University of
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Fakultät für
Maschinenbau und Mechatronik

Characterization, Calibration, and Performance Analysis of Sensor-integrating Bolts

Master's Thesis Defense

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Problem Statement & Motivation

Critical Role of Bolted Joints: Essential structural elements in mechanical engineering, responsible for load transfer and structural integrity in critical applications.

Temperature Effects: Thermal conditions significantly impact joint behavior, creating a need for temperature-robust monitoring solutions.

Preload Monitoring Challenge: Up to 90% of bolted joint failures are attributed to incorrect preload, yet conventional monitoring methods are limited to installation phase only.

Industry Need: Continuous, real-time monitoring of both axial forces and bending moments across varying temperatures for improved safety and maintenance.

The Research Gap: From Uniaxial to Multiaxial Measurement

State of the Art: Current sensor bolts primarily focus on measuring a single parameter: axial force.

Real-World Conditions: Bolts are often subjected to complex, multiaxial loads (axial force + bending moments).

The Gap: A lack of robust systems capable of measuring the complete load vector, especially under the influence of significant temperature variations.

Thesis Objectives

1. **Characterize the Isothermal Mechanical Response using Machine Learning:**
   To analyze the provided IPEK dataset to characterize the sensor's behavior under complex mechanical loads (axial, bending, eccentric).
   To develop a high-fidelity, data-driven baseline model for load prediction at ambient temperature.

2. **Investigate Thermo-Mechanical Effects:**
   To design and build an experimental setup for testing within a climatic chamber (23°C to 80°C).
   To experimentally quantify the sensor’s thermal drift and characterize its hysteretic behavior.

3. **Develop and Validate a Robust Thermal Compensation Model:**
   To process the newly acquired thermal data to create a novel, dual-phase compensation framework.
   To integrate this framework with the mechanical model and validate the final system's accuracy across the full range of operating conditions.

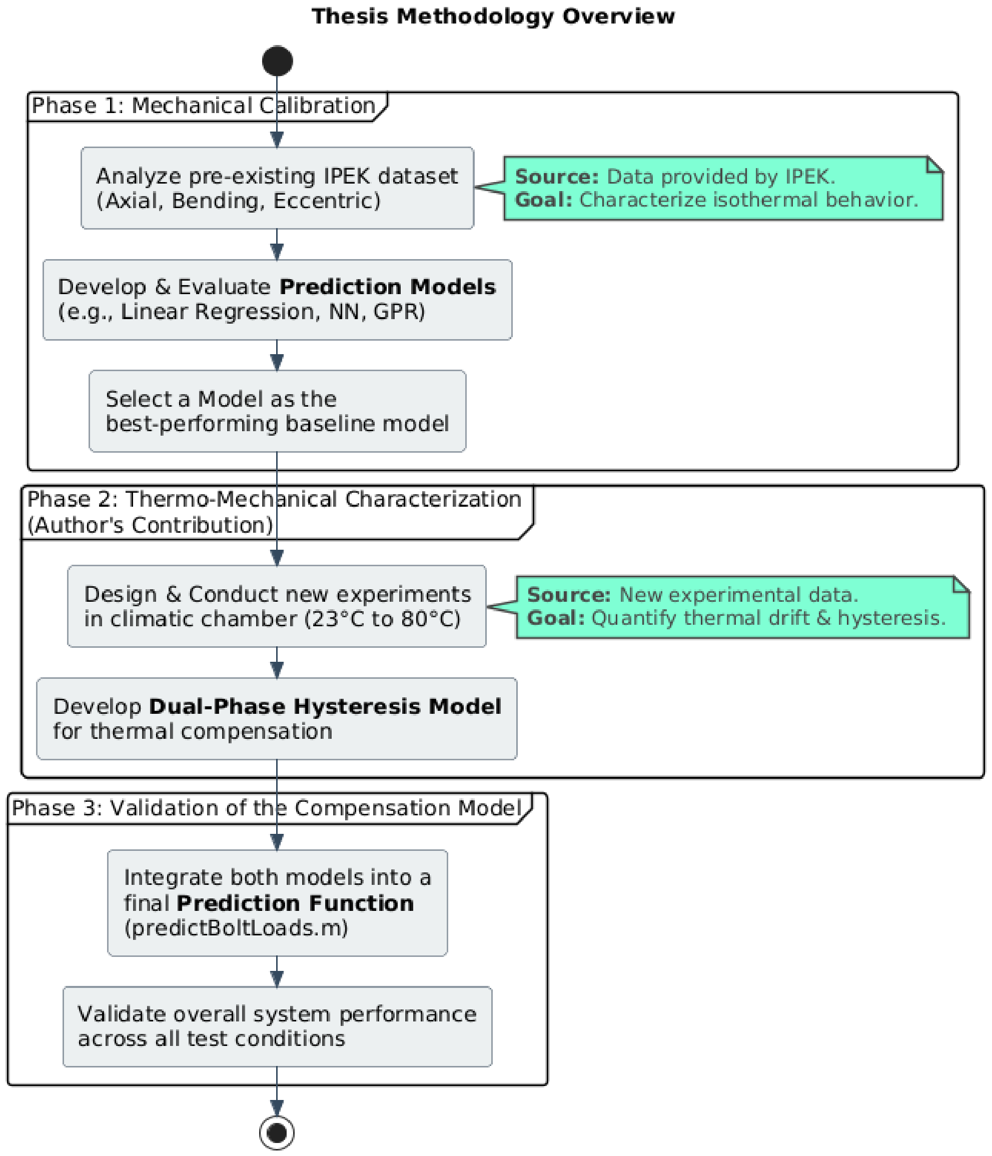
Methodology overview

Baseline Mechanical Calibration Model (Isothermal)

- **Develop and evaluate prediction model**
- Feature engineering to improve prediction
- Combined dataset from all loading conditions
- Cross-validation with k-fold technique

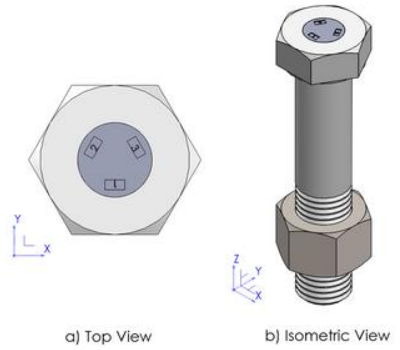
Thermal Compensation Model

- **Dual-phase approach** (heating/cooling)
- Non-linear curve fitting for each phase
- Hysteresis-aware compensation
- Integration with mechanical model

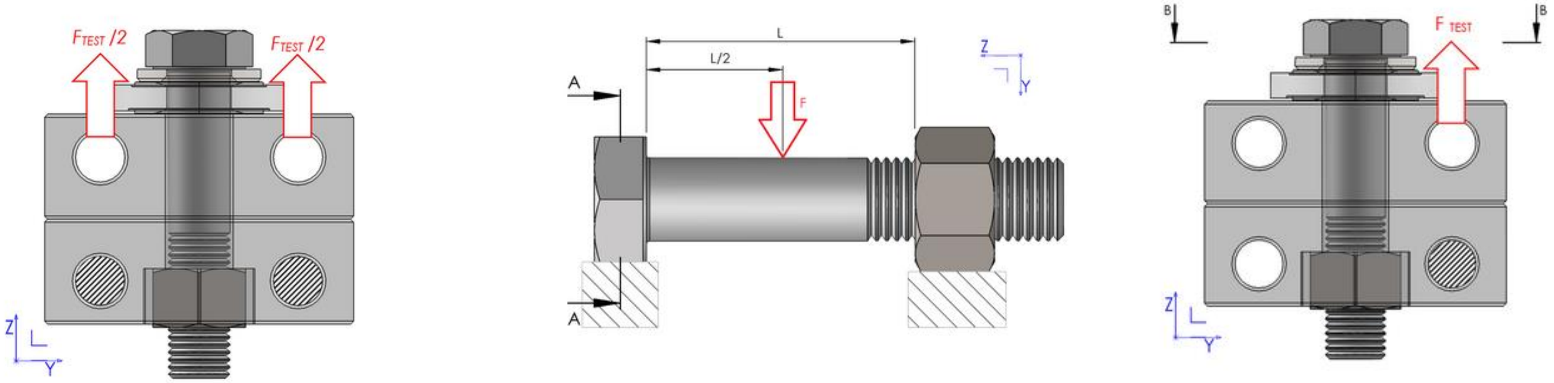


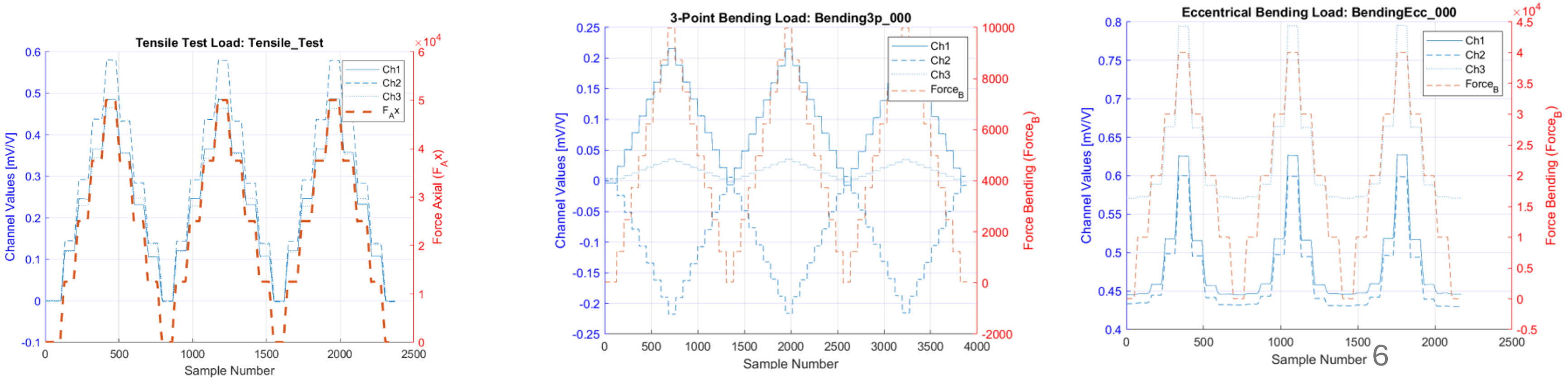
Phase 1: Experimental Setup & Data Acquisition

- **Sensor-integrating Bolt:** M20 bolt with three-beam sensing element, strain gauges arranged at 120° intervals



- **Mechanical Calibration:**
  - Concentric loading: 0-50 kN
  - Three-point bending: 0-10 kN
  - Eccentric loading: 0-40 kN + 40kN (pre-tension)





Phase 1: Iterative Model Development Strategy

Approach 1: Processed Data with3 Predictors (Concentric & 3-Point Bending load)

Model Architecture	Axial Force (F_{Ax})		Torque (U)		Angle (θ)	
	$RMSE$ [N]	R^2	$RMSE$ [Nm]	R^2	$RMSE$ [deg]	R^2
GPR	26426.35	0.4202	602.72	-0.1467	57.37	0.6761
Wide Neural Network	6827.99	0.9613	590.36	-0.1001	81.38	0.3483
Medium Neural Network	12714.39	0.8658	598.66	-0.1313	76.02	0.4313
Linear Regression	22336.02	0.5858	631.60	-0.2592	128.31	-0.6202

Predictors
Strain Gauge 1 (Ch1)
Strain Gauge 2 (Ch2)
Strain Gauge 3 (Ch3)

Approach 2: Processed Combined Data with 3 Predictors (Concentric, 3-Point Bending and eccentrical load)

Model Architecture	Axial Force (F_{Ax})		Torque (U)		Angle (θ)	
	$RMSE$ [N]	R^2	$RMSE$ [Nm]	R^2	$RMSE$ [deg]	R^2
GPR	934.69	0.9993	28.84	0.9974	28.75	0.9187
Wide Neural Network	2660.71	0.9941	44.05	0.9939	43.32	0.8153
Medium Neural Network	7891.63	0.9483	60.05	0.9886	57.82	0.6710
Linear Regression	14850.85	0.8169	624.96	-0.2328	115.96	-0.3232

Predictors
Strain Gauge 1 (Ch1)
Strain Gauge 2 (Ch2)
Strain Gauge 3 (Ch3)

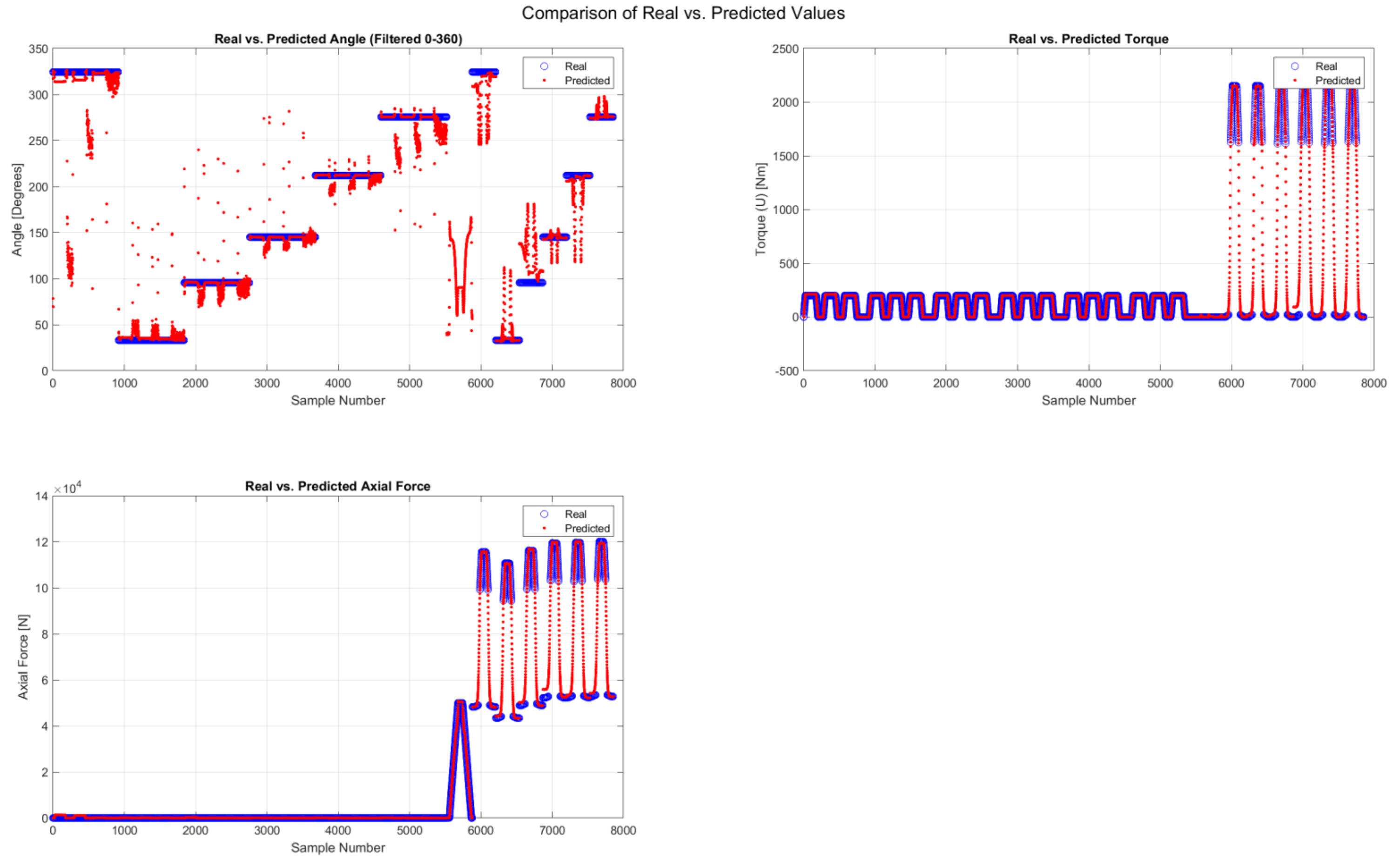
Approach 3: Processed Combined Data with Engineered Features, 7 Predictors

Model Architecture	Axial Force (F_{Ax})		Torque (U)		Angle (θ)	
	$RMSE$ [N]	R^2	$RMSE$ [Nm]	R^2	$RMSE$ [deg]	R^2
GPR	970.86	0.9992	25.05	0.9980	24.05	0.9431
Wide Neural Network	1527.53	0.9981	74.23	0.9826	49.34	0.7604
TREE	5146.58	0.9780	39.35	0.9951	24.47	0.9411

Predictors
Strain Gauge 1 (Ch1)
Strain Gauge 2 (Ch2)
Strain Gauge 3 (Ch3)
Ch_{Sum}
Ch_{Diff} 12
Ch_{Diff} 23
Ch_{Diff} 31

Phase 1: Final Model Selection

Development Approach	Max Dec. Error FAx [%]	Max Dec. Error U [%]	Max Dec. Error θ [%]
Approach 1 (Pure Data, 3 Feat.)	79.50%	96.64%	447.26%
Approach 2 (Combined Data, 3 Feat.)	24.53%	9.86%	383.98%
Approach 3 (Combined Data, 7 Feat.)	17.62%	12.65%	400.19%



The GPR model, trained on IPEK's mechanical test data, showed excellent goodness-of-fit.

It accurately predicts Axial Force and Torque under combined loading conditions at a stable room temperature

Characteristic	Axial Force (FAx)	Torque (U)	Angle (θ)
Linearity Error (% FSO)	9.62%	21.02%	80.43%
Max. Decoupling Error (%)	17.62%	9.86%	383.98%
Crosstalk (FAx→U)	0.1059 % (Nm signal / N FSO)		
Crosstalk (U→FAx)	673.22 % (N signal / Nm FSO)		

Phase 1: Final Model Selection

Axial Force (F_{Ax})

$$F_{Ax}(x) = 45281 + \sum_{i=1}^{433} \alpha_i \cdot K(x, sv_i)$$

where the specific Exponential Kernel function is defined as:

$$K(x, sv_i) = (82708)^2 \cdot \exp\left(-\frac{||x - sv_i||}{19.102}\right)$$

and where:

$F_{Ax}(x)$ is the predicted Axial Force in Newtons.

x is the 7-dimensional input feature vector: $[S_{\text{comp1}}, S_{\text{comp2}}, S_{\text{comp3}}, Ch_{\text{Sum}}, Ch_{\text{Diff12}}, Ch_{\text{Diff23}}, Ch_{\text{Diff31}}]$.

$\beta = 45281$ is the learned bias of the model.

$N = 433$ is the total number of support vectors.

α_i is the learned weight corresponding to the i-th support vector.

sv_i is the i-th support vector (a 7-dimensional vector from the training data).

$||x - sv_i||$ is the Euclidean distance between the input vector and a support vector.

$\sigma_l = 19.102$ is the characteristic length-scale kernel parameter.

$\sigma_f = 82708$ is the signal standard deviation kernel parameter.

Angle (θ)

$$\theta(x) = 169.0223 + \sum_{i=1}^{1120} \alpha_i \cdot K(x, sv_i)$$

where the specific Exponential Kernel function is defined as:

$$K(x, sv_i) = (126.3262)^2 \cdot \exp\left(-\frac{||x - sv_i||}{0.033691}\right)$$

and where:

$\theta(x)$ is the predicted Angle in degrees.

x is the 3-dimensional input feature vector: $[S_{\text{comp1}}, S_{\text{comp2}}, S_{\text{comp3}}]$.

$\beta = 169.0223$ is the learned bias of the model.

$N = 1120$ is the total number of support vectors.

α_i is the learned weight corresponding to the i-th support vector.

sv_i is the i-th support vector (a 3-dimensional vector from the training data).

$\sigma_l = 0.033691$ is the characteristic length-scale kernel parameter.

$\sigma_f = 126.3262$ is the signal standard deviation kernel parameter.

Torque (U)

$$U(x) = 961.8596 + \sum_{i=1}^{1051} \alpha_i \cdot K(x, sv_i)$$

where the specific Exponential Kernel function is defined as:

$$K(x, sv_i) = (804.1485)^2 \cdot \exp\left(-\frac{||x - sv_i||}{0.03612}\right)$$

and where:

$U(x)$ is the predicted Torque in N·m.

x is the 3-dimensional input feature vector: $[S_{\text{comp1}}, S_{\text{comp2}}, S_{\text{comp3}}]$.

$\beta = 961.8596$ is the learned bias of the model.

$N = 1051$ is the total number of support vectors.

α_i is the learned weight corresponding to the i-th support vector.

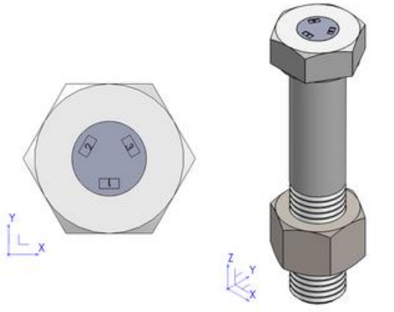
sv_i is the i-th support vector (a 3-dimensional vector from the training data).

$\sigma_l = 0.03612$ is the characteristic length-scale kernel parameter.

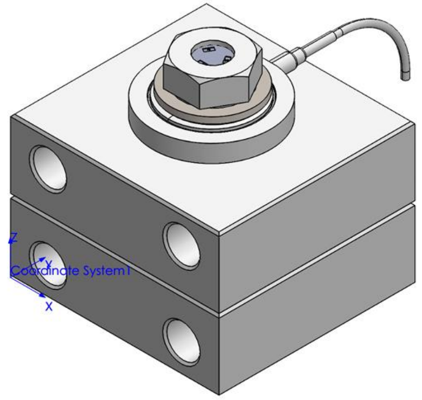
$\sigma_f = 804.1485$ is the signal standard deviation kernel parameter.

Phase 2: Experimental Setup & Data Acquisition

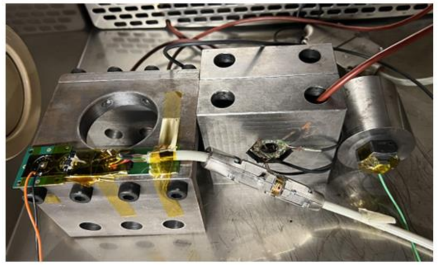
- **Sensor-integrating Bolt:** M20 bolt with three-beam sensing element, strain gauges arranged at 120° intervals
- **Thermo-Mechanical Characterization:**
  - Climatic chamber: 23°C to 80°C
  - Controlled heating/cooling cycles
  - Zero-load thermal response analysis



a) Top View b) Isometric View

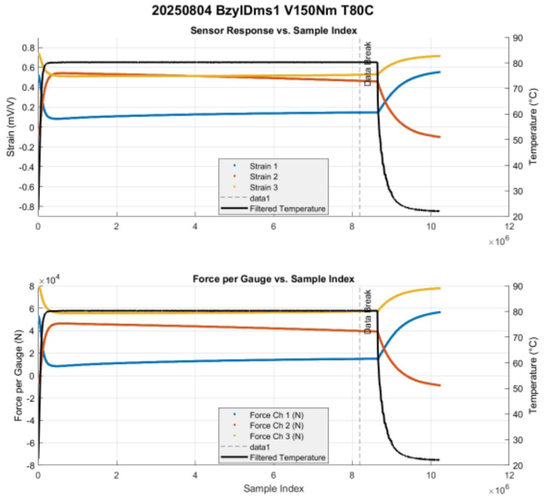


(a) Isometric CAD view of the joint assembly.

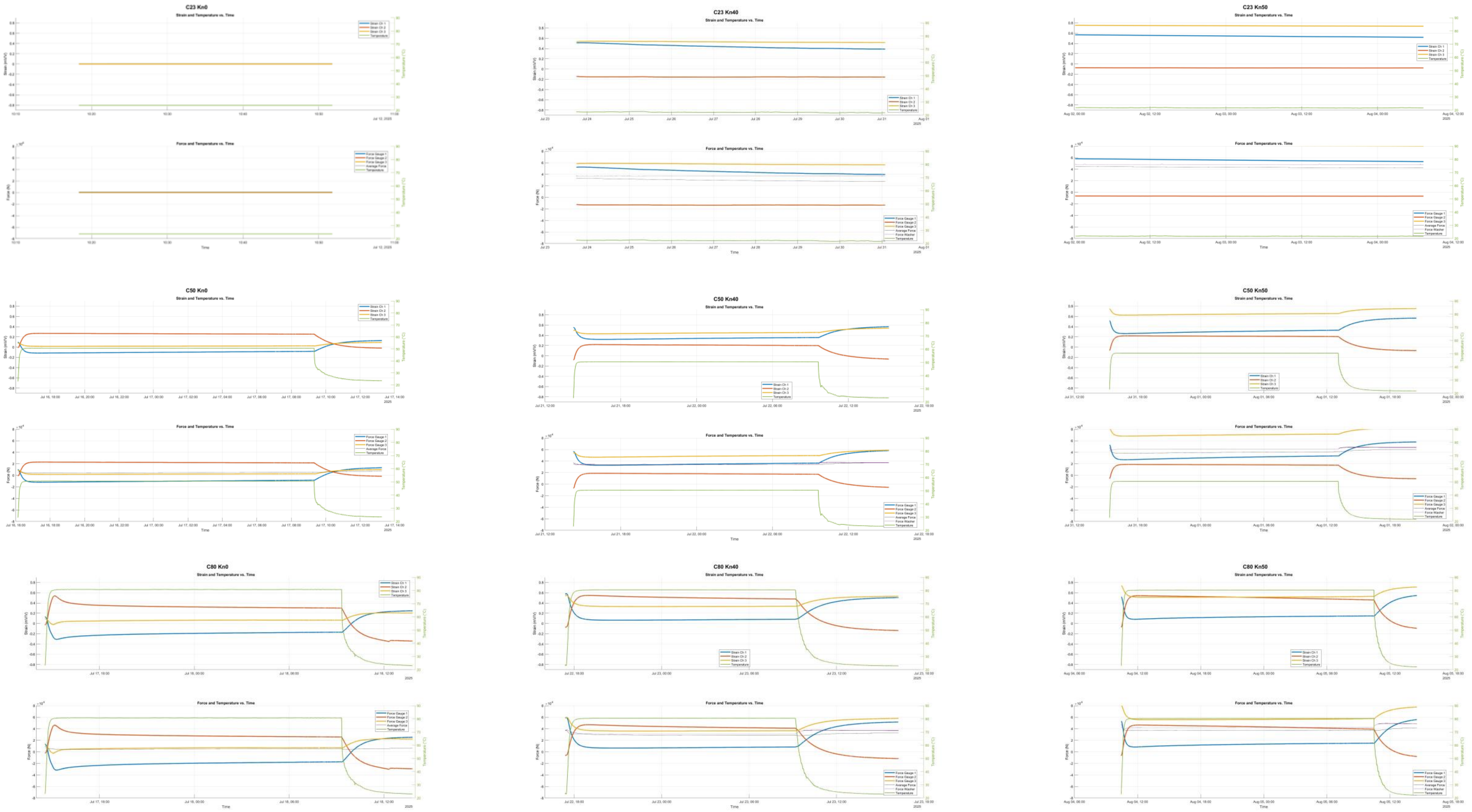


(b) Photograph of the experimental setup.

Test No.	Temperature (°C)	Applied Torque (Nm)	Approx. Preload (kN)
1	23	0	0
2	50	0	0
3	80	0	0
4	23	100	≈ 37
5	50	100	≈ 37
6	80	100	≈ 37
7	23	150	≈ 47
8	50	150	≈ 47
9	80	150	≈ 47



	0 kN	≈37 kN	≈47 kN
23°C			
50°C			
80°C			



Phase 2: The Thermal Challenge - A Complex Hysteresis

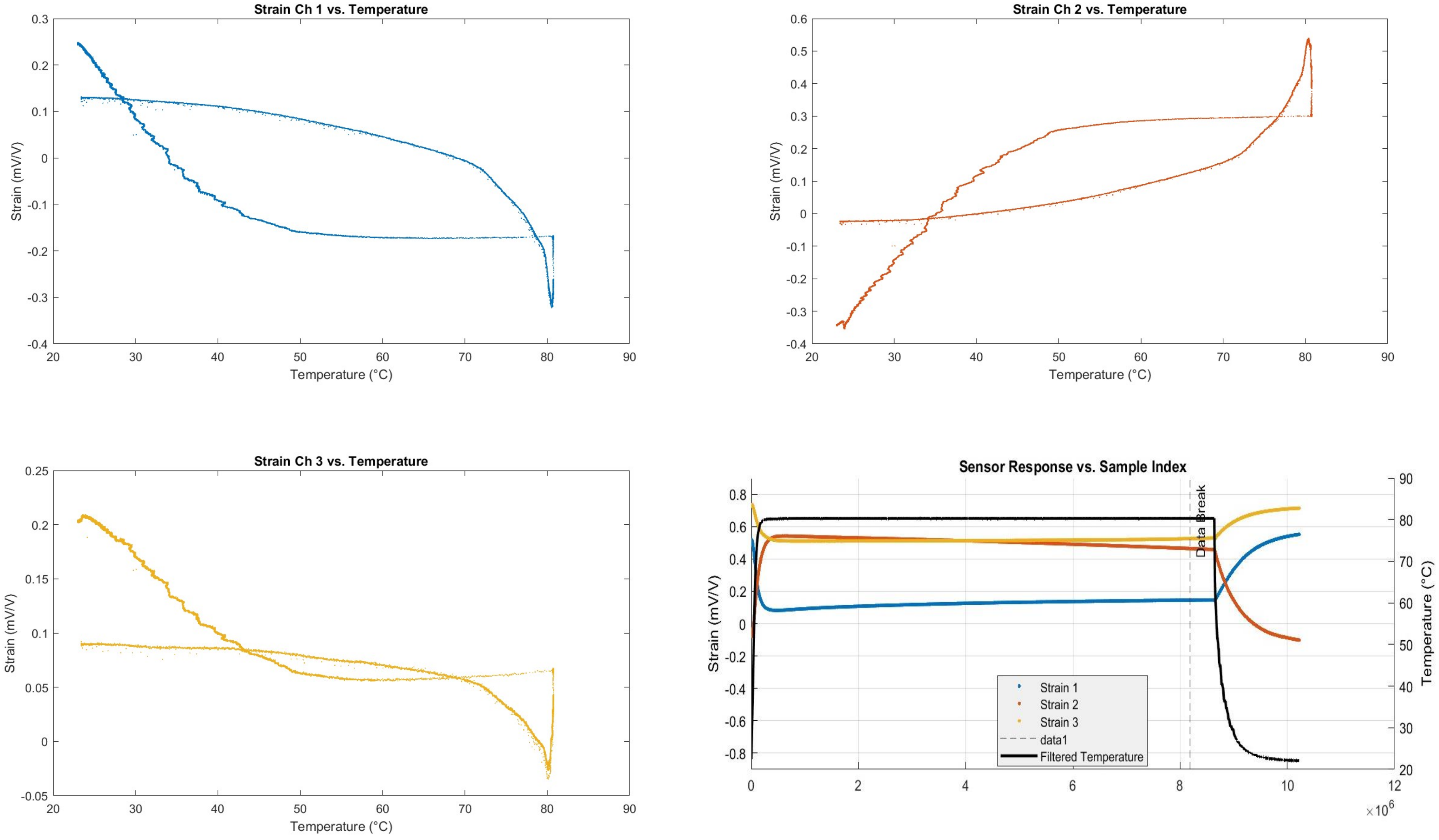
Zero-load tests in the climatic chamber revealed the dominant thermal error source.

The sensor's thermal drift is not a simple linear function.

It exhibits a significant and non-linear thermal hysteresis.

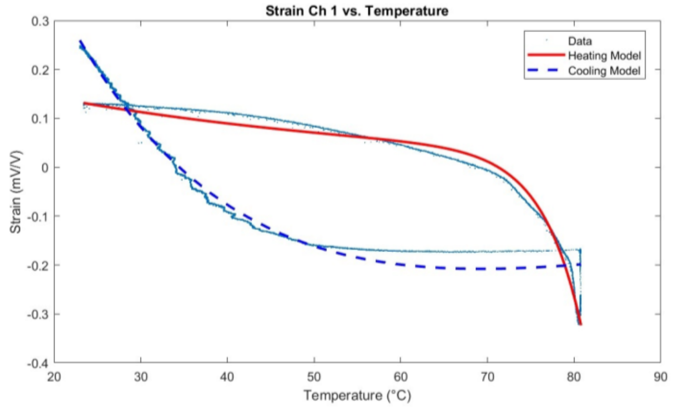
This means the sensor's output depends on its thermal history (heating vs. cooling).

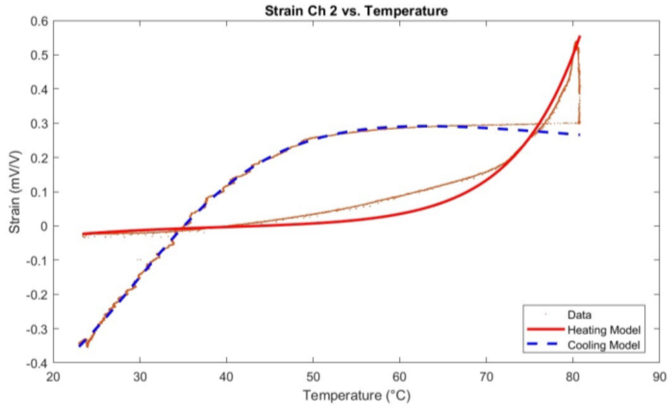
zero load data

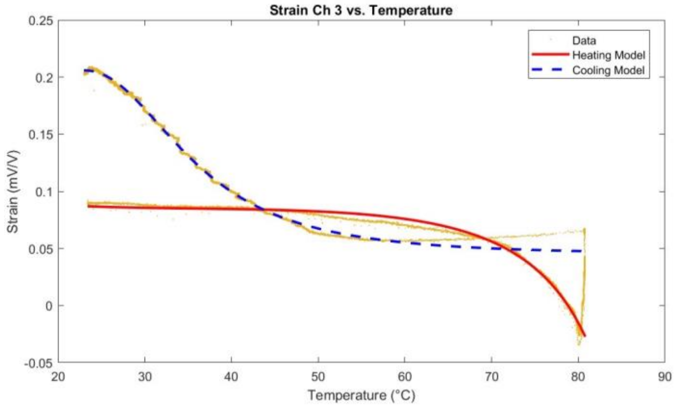


Phase 2: Identifying the optimal mathematical model

Fit of the Curve Fitter App model. The model provides the most accurate representation of the hysteretic thermal drift.







Model Type	Strain Channel	Thermal Phase	R-squared (R^2)	*RMSE* [mV/V]
Polynomial (2nd-Degree)	Strain 1	Heating	0.9262	0.038894
		Cooling	0.9886	0.012667
	Strain 2	Heating	0.9241	0.054875
		Cooling	0.9897	0.017102
	Strain 3	Heating	0.9305	0.010913
		Cooling	0.9728	0.006552
Polynomial (3rd-Degree)	Strain 1	Heating	0.9685	0.025420
		Cooling	0.9953	0.008097
	Strain 2	Heating	0.9692	0.034972
		Cooling	0.9915	0.015558
	Strain 3	Heating	0.9793	0.005948
		Cooling	0.9735	0.006465
Curve Fitter	Strain 1	Heating	0.9824	0.018972
		Cooling	0.9936	0.009504
	Strain 2	Heating	0.9836	0.025468
		Cooling	0.9899	0.016908
	Strain 3	Heating	0.9950	0.002940
		Cooling	0.9900	0.003985

Channel 1 Models:

$$T_{\text{norm}} = \frac{T-\mu}{\sigma}$$

Heating Phase (Exponential 2 Model):

$$S_{\text{drift}}(T_{\text{norm}}) = -0.01879 \cdot e^{4.258 \cdot T_{\text{norm}}} + 0.04754 \cdot e^{-0.4458 \cdot T_{\text{norm}}}$$

where T_{norm} is calculated using Equation 6.3 with $\mu = 67.44$ and $\sigma = 19.32$.

Cooling Phase (Exponential 2 Model):

$$S_{\text{drift}}(T_{\text{norm}}) = -3284 \cdot e^{-0.2005 \cdot T_{\text{norm}}} + 3284 \cdot e^{-0.2006 \cdot T_{\text{norm}}}$$

where T_{norm} is calculated using Equation 6.3 with $\mu = 27.9$ and $\sigma = 6.979$.

Channel 2 Models:

Heating Phase (Exponential 2 Model):

$$S_{\text{drift}}(T_{\text{norm}}) = 0.09569 \cdot e^{2.542 \cdot T_{\text{norm}}} - 0.0005507 \cdot e^{-1.649 \cdot T_{\text{norm}}}$$

where T_{norm} is calculated using Equation 6.3 with $\mu = 67.44$ and $\sigma = 19.32$.

Cooling Phase (Rational 34 Model):

$$S_{\text{drift}}(T) = \frac{21.13T^3 - 742.7T^2 + 30.4T + 6.253}{T^4 - 53.47T^3 + 1420T^2 + 129.3T + 8.776}$$

where T is the temperature in degrees Celsius.

Channel 3 Models:

Heating Phase (Rational 34 Model):

$$S_{\text{drift}}(T) = \frac{-12.99T^3 + 964.1T^2 + 4667T + 402.3}{T^4 - 259T^3 + 15410T^2 + 90.57T - 20.27}$$

where T is the temperature in degrees Celsius.

Cooling Phase (Rational 33 Model):

$$S_{\text{drift}}(T) = \frac{0.04931T^3 - 3.144T^2 + 91.77T - 72.85}{T^3 - 49.58T^2 + 814.4T + 67.79}$$

where T is the temperature in degrees Celsius.

Phase 3: Validation of the Compensation Model

The compensation logic is defined as:

$$S_{\mathrm{comp}} = S_{\mathrm{meas}} - (f(T_{\mathrm{actual}}) - f(T_{\mathrm{ref}}))$$

where:

S_{comp} is the final compensated strain signal [mV/V],

S_{meas} is the raw measured strain signal [mV/V],

$f(T)$ is the thermal drift model for the selected phase (heating or cooling),

T_{actual} is the current measured temperature [°C],

T_{ref} is the reference temperature at which the GPR model was trained (23°C).

Metric	Value	Error (%)
Nominal Applied Preload	42.04 kN	-
Prediction WITH Compensation	41.336 kN	1.69 %
Prediction WITHOUT Compensation	36.929 kN	12.17 %

**Test conducted at 80°C

Discussion

- Duality of Performance: The thesis highlights a critical duality: a model can have high statistical accuracy (R^2) but still fail in practical engineering scenarios (poor decoupling).
- Data is Key: The root cause of the decoupling failure was not the algorithm, but the representativeness of the training data. This underscores the importance of a well-designed experimental campaign.
- Hysteresis is Real: The work confirms that for this sensor, a sophisticated, dual-phase model is not just an improvement but a necessity for thermal compensation.

Conclusion

1. Developed a high-accuracy GPR calibration model and identified its primary limitation: load decoupling.
2. Successfully characterized the sensor's dominant thermal error source as a complex, non-linear hysteresis.
3. Designed, built, and validated a novel dual-phase thermal compensation model that eliminates this error.
4. Delivered a complete, validated methodology that enables the sensor system to provide reliable force measurements across a wide range of operating temperatures.

Recommendations for Future Work

Formal Metrological Calibration

Conduct dedicated calibration according to DIN EN ISO 376 standard to formally classify sensor performance (repeatability, reversibility, creep)

Enhanced Thermal Model

Validate thermal compensation over wider industrial temperature range (-20°C to 120°C) and under thermal transient conditions

Dynamic Load Characterization

Extend calibration to include dynamic loading conditions (vibration, impact, fatigue) for comprehensive sensor performance profile

Field Testing & Integration

Deploy sensor-integrating bolts in real-world applications to validate performance and develop industry-specific implementation guidelines

Questions

Thank you for your attention!

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