errors ($\delta\theta_1$, $\delta\theta_2$) and link-length errors (δl_1 , δl_2) move the tool point from its nominal position by $(\delta x, \delta y)$. Errors are exaggerated for clarity.

$$\begin{bmatrix} \delta x \\ \delta y \end{bmatrix} = \begin{bmatrix} -l_1 s_1 - l_2 s_{12} & -l_2 s_{12} \\ l_1 c_1 + l_2 c_{12} & l_2 c_{12} \end{bmatrix} \begin{bmatrix} \delta\theta_1 \\ \delta\theta_2 \end{bmatrix} + \begin{bmatrix} c_1 & c_{12} \\ s_1 & s_{12} \end{bmatrix} \begin{bmatrix} \delta l_1 \\ \delta l_2 \end{bmatrix} \quad (12)$$

where $s_1 = \sin\theta_1$, $c_{12} = \cos(\theta_1 + \theta_2)$, and so on.

The compact structure makes SCARA calibration attractive

but also exposes the arm to small joint and link errors. Toyama et al. calibrated a SCARA robot using a condition-number and error-map method [10], Furuya compensated SCARA positioning error with a stereo camera and a 3D error model [17], and Kamiya et al. proposed a positioning-accuracy measurement method specific to SCARA robots [18]. Fukada examined positioning accuracy of a planar multi-joint positioning system and its improvement [48], and Ibaraki and Usui mapped bidirectional angular positioning deviation of the rotary axes of a SCARA-type robot with a tracking interferometer [47]. A fully automatic vision-based calibration for a selective compliance assembly robot arm has been applied to intelligent wafer inspection scheduling [51]. For hand-eye calibration of SCARA robots, a third-order polynomial mapping from image to robot coordinates with selective regularisation was proposed [95]:

$$x = \sum_{i+j \leq 3} a_{ij} u^i v^j, \quad \min_a \|\Phi a - x\|^2 + \lambda \|Ra\|^2 \quad (13)$$

where (u, v) are image coordinates, Φ the polynomial design matrix, and R a regularisation operator.

B. Parallel and Hybrid Mechanisms

Parallel mechanisms are calibrated with implicit residuals, since closed loops make forward kinematics hard to evaluate. A common form uses the loop constraints,

$$\rho_i(p, q_i; \phi) = 0, \quad \hat{\phi} = \arg\min_{\phi} \sum_k \sum_i \rho_i^2(p_k, q_{ik}; \phi) \quad (14)$$

so that no forward solution is needed. Daney, Papegay and Merlet gave a numerical and experimental study of parallel-robot calibration [97], and Daney et al. proposed an interval method with vision-based experiments [67]. Varziri and Notash calibrated a wire-actuated parallel robot [68]. For planar mechanisms, Joubair and Bonev calibrated a five-bar planar parallel robot using all working modes [69], [99] and a three-DOF planar parallel robot [70]. For machine tools, an orientation constraint was used to calibrate parallel kinematics machines [71], and a six-DOF hybrid robot was calibrated while considering multicollinearity in the identification Jacobian [72]. Stiffness analysis of overconstrained parallel manipulators [65] and calibration with internal deformation [44] show that compliance matters for these architectures as much as for serial arms.

Architecture	Typical issue	Approach	Refs.
SCARA	Joint and link errors map directly to planar error	Condition-number calibration; stereo and vision methods; interferometer mapping	[10], [17], [18], [47], [48], [51], [95]
Serial (6R)	Geometric and compliance errors	POE, stiffness, partial-pose methods	[23], [26], [43], [62], [63]
Planar parallel	Several working modes	Calibration using all modes	[69], [70], [99]

General parallel	No forward solution	Implicit residuals; interval methods	[67], [68], [71], [97]
Hybrid / over-constrained	Multicollinearity; internal deformation	Regularised identification; deformation models	[44], [65], [72]
Wire-actuated	Cable behaviour	Kinematic calibration of the cable robot	[68]

Table V: Architecture-Specific Calibration Work

SCARA calibration is well supported by measurement methods but less so by non-geometric models, which is one of the gaps examined in Section 9.

VII. DATA-DRIVEN ERROR COMPENSATION

When a physical model leaves residual error, a learned map from pose or joint values to error can absorb it. This section reviews neural, deep, and hybrid compensation, and the practical question of how much data they need.

A. Neural-Network Compensation

Inverse calibration with artificial neural networks was proposed by Zhong, Lewis and Nagy [19], and a neural network combined with a camera-based measurement system has been used for manipulator calibration [20]. Back-propagation networks are a general tool for modelling complex systems [88]. For non-geometric errors, Aoyagi et al. combined laser tracking with a neural network to compensate residual errors after kinematic calibration [36].

The common structure is a network $\mathcal{N}$ that predicts the pose error from the joint values or the target pose, trained on measured residuals,

$$\min_w \sum_{k=1}^N \|e_k - \mathcal{N}(q_k; w)\|^2 + \lambda \|w\|^2 \quad (15)$$

and the compensated command is obtained by correcting the target before inverse kinematics,

$$q_c = \text{IK}(p_d - \hat{e}(p_d)) \quad (16)$$

where $\hat{e}$ is the predicted error at the desired pose p_d . Hybrid schemes first calibrate the geometry and then learn the remainder: a method combining model-based identification with neural-network error compensation has been reported to improve position accuracy [32], and neural-network positioning-error compensation with an experimental study has been presented for an industrial robot [33]. A deep neural network has also been used for positioning-error compensation [34], and a compensation method for multi-degree-of-freedom robot arms uses the measured and target position error [89]. The structure of such a hybrid scheme is shown in Fig. 6.

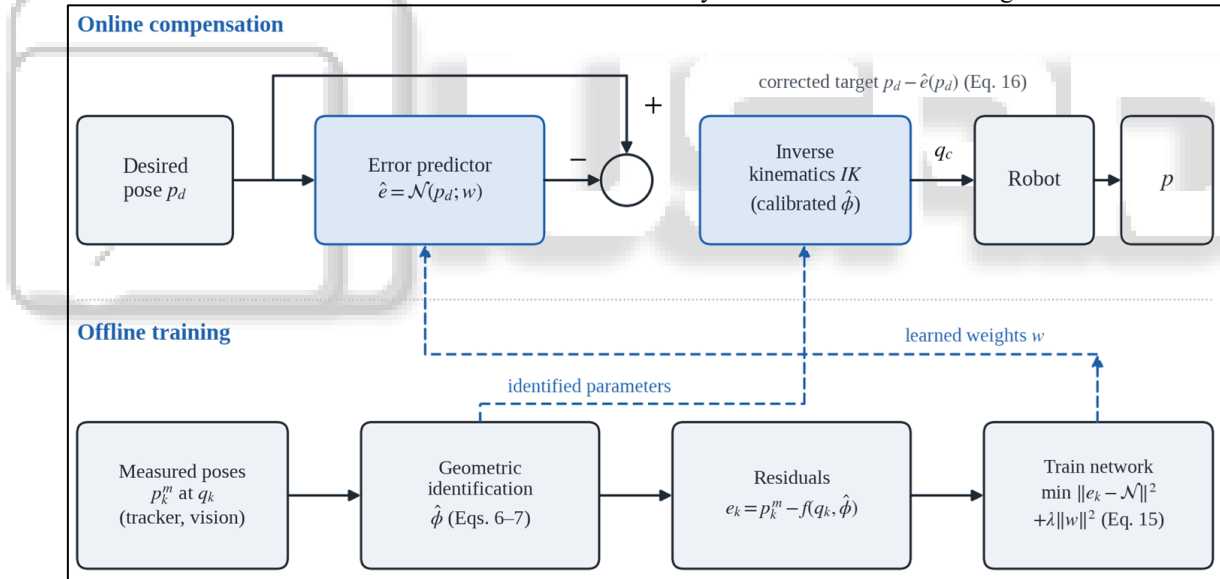


Fig. 6: Hybrid model-plus-learning compensation: geometric identification supplies the calibrated model, and a network trained on the remaining residuals corrects the target pose before inverse kinematics.

B. Deep and Evolutionary-Assisted Models

More recent work uses deeper architectures and tuned training. An off-line error compensation method for absolute positioning accuracy combines differential evolution with deep belief networks [50], and end-effector position error compensation has been studied with an ECOA-BP network [90]. Data-driven compensation of robot positioning errors using deep learning appears in [93], and machine-learning-based positioning error compensation has been reported in [100]. These studies report that learning can reduce residual positioning error, but the reported benefits depend on the dataset, the workspace region covered, and the evaluation protocol.

C. Reduced Data and Surveys

Data collection is the main cost. A machine-learning-based tool for enhancing position accuracy in industrial robots with a reduced dataset addresses this directly [91], and a comprehensive survey of data-driven calibration of industrial robots organises the field [92]. Hybrid approaches that use a physical model to reduce the learning burden follow the logic of comparing model-based and modelless calibration [83]. For SCARA robots, learning-based hand-eye calibration, as in the polynomial mapping with selective regularisation [95], shows that structure in the model can limit overfitting.

D. Limits of Learned Compensation

Several cautions apply. Learned compensators interpolate within the sampled region and may degrade outside it. Their performance depends on the payload and the conditions

during data collection, which parallels the load-dependence of compliance errors in Section 5. They give no guarantee of bounded error, and the lack of standard datasets makes comparison between studies difficult.

Method	Idea	Strength	Limitation	Refs.
Early neural networks	Inverse calibration; camera-based	Little geometry needed	Small datasets; limited scope	[19], [20], [88]
Neural + laser tracking	Compensate non-geometric residual	Complements kinematic calibration	Needs tracker data	[36]
Model identification + ANN	Hybrid geometric and learned	Reported accuracy gains	Two-stage design	[32], [33]
Deep neural networks	Learn error maps	Flexible	Data and training cost	[34], [89], [93], [100]
Evolutionary-assisted deep models	Tuned training	Reported accuracy gains	Complex to reproduce	[50], [90]
Reduced-dataset learning	Fewer samples	Lower measurement effort	Accuracy bounds unclear	[91]
Surveys	Organise the field	Common view	No new data	[92]

Table VI: Data-Driven Compensation Methods

Open issues include dataset standards, accuracy guarantees outside the sampled region, load-aware models, and transfer between robots of the same type.

VIII. ACCURACY, DYNAMICS, AND CONTROL

Calibrated kinematics supplies the reference that dynamics and control must follow. This section links the calibration literature to the dynamics and control work on SCARA and related mechanisms.

A. Calibrated Kinematics in the Control Loop

A controller tracks joint references produced by inverse kinematics. With identified parameters $\hat{\phi}$, the reference becomes

$$q_d = \text{IK}(p_d; \hat{\phi}) \quad (17)$$

so errors in $\hat{\phi}$ appear as a task-space offset that the joint-level controller cannot see. Joint-space tracking can therefore be excellent while absolute accuracy remains poor, which is why calibration and control are complementary. Modelling, identification, and control are treated together in a reference text [85].

B. SCARA Dynamics and Control

Dynamic modelling of a SCARA robot with the Udwadia–Kalaba theory treats constraints through an explicit equation of motion [56]. For a system $M\ddot{q} = Q$ subject to constraints $A\ddot{q} = b$, the constrained acceleration is

$$\ddot{q} = M^{-1}Q + M^{-1/2}(AM^{-1/2})^+(b - AM^{-1}Q) \quad (18)$$

where $^+$ denotes the pseudo-inverse. A robust dynamic control for a SCARA robot has been implemented in [57], and an adaptive feed-forward PID controller for a SCARA parallel robot with pneumatic artificial muscles uses a neural network and a modified differential evolution algorithm [55]. These show how tuning and learning methods enter SCARA control alongside calibration. Dynamics of closed-link mechanisms with non-redundant and redundant actuators [86] and the computation of input generalised forces for robots with closed kinematic chains [87] provide the dynamic counterpart to the closed-loop kinematics met in parallel-robot calibration.

C. Disturbance-Dominated Accuracy

Accuracy is not only geometric. For an aerial manipulator under composite disturbances, precise end-effector control has been addressed with theory and experiments [94], showing that for floating-base systems disturbance rejection, not geometry, may dominate the end-effector error. The same viewpoint applies to contact tasks on fixed-base robots, where force-induced compliance errors (Section 5) and controller design interact.

Topic	Link to accuracy	Refs.
Calibrated inverse kinematics	Corrects the reference passed to the controller	[85]
SCARA dynamic modelling	Constraint-based equations of motion	[56]
SCARA robust and adaptive control	Tracking under uncertainty	[55], [57]
Closed-chain dynamics	Dynamic counterpart to parallel-robot calibration	[86], [87]
Disturbance-dominated systems	Accuracy limited by disturbances	[94]

Table VII: Links Between Calibration, Dynamics, and Control

Open issues include joint treatment of calibration and controller adaptation, and dynamic models that include the same compliance parameters identified in calibration.

IX. RESEARCH GAPS, FUTURE DIRECTIONS, AND CONCLUSIONS

A. Synthesis of Findings

The reviewed literature shows a clear progression. Foundational studies established the distinction between accuracy and repeatability and the first identification methods [1]–[9], [81], [82]. Model families were then refined: CPC and POE formulations gave parametrically continuous models [13], [23], [74], observability indices guided pose selection [8], [11], [75], [79], and compliance and stiffness modelling addressed the errors left after geometric calibration [14], [15], [22], [37], [62]–[65]. Measurement moved from external instruments to robot-mounted, constraint-based, and

vision-based methods [28], [40], [41], [52]–[54], [80], [96]. Learned compensators now supplement physical models [32], [33], [50], [91], [100], and SCARA-specific work adds measurement, vision, and hand-eye methods [10], [17], [18], [47], [51], [95]. A recurring theme is that the best results combine physical models with learned or empirically fitted corrections.

B. Research Gaps

- 1) Modelling gaps: SCARA robots have good measurement-oriented studies but few models that include compliance, backlash, and transmission effects together [10], [17], [47], [48]. Compliance models are

usually identified at a limited set of loads [37], [45], [62], [84].

- 2) Methodological gaps: Observability indices, estimators, and compensators are rarely compared on the same robot and dataset, although some comparisons exist [11], [27]. Reduced-dataset learning is promising but accuracy bounds are not well characterised [91], [92].
- 3) Evidential gaps: Reported accuracies depend on test-pose selection and evaluation protocol, and datasets are rarely shared. Drift over time, wear, and environmental change are seldom studied, despite fast re-calibration methods [52].

Area	Gap	Suggested direction	Refs.
SCARA models	Limited non-geometric modelling	Joint compliance and transmission models for SCARA	[10], [47], [48], [51]
Compliance	Few load cases	Load-aware stiffness calibration	[37], [45], [62]
Measurement	Uncertainty of vision methods	Uncertainty budgets; standard comparisons	[28], [40], [41]
Experiment design	No common benchmark	Shared observability-index tests	[8], [11], [75]
Learning	Data cost; no guarantees	Hybrid models; reduced datasets	[32], [91], [92]
Self-calibration	Fewer parameters	Constraint and vision hybrids	[52]–[54], [96]
Reporting	Inconsistent metrics	Common protocol following accuracy and repeatability definitions	[1], [31], [82]
Control link	Calibration and control treated apart	Joint calibration and controller adaptation	[55]–[57], [85]

Table VIII: Research Gaps and Suggested Directions

C. Future Research Directions

- 1) Compliance-aware SCARA calibration that extends planar kinematic models with joint and transmission compliance, building on the stiffness literature [62]–[65].
- 2) Hybrid physics–learning compensation in which a calibrated geometric and compliance model is followed by a regularised learned correction [32], [33], [95].
- 3) Self-updating calibration combining constraint, vision, and filter-based estimation so that parameters follow drift [35], [52]–[54].
- 4) Open benchmarks with shared robots, poses, and metrics for comparing models, instruments, and compensators [11], [92]. Further topics include calibration of parallel and hybrid mechanisms with internal deformation [44], [65], [72] and the integration of calibration with dynamics and control [55]–[57], [86], [87], [94].

39]. Stiffness models exist [62–65, 84] but are usually identified at few load cases, so their validity at other payloads is uncertain. Geometric and stiffness parameters should therefore be identified jointly, with poses and forces selected by an observability or design-of-experiments criterion that reflects the task [26, 37, 45, 61]. For SCARA robots, measurement and vision methods are well developed [10, 17, 47, 51, 95], but models treating compliance, backlash, and transmission errors together are scarce. Adapting existing stiffness and elastostatic approaches [45, 62, 63] to the SCARA structure would close this gap.

Data-driven compensators reduce residual error in reported cases [32–34, 36, 50, 89–91, 100], yet the results are tied to specific robots, datasets, and workspace regions, and few studies test unseen poses or loads. A calibrated geometric and compliance model followed by a regularised learned correction, validated outside the training region, would improve reliability. Uncertainty budgets for low-cost in-situ measurement [28, 40, 41, 52–54], benchmarked observability indices and estimators [8, 11, 75, 79], and self-updating calibration that tracks drift [35, 52] also remain open. Shared datasets and common reporting based on the accuracy and repeatability definitions [1, 31, 82] would make results comparable across robots.

In conclusion, geometric calibration alone no longer meets the accuracy demands of modern robot applications. Future progress depends on four developments: compliance-aware models, including for SCARA robots; hybrid physics-plus-learning compensation that is validated beyond its training data; in-situ and self-updating calibration that follows parameter drift; and shared benchmarks with consistent reporting. Together, these would turn calibration

X. CONCLUSIONS

This review examined 100 studies on kinematic calibration and positioning-error compensation of industrial and SCARA robots. The central finding is that absolute positioning accuracy is bounded by the fidelity of the kinematic and non-kinematic model embedded in the controller, and by the quality of the measurements and estimation used to parameterise it. The foundational geometric formulations are mature [3, 13, 23, 74, 77, 78]. The main limitations lie in what these models omit, how they are identified, and how thinly the results are validated.

Much of the residual error after geometric calibration originates in joint and link compliance, transmission effects, and base deformation [14, 15, 22, 30,

from a procedure tailored to each robot into a verifiable, transferable step in industrial practice.

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