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Enhancing Dynamic Measurement Methods: From Concepts to Calibration Standards

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Summary:
Dynamic measurements, particularly in thermometry, are crucial for capturing rapid variations in physical systems. However, such measurements face challenges due to noise, system distortions, and the inherent uncertainty of capturing time-dependent phenomena. This study presents a methodological approach to improve dynamic measurements through advanced signal processing and calibration model enhancement. By integrating Fourier transforms, dynamic Kalman filtering, and temperature correction models, the research aims to enhance precision while ensuring traceability. The results demonstrate the effectiveness of these approaches in providing reliable, accurate, and standardized measurements for industrial and scientific applications.

Keywords: dynamic measurements; calibration; response time; metrology.

Introduction

Dynamic measurements are indispensable in fields like fluid dynamics, thermometry, and acoustics, where rapidly changing conditions demand accurate and responsive measurement techniques. Traditional static calibration methods, designed for steady-state scenarios, often fail to account for the transient and time-dependent behaviors of dynamic systems. This limitation necessitates the development of dynamic calibration methodologies, which incorporate sensor response times and temporal variations to ensure reliability and accuracy.
Key advancements include Monte Carlo simulations for uncertainty evaluation (1), frequency response and impulse response testing to characterize system behavior (2) (3) (4), and real-time data processing with compensation filters to manage large data volumes and correct distortions (5) (6).
These innovations, combined with fast-response sensors and adaptive signal processing techniques, address critical challenges in capturing accurate data in evolving conditions (7) (8). However, gaps in existing standards, such as the GUM (14) and VIM (15), highlight the need for greater emphasis on dynamic considerations, particularly in accounting for sensor response times, to improve replicability and precision in dynamic measurement systems.
In this study, calibration models are enhanced to better account for sensor response times and reduce uncertainties, enabling accurate measurement of rapid changes. Advanced data processing methods, including adaptive and real-time algorithms, are employed to optimize noise reduction and manage system uncertainty.

Methodology

Signal Processing

A robust signal processing framework was developed to address the challenges of dynamic measurements. The first step involved applying Fourier transforms to filter out noise and reconstruct the original signal. This technique effectively isolated the relevant frequency components, allowing for more accurate signal analysis.
A dynamic Kalman filter has been used to estimate the measurand by optimally balancing noise reduction and system uncertainty.

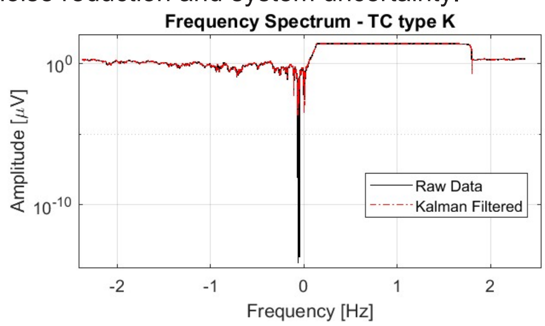


Figure 1 : application of Kalman filter on raw data of thermocouple type K.

Next, an inverse transfer function *($H_{inv}(\omega)$)* was designed to correct distortions introduced by the measurement system. By restoring the original signal, this approach improved the fidelity of the measured data. Finally, a dynamic Kalman filter was employed to optimally balance noise reduction with system uncertainty. This adaptive filtering technique allowed for real-time adjustments, ensuring the accuracy of the measurements under varying conditions.

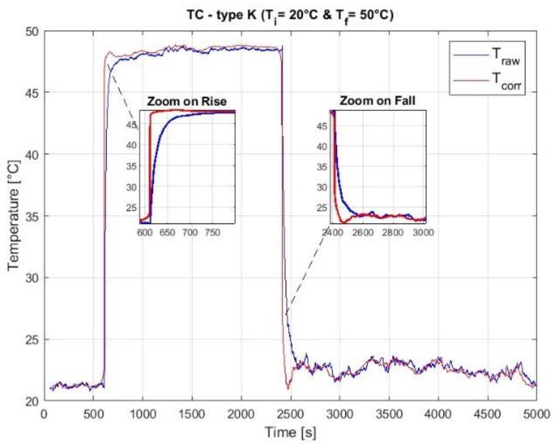
Sensor temperature correction

This phase assesses thermocouple response time to ensure accurate and reliable dynamic temperature measurements. The thermocouple operates on the Seebeck effect (20), here two different metals generate an electrical voltage at their junction, which is temperature-dependent (21). Thermocouple temperature readings often deviate from the actual surrounding temperatures due to factors like radiation, convective heat transfer, and the thermocouple's response time. To account for these discrepancies, adjustments are made to the measured temperature, as explained by Pitts et al. (22). The formula that relates the environmental temperature (T_g) to the measured temperature (T_j) incorporates these elements and is given by:

$$T_g = T_j + \tau \frac{\mathrm{d}T_j}{\mathrm{d}t} + \frac{\epsilon\sigma}{h_{cov}}(T_j^4 - T_w^4)$$

Results and Discussion

The study demonstrates the effectiveness of the proposed methodologies in enhancing dynamic measurements.



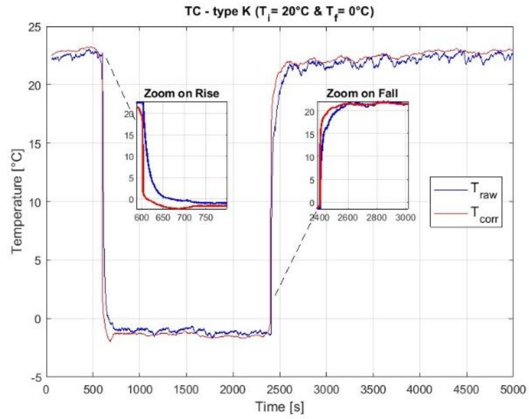


Figure 2 : example of temperature correction for a thermocouple Type K at two different temperatures.

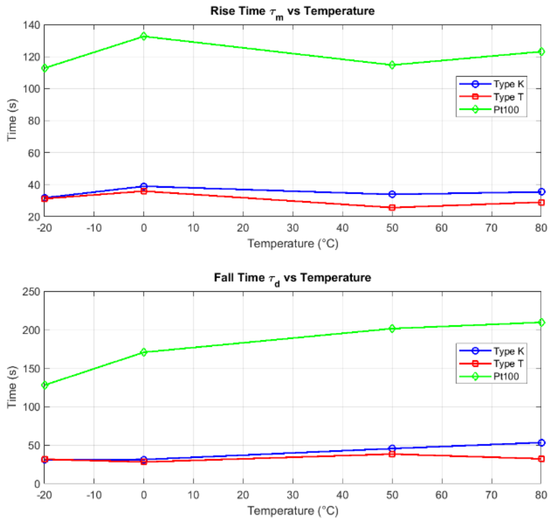


Figure 3 : Sensor Response Times vs. Temperature

The comparison of response time of different types of sensors like Pt100, TC type K and TC type T. It shows that Pt100 sensors have significantly slower response times compared to Type K and T thermocouples, making them less suitable for dynamic environments. In contrast, Type K and T thermocouples exhibit faster, consistent response times. Dynamic signal processing techniques reduced uncertainties, leading to more precise measurements. The temperature correction model addressed environmental and system-specific distortions, aligning measurements with metrological standards. The study also emphasized the importance of uncertainty propagation, with noise, filtering, and modeling errors identified as key contributors. The methodologies effectively minimized these uncertainties.

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