ISSN 1330-3651 (Print), ISSN 1848-6339 (Online)
https://doi.org/10.17559/TV-20240606001753
Original scientific paper

Dual-Approach Calibration Unlocks Potential of Low-Power, Low-Cost Temperature and Humidity Sensors

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Abstract: Calibration of low-cost humidity sensors such as the HTS221TR is critical for accurate measurements, especially in smart devices. This study compares two calibration methods: machine learning (PyTorchNeural Network regression model) and optimization algorithm with Engineering Equation Solver. The critical role of temperature in humidity measurement emphasizes that it must be included for a valid calibration. The machine learning approach significantly reduced the average deviation of humidity, reaching ±2,5% compared to the original ±13,4%. Additionally, it aligned mean values along the identity line. However, the performance of the model varied across the different humidity ranges. Applying the model to real-world scenarios showed that the model underestimates humidity, likely due to the sensor's inherent tendency to overestimate humidity, especially at higher temperatures. Despite these challenges, both calibration methods offer simple and effective approaches for correcting low-cost sensor measurements, with machine learning enabling faster processing. This study not only improves the accuracy of the HTS221TR sensor, but also paves the way for more accurate and affordable humidity measurement technologies in general.

Keywords: data processing; machine learning; optimization algorithm; pytorch neural network; supply chain monitoring

1 INTRODUCTION

In today's globalized world, supply chains are becoming increasingly complex, making the assurance of quality and preservation of products during transportation and storage crucial. Irregularities in temperature and humidity control can significantly shorten the service life of sensitive products such as food, pharmaceuticals, electronics, and various other goods. Low temperatures have traditionally been used to extend the service life of temperate fruits and vegetables, while tropical plants and products are sensitive to low-temperature regimes. Harvest time, delays in cooling after harvest, and inadequate temperature conditions in the distribution chain can further impair product quality [1]. Various studies show concerning deviations from set temperature regimes during transportation: in 30% of shipments from suppliers to distribution centers, the temperature exceeds the set value, and in 15% of shipments from distribution centers to stores. Furthermore, temperatures lower than required occur in 19% of shipments from suppliers to distribution centers and in as much as 36% of shipments from distribution centers to stores [2]. However, it has been observed that modulated cooling allows for a more homogeneous temperature distribution, whereas classic on/off cooling results in temperature differences of up to 8 °C [3].

The development of the innovative "Smart Sticker" (Fig. 4) arises precisely from the need for more efficient monitoring of microclimatic conditions during all phases - from production, transportation and warehouse to retail (Fig. 1).

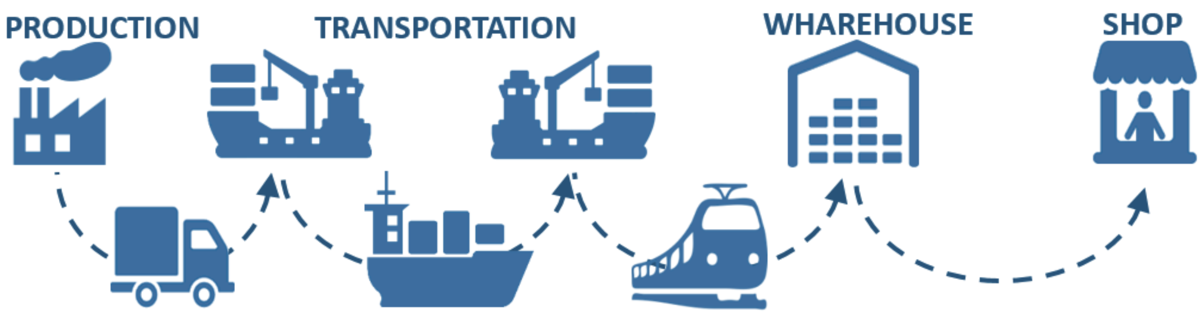

Figure 1 Product supply chain

The Smart Sticker enables continuous monitoring of critical parameters such as temperature, humidity, and other environmental factors in real-time. By integrating advanced sensors and wireless communication, this device provides uninterrupted insight into the condition of the product throughout its journey to the end customer. One of the promising technologies for monitoring temperature-sensitive products during distribution is the Wireless Sensor Network (WSN). Carullo et al. [4] propose an inexpensive measuring node in the form of a cap that can be inserted into bottles or other packaging materials. Such measuring nodes communicate wirelessly with a base station that collects and processes data, enabling monitoring of temperature integrity along the entire supply chain at a low cost, making it suitable even for end consumers. However, their closed form proved unsuitable for continuous measurement of relative air humidity, a key parameter for numerous products, so a humidity sensor was integrated into the Smart Sticker design. Unlike such embedded sensors, the Smart Sticker allows flexible placement on packaging without the need for pre-installed measuring nodes or compromising the packaging, thereby avoiding the risk of content contamination.

Numerous sectors, such as electronics manufacturers, information and communication technology (ICT) equipment, food, pharmaceutical, and other industries, distributors, and retailers, could benefit from the application of the Smart Sticker. Each of these sectors has specific requirements for controlling environmental conditions - from vibration monitoring for sensitive electronics [5] to the strict regulation of temperature and humidity for preserving food freshness [1, 2], drug stability, or preventing metal corrosion due to unfavorable storage conditions [6]. Monitoring these critical parameters with the Smart Sticker enables maintaining quality and extending the service life of various products. Retail chains are realizing the benefits of analyzing quality losses by product, season, and supply source, which influences their procurement and product display strategies.

Unlike permanently embedded devices in transportation vehicles [7, 8], the Smart Sticker continues to monitor the product even after transportation, during storage in distribution centers and stores. This enables continuous monitoring of critical parameters all the way to the point of sale. Key elements for the successful implementation of the Smart Sticker include low power consumption, long-term operation with small batteries, sensitive and accurate sensors, and reliable and energy-efficient wireless communication [9]. The Smart Sticker enables the detection of irregularities, real-time alerts, and detailed analysis of collected data - all with the aim of continuously improving supply chain management and protecting products across all segments.

Conducting simulation studies under realistic conditions that mimic average or better commercial practices is necessary. This approach ensures the most accurate results regarding service life and the effects of different temperature and humidity regimes. Ensuring precise and reliable measurement of parameters such as temperature and relative air humidity requires thorough calibration of sensors under controlled conditions, such as those provided by climate chambers. However, in addition to calibrating the sensors themselves, it is essential to thoroughly understand the operating principles and characteristics of the climate chamber used, as well as the potential influences of its components, such as compressors, heaters, humidifiers, and other parts, on the controlled temperature and humidity conditions [10]. Researchers emphasize the importance of this aspect for obtaining valid data on microclimatic conditions in a controlled environment [11-14]. Therefore, in this research, special attention was paid to the characterization and calibration of the temperature and relative humidity sensors integrated into the Smart Sticker, with the controlled conditions of the climate chamber used for calibration, considering the influence of the chamber's operation on the measured values of temperature and relative air humidity.

Overall, the Smart Sticker represents a promising solution that can improve product quality monitoring and management throughout the supply chain - from the moment of production to delivery to the customer. Further research and commercial implementation of this system could bring significant benefits to various industries.

2 TESTING FACILITIES AND SENSOR TECHNOLOGY

Precise measurement and regulation of temperature and humidity require a fundamental understanding of the properties of moist air. The air surrounding us is a gaseous mixture of nitrogen, oxygen, argon, carbon dioxide, and other gases. However, in nature and most technical applications, air also contains a certain amount of moisture in the form of water vapor. This humidity affects the properties of the air, and such a mixture is called moist air.

Moist air is a binary mixture of dry air and water vapor to which Dalton's law of partial pressures applies [15]. According to this law, each gas in the mixture occupies the full available volume and behaves independently of the other gases. The total pressure of moist air is equal to the sum of the partial pressures of dry air and water vapor.

The state properties of moist air can be calculated using basic expressions, but a more efficient way is to apply specialized diagrams such as the Mollier *h-x* diagram and the psychrometric *x-ϑ* diagram. These diagrams enable the graphical depiction and monitoring of moist air processes, accounting for the phase transitions of water vapor.

Knowledge of the properties and methods of graphically representing the state of moist air is crucial for the design of systems for precise measurement and regulation of temperature and humidity. The Smart Sticker, integrated with sensitive sensors, enables continuous monitoring of these critical microclimatic parameters throughout the entire supply chain.

2.1 Temperature and Humidity Test Chamber

Precise measurement of temperature and humidity is critical for preserving the quality of sensitive products such as food, pharmaceuticals, and electronics during transportation and storage. To obtain a valid measurement results, it is crucial to calibrate and adjust the sensors of the Smart Sticker under the controlled conditions of climate chambers.

Climate chambers are specialized devices designed to create controlled environmental conditions with specific variations in temperature and humidity. This is achieved by combining basic processes such as heating, cooling, drying, mixing air streams, and adding water or water vapor. The preparation of moist air takes place in an open system with continuous exchange and replenishment of air in accordance with the laws of conservation of mass and energy. In this process, $\dot{W}_{1\text{-}2} = 0$, so the exchanged thermal energy is equal to the difference between the final and initial enthalpy, as shown by the expression:

$$\dot{Q}_{1-2} = \dot{H}_2 - \dot{H}_1 \tag{1}$$

Precise humidity measurement in the climate chamber is key to achieving and maintaining the set conditions. This is carried out using a psychrometer, which measures the difference in temperatures between the dry and wet bulb thermometers due to evaporative cooling [15]. The relative humidity is then determined using equations or diagrams for moist air.

The psychrometric procedure involves air flowing over the thermometers, with the dry bulb thermometer measuring the actual air temperature, while the wet bulb measures the cooling temperature. To determine the state of the moist air, in addition to the temperatures, the total pressure must also be known. The relative humidity is calculated according to a specific expression, where the constant A depends on the air flow rate.

$$\varphi = \frac{p_{\mathrm{dry}}\left(\vartheta_{\mathrm{wet}}\right) - A\left(\vartheta_{\mathrm{dry}} - \vartheta_{\mathrm{wet}}\right) p_{\mathrm{atm}}}{p_{\mathrm{dry}}\left(\vartheta_{\mathrm{dry}}\right)} \tag{2}$$

In this equation, p_{dry} represents the partial pressure of dry air, p_{wet} represents the partial pressure of humid air, and T represents the temperatures of dry and wet thermometers. Another way to determine relative humidity is graphically, using a diagram for moist air. The dry and wet bulb temperatures are plotted on the Mollier h-x diagram or the psychrometric x-ϑ diagram. Using the specific heat capacity for water c_{w} and the dry bulb temperature ϑ_{dry}, the specific enthalpy h_{w} is calculated, which allows for the determination of relative humidity and other properties of humid air.

$$h_{\mathrm{w}} = c_{\mathrm{w}} \vartheta_{\mathrm{dry}} \tag{3}$$

This measurement method can be less accurate due to the additional water vapor from the wet cloth, which is undesirable in some applications.

A climate chamber is a device used to test the effects of environmental conditions on products, including variations in temperature and humidity. According to data from the website "Industrial Quick Search" [16], manufacturers use these chambers to test the resistance of their products to different conditions, thereby assessing their service life and failure points. The collected data help engineers adjust designs and select more durable materials.

Climate chambers are used for final testing, assessing the effects of weather conditions on the physical, chemical, and mechanical properties of products, which is crucial for industry. Scientific test chambers are similar to industrial ones, creating an artificial environment to test products for potential defects. Data from these tests are key to product development in the food, pharmaceutical, or electronics industries.

The climate chamber used for measuring air humidity in this work comes from the manufacturer Labtron, specifically the LTHC-A1 series and LTHC-A10 model (Fig. 2).

Figure 2 Climate chamber - Labtron temperature and humidity test chamber rLTHC-A10

The durability of climate chambers depends on the materials used, which must ensure longevity, accuracy, and reliability of data. Key design elements include double walls, sealing, doors, humidity regulation, and temperature monitoring. The control mechanism, heating and cooling systems, and air and humidity supply are crucial for ensuring testing stability and accuracy.

The test space is made of stainless steel with resistance to a wide temperature range. Technical parameters, such as the space size, operating temperature, time, relative humidity, type, water supply, and control, are important when selecting a climate chamber (Tab. 1).

The climate chamber has a usable volume of 50 liters and can simulate temperatures from –20 °C to approximately +150 °C and relative humidity from 20% to 98%. This climate chamber is a benchtop model, which is one of the recommended types alongside reach-in models. Benchtop climate chambers are economical solutions for product testing, especially electronic components, sensors, and mobile devices. They are intended for research laboratories and small production facilities. Their volume ranges from 25 to 150 litres. The name "benchtop" suggests their size, suitable for desktop use. Water supply is important for creating humidity, with the need for drainage at the end of testing. Control depends on the type of regulator, with microcontroller-based controllers recommended for optimal results.

Table 1 Technical parameters for climate chamber model LTHC-A10 [17]

Model	LTHC-A10
Capacity	50 l
Temperature range	−20 °C ~ +150 °C
Environmental condition	5 °C ~ + 40 °C 85%
Temperature fluctuation	±0,5 °C
Temperature deviation	±2 °C
Relative Humidity deviation	±2%
Relative Humidity range	20% ~ 98%
Heating rate	3 °C/min
Cooling rate	1 °C/min
Temperature sensor	PT 100 Ω/MV A-class
Temperature resolution	±0,001 °C
Humidity sensor	Dry and wet bulb sensor
Humidity resolution	±1%
Power supply	230 VAC, 50 Hz, 23 A, 5 kW

2.2 Smart Sticker

During the development of the Smart Sticker, the technical requirements were defined in order to achieve a compact device size. The dimensions are crucial to ensure that the Smart Sticker can be applied to various products and packaging without hindering distribution and storage or taking up additional space. At the same time, minimizing energy consumption is a priority to ensure that the sticker lasts throughout the supply chain while enabling the storage of a large amount of data.

The data from the Smart Sticker would be transmitted wirelessly via existing devices such as cell phones, tablets, or laptops using a specially developed application. It is important that this data transmission has minimal energy consumption, or ideally uses the energy of the transmitting device. Given the wide range of possible applications, it is crucial that the sticker also works at low temperatures so that it can also be used in extreme conditions, such as in refrigerators [9]. In addition, the flexibility and pliability of the sticker are desirable so that it can adapt to various product and packaging shapes. All these technical characteristics are crucial for the device to be widely used.

The Smart Sticker was developed using modern technology that is widely available on the market. Microcontrollers and sensors with extremely low energy consumption were used to manage the sticker and collect relevant data. To ensure the flexibility of the sticker, a flexible and replaceable battery was also integrated into the final prototype. Radio Frequency Identification (RFID) system was used for energy and data transmission (Fig. 3) [5]. To meet the requirements for the humidity tests, the components were designed to be splash-proof, although there is currently no official IP certification. This is particularly important as water droplets can come into contact with the sticker and its components, which could affect the accuracy of data testing and monitoring results.

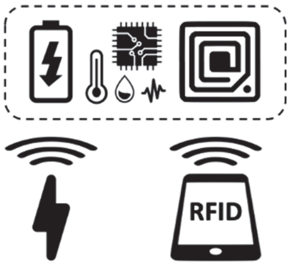

Figure 3 Technology and sensors used in the development of the smart sticker

Finally, the design of the circuit board is flexible, allowing users to customize the sticker according to their needs by incorporating only the sensors required to monitor their products. It is important to note that the maximum size of the sticker is limited to that of a credit card. This approach provides users with the flexibility and customizability of the smart sticker to meet the specific requirements of their products or packaging (Fig. 4).

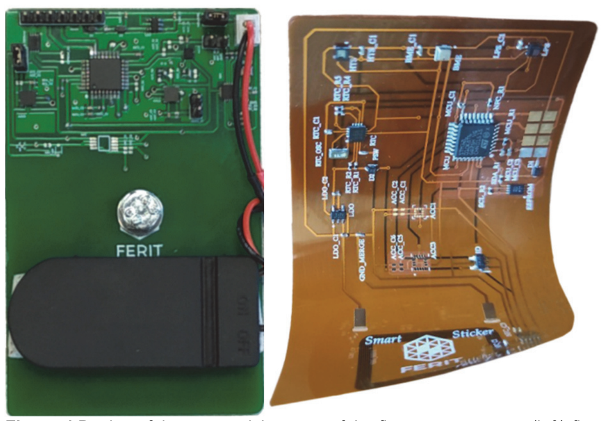

Figure 4 Design of the smart sticker- one of the first test prototypes (left)-final flexible version of smart sticker (right)

Low-cost sensors for the controlled monitoring of goods in the distribution chain using the innovative Smart Sticker design is a promising solution for tracking the condition of goods. However, these sensors are not particularly reliable due to their low accuracy, short lifespan and calibration issues. In the examined case of the Smart Sticker, three sensors were used: the Bosch BME280 sensor for measuring temperature, relative humidity and pressure, the STMicroelectronics HTS221TR sensor for measuring temperature and relative humidity and the STMicroelectronics LPS22HBTR sensor for measuring temperature and pressure as shown in Tab. 2.

Table 2 Technical parameters of smart sticker sensors

Parameter	Technical data		
	BME280	HTS221TR	LPS22HBTR
Operation range	−40-80 °C 10-90% RH 300-1100 hPa	−40-120 °C 0-100% RH -	−40-85 °C - 260-1260 hPa
Temperature sensor	Resolution 0,01 °C Accuracy ±0,5 °C	Resolution 0,016 °C Accuracy ±1 °C	Resolution 0,016 °C Accuracy ±1,5 °C
Humidity sensor	Resolution 0,008% Accuracy ±3%	Resolution 0,004% Accuracy ±5%	-
Pressure sensor	Resolution 0,18 Pa Accuracy ±1,7 hPa	-	Resolution 0,18 Pa Accuracy ±1 hPa

According to Vajs et al. [18], various studies have shown that low-cost sensors are sensitive to changes in relative humidity and temperature. In this study, methods to further improve the calibration algorithms were investigated to enhance measurement accuracy by considering the effects of temperature and humidity on the readings through machine learning and optimization algorithms.

The potential of smart stickers goes beyond simply tracking goods during transportation. They can be permanently or temporarily integrated into various general-purpose devices, including consumer electronics and appliances such as condensing boilers. Although these devices are not sensitive to minor fluctuations in temperature and humidity, they are susceptible to extreme changes or those caused by vibrations and impacts. In the case of condensing boilers, these stickers could potentially monitor flue gasses and thermal efficiency, if necessary sensors are provided during installation [19].

3 TEMPERATURE AND HUMIDITY MEASUREMENT

To determine the state of humid air, one needs to know the temperature and relative humidity, which is achieved by measurement. Measurement errors are divided into absolute, relative and percentage errors according to their representation and into gross, random and systematic errors according to their cause. Gross errors are caused by carelessness or improper methods and lead to incorrect measurements that have to be repeated. Random errors are caused by unforeseeable changes in the environment, the object or the measuring device and lead to inconsistent results. Their effects are reduced by taking several measurements and calculating the average value. Systematic errors are predictable and consistent. Their effects can be compensated by applying a correction to the measurement result.

Temperature describes the thermal state of a body and its ability to transfer heat, which is achieved by conduction, convection, and radiation. In liquids and gases, heat conduction occurs through diffusion and collision of molecules at different temperatures, while in solids it occurs through molecular vibrations and the movement of free electrons. Convection takes place at the contact between solid walls and liquid and can be forced or free. Radiation is realized by electromagnetic waves, as all bodies emit thermal radiation. During temperature measurement, a thermal equilibrium is established between the sensor and the environment, resulting in various physical phenomena such as changes in volume, electrical resistance, radiant energy, or electromotive force. Measuring transducers are divided into contact and non-contact types. Contact transducers, which work on the principles of heat conduction and convection, include strain-based transducers, resistance transducers, and thermocouples.

The LTHC used and described in detail in this paper is equipped with a PID system. Nevertheless, there are occasional fluctuations in the results, especially when measuring humidity. Air temperature and humidity are strongly linked and influence each other. It is also possible that condensation on the walls of the LTHC and on the sensors of the Smart Sticker additionally influences the readings. The measurement uncertainty is therefore higher when measuring humidity. This phenomenon is also discussed by Wang and Zhu [20] in their paper, in which they describe and investigate the effectiveness of control algorithms in a simulation model of a test chamber.

3.1 Experimental Setup and Measurements

The experimental setup consists of a climate chamber, more precisely a Temperature and Humidity Test Chamber (LTHC-A10), KIMO measuring devices for monitoring temperature and humidity as well as the corresponding thermocouples and probes. The test setup is shown in Fig. 5.

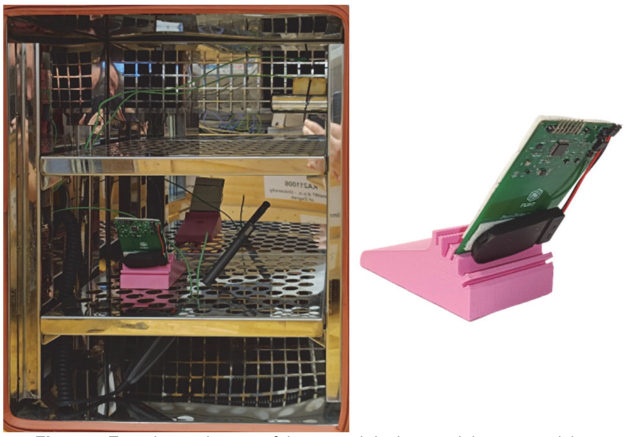

Figure 5 Experimental setup of the control devices and the smart sticker sensors for measuring the temperature and relative humidity data points values

The Smart Sticker is placed on a 3D-printed stand-in such a way that the direct influence of the fan, moisture injection, and the heater from the experimental station is minimized while still being in the zone with the measuring sensors. The stand has 3 positions with several mounting options for measuring and testing the Smart Sticker sensors. However, during the study, the middle position was used at a 60° angle with the front facing down to avoid condensation forming on the sensors.

During the investigation, measurements were taken with several devices. The most important device, which was also used for data calibration, was the measurement equipment of the climate chamber, in particular the dry bulb and wet bulb thermometers. Subsequently, two KIMO devices were used to verify the measurements in the climate chamber: the temperature measuring device KIMO TM200 for controlling measurements of wet and dry bulb temperature and the relative humidity measuring device HD 200 for electronic humidity measurements.

The temperature measuring device was used with four different thermocouples. The first thermocouple was placed outside the climate chamber to measure and control the ambient temperature. The others were placed inside the climate chamber so that one was close to the Smart Sticker, while the other two represented the dry and wet bulb thermometers. The conversion from temperature to humidity was done using psychrometric equations and the Engineering Equation Solver (EES) functions, which was later used to implement the optimization algorithm to correct, i.e. calibrate, the measurement data.

The humidity measuring device has its own probe that electronically measures relative humidity and other parameters that are not the subject of this study. Due to the inherent "inaccuracy" of electronic devices and sensors in measurement, this data was not used for the further testing and calibration process, but served as control instruments for the LTHC measurement sensors.

The study confirmed that electronic devices, especially inexpensive sensors, are not always very accurate. Three types of sensors were evaluated: the BME280 (measuring temperature, humidity and pressure), the HTS221TR (measuring temperature and humidity) and the LPS22HBTR (measuring temperature and pressure). As shown in Fig. 6, these sensors measure different values for relative humidity.

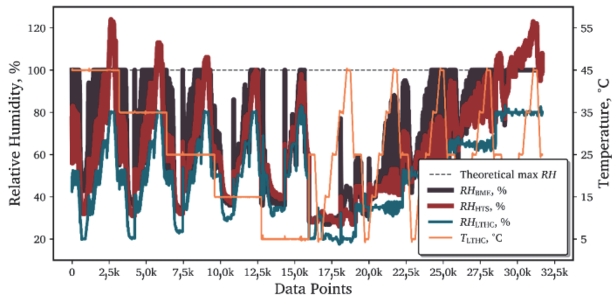

Figure 6 Relative humidity measurements from two smart sticker sensors (BME280 and HTS221TR) and a dry/wet thermometer-based "ground truth" values over different humidity and temperature ranges.

The graph shows the relative humidity data from these two sensors that can measure RH values, together with the readings from LTHC that were later used as the "Ground Truth" value in the calibration process.

All three sensors were found to provide relatively accurate values when it comes to temperature, with an absolute difference of 0,34 °C for the LPS22HBTR sensor, 0,36 °C for the HTS221TR sensor, and 0,67 °C for the BME280 sensor. On the other hand, some of the sensors tested are unusable when it comes to measuring relative humidity and cannot even be calibrated, which is the case with the BME280 sensor for measuring temperature, relative humidity and pressure. This sensor can still be used to measure temperature and pressure, but it also proved to be the worst sensor of all three types tested.

The BME280 sensor exhibits a "clipping problem" for relative humidity measurements. Values exceeding a certain threshold, dependent on temperature (as shown in Fig. 6), are capped at the theoretical maximum of 100%. This behavior would not be an issue if the sensor were perfectly precise and accurate, reflecting real-world humidity. In contrast, the HTS221TR sensor demonstrates a trend of increasing relative humidity readings with rising temperatures, but to a disproportionate degree. Both sensors exhibit higher relative humidity readings at higher temperatures within the climate chamber compared to lower temperatures. However, these readings consistently exceed the expected actual values, regardless of temperature. Notably, the data trends (rising and falling) somewhat reflect the actual fluctuations intended to be captured. Due to the HTS221TR sensor's demonstrated accuracy in temperature measurement and its moderately useful humidity data, this sensor remains the primary focus for further study.

While the target relative humidity of 20% was set for all temperatures tested, the LTHC system seems to struggle to reach this level at lower temperatures (5-15 °C), as can be seen in the first part of the graph in Fig. 6. It is possible that the LTHC could reach the target relative humidity with more time, but this aspect is beyond the scope of this study. However, the lack of data points at lower temperatures being a limitation when calibrating the results. Although the lack of data is less evident in the "ground truth" dependence plot (Fig. 7), the scatter of the data (dispersion) is important for the analysis and calibration of the measured data.

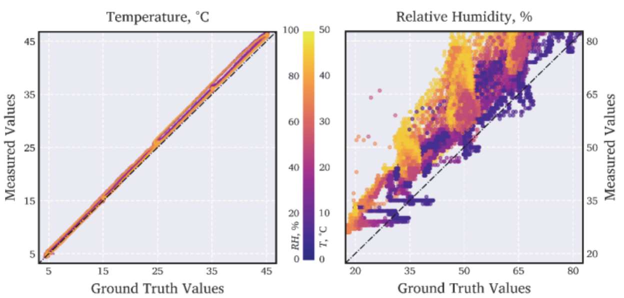

Figure 7 Correlation between measured data with smart sticker sensors and "ground truth" values for temperature (left) and relative humidity (right)

The graph shows the values of the data measured with the HTS221TR sensor in relation to the "ground truth" data for temperature and relative humidity measured with the LTHC. The values are colored according to the paired measurement parameter, to better determine the impact on data dispersion. For temperature, the color represents relative humidity values, while for relative humidity, it represents temperature values. As temperature sensors have developed considerably nowadays, there are not many problems in this regard. At higher temperatures, there is only a slight deviation, while at lower temperatures the values match extremely well.

The dispersion of data points is most evident in the relative humidity measurements. Notably, higher temperatures exhibit greater spread, as indicated by the color variation in the data points. Conversely, lower temperatures show tighter clustering. Additionally, the majority of data points reside above the central diagonal (identity line) of the plot, indicating a systematic bias towards higher sensor readings compared to the LTHC's "ground truth" values. The identity line ($y = x$) represents perfect agreement between the two datasets. Ideally, all points would fall on this line, signifying a perfect match between sensor measurements and LTHC values.

4 CALIBRATIONS OF SMART STICKER SENSORS

Given the measured values, it is evident that the data must be calibrated. The goal is to reduce data dispersion and center it as much as possible around the identity line of the diagram from Fig. 7. Data calibration is the process of adjusting measurement data to increase its accuracy and reliability. This process can be achieved through various methods depending on the specifics of the measurement, the resources available and the application requirements.

There are different methods of data calibration:

- **Linear Regression:** Fits a linear function to the relationship between the measured data and reference data ("Ground Truth"data values).
- **Polynomial Regression:** Uses higher-order polynomials to capture more complex relationships.
- **Neural Networks:** Learns complex, non-linear relationships between measured and reference data.
- **Piecewise Linear Calibration:** Divides data into segments and applies linear regression to each.
- **Kalman Filtering:** Recursively estimates the state of a dynamic system using noisy measurements.
- **Bayesian Methods:** Uses prior knowledge and observed data to update the probability distribution.
- **Look-up Tables:** Maps measured values to calibrated values using pre-determined tables.
- **Physical Model-Based:** Uses physics-based models to understand and correct sensor behavior.
- **Multi-Point Calibration:** Calibrates at multiple points across the measurement range.
- **Optimization-Based Algorithms:** Uses optimization algorithms to minimize the difference between measured and reference data.

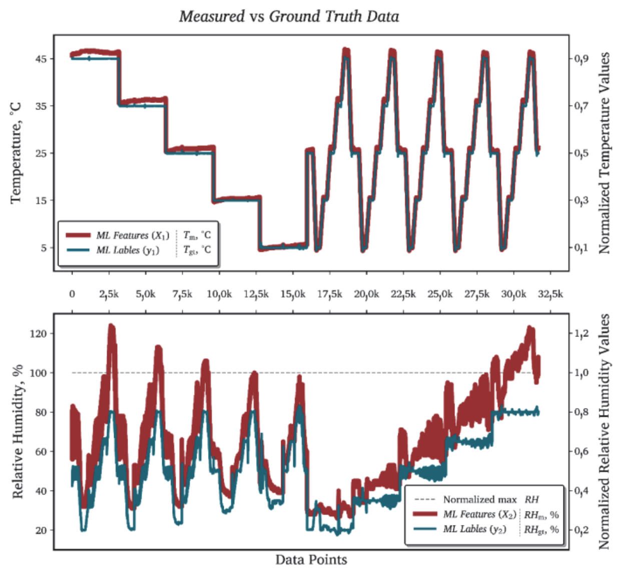

Figure 8 Measured and normalized input "Features" and output "Labels" parameters for the ML Python PyTorch "NN Regression model" and EES "optimization algorithm"

To perform a calibration, the data must be collected and tested using a laboratory-calibrated measuring device. The usage of the method depends on the specific use case, the precision requirements, the availability of reference data and calibration tools, and the size of the data set. High-quality calibration is the key to ensuring the accuracy and reliability of measurement data, which is essential in many scientific, industrial and technical applications. Carefully designed test conditions were used to calibrate the HTS221TR sensor, as shown in the diagram in Fig. 8.

The experiment involved two sequential phases, each with a "change phase" and a "stationary phase", and was conducted across various ambient temperature and relative humidity combinations in two steps. In the first step, temperature remained constant while relative humidity was cycled through pre-defined values (listed in Tab. 3) at 20-minute intervals. Data was logged every 5 seconds on all devices, ensuring synchronized timekeeping across the system. The second step mirrored this process, but with constant relative humidity and temperature variations following predetermined changes. Similar to the first step, each change was followed by a 20-minute stationary phase.

Table 3 Values of the experimental phases of temperature and relative humidity required for the calibration of the smart sticker sensor

First step	T = const.							
	RH, %	50	20	35	50	65	80	50
Second step	RH = const.							
	T, °C	25	5	15	25	35	45	25

The most extensively tested data is around a temperature of 25 °C and a relative humidity of 50%. This reflects the conditions where people's well-being is paramount, as these are the environmental conditions usually encountered. Similar considerations could influence humidity preferences in applications such as electronics or food transportation, where moderate humidity is often desirable. It is worth noting that very low temperatures (below 5 °C for perishables or freezing point) are not the subject of this study, as humidity plays a less important role in these controlled environments.

Two different calibration approaches are used in this study. The first uses machine learning, specifically a neural network implementing linear regression with PyTorch in Python. The second method uses a classical optimization algorithm programmed and implemented in commercially available software such as Engineering Equation Solver (EES).

4.1 Calibration using ML PyTorch "NN Regression Model"

The code for the ML model was written in the open-source programming language Python using the PyTorch library. A linear regression model was used and the code was written to be robust enough to be used for other forms of calibration. A schematic representation of the neural network can be found in Fig. 9.

In this particular case, the model consists of two input parameters, or features in the input layer, which are the measured temperature and relative humidity of the HTS221TR sensor. X_1 represents the normalized temperature, while X_2 represents the normalized relative humidity. A linear normalization was used, where $L_N(T_m) = T_m$ / 50 °C and $L_N(RH_m) = RH_m$ / 100%. Similarly, with the output parameters or labels in the output layer, "Ground Truth" values are used. The aim is to obtain corrected, or calibrated, values of the input measurements from the Smart Sticker sensor.The neural network model incorporates deep learning capabilities. This allows us to configure the number of hidden layers (often called the "black box") and the number of neurons within each layer. Each neuron utilizes the ReLU (Rectified Linear Unit) activation function. This function acts as a gatekeeper, only allowing positive values (greater than zero) to pass through to the next layer. Essentially, it filters out negative or zero outputs from the neuron, preventing them from influencing the network's overall output.

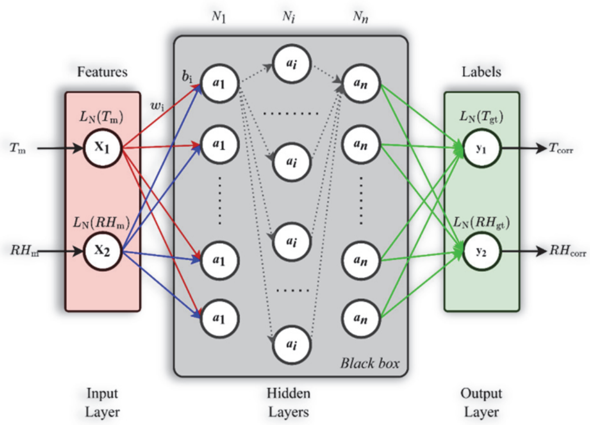

Figure 9 Machine Learning - schematic representation of the Neural Network graph for the linear regression model

To calibrate the model, the neural network was configured with a single hidden layer of ten neurons. The learning rate, which controls how much the weight of neurons adjusts based on errors, was set to 5%. Dropout was not used, a technique that helps to prevent overfitting. The loss function used was the Mean Squared Error (MSE), which measures the average difference between the model's predictions and the actual values. Stochastic Gradient Descent (SGD) was chosen as the optimization algorithm for fine-tuning the weights of the network during training. For each training iteration, a batch size of 64 data points was processed. One epoch represents one complete pass through the entire training dataset, and the training process was performed over 100 epochs. It is important to note that PyTorch requires all training and test data to be in the form of tensors, which are multidimensional arrays that can handle scalars, vectors and matrices. Ideally, both the input data fed to the network and the output it produces should be normalized to a certain range, often between 0 and 1. This normalization step can improve the training efficiency and the overall performance of the neural network.

The training itself consists of several steps, but in general it can be divided into two main steps: Forward Pass and Backpropagation.

1. The **Forward Pass** is a straightforward process where data propagate from the input layer, through hidden layers (if any), and reache the output layer. During this transformation, each layer performs a simple calculation:

- **Linear Transformation**: A linear function $g(x) = \boldsymbol{W} \cdot x + b$ is applied. Here, $\boldsymbol{W}$ represents a weight matrix, x denotes the input vector, b is the bias vector, and g is the output of the current layer.

- **Activation Function**: The result g then goes through an activation function, such as the ReLU function used in this case $\sigma(x) = \max(0, g(x))$. This function introduces non-linearity, allowing the network to learn complex patterns.

Initially, the weight matrix $\boldsymbol{W}$ and bias vector b are assigned random values or chosen based on specific rules.

2. **Backpropagation**, often called "backward propagation of errors," is the heart of the training process. Here's where the network learns by adjusting the weights and biases to minimize errors in the predictions.

- **Loss Calculation**: After the forward pass, a loss function (e.g., Mean Squared Error) calculates the difference between the predicted output and the actual target values.
- **Gradient Descent**: The network calculates the gradient, which indicates the direction in which weights and biases need to be adjusted to reduce the loss. It is like rolling down a hill, aiming to reach the lowest point (minimum loss).
- **Weight and Bias Update**: Finally, using the learning rate (a small value controlling the update step size), the weights and biases are adjusted in the direction suggested by the gradient. This process aims to gradually minimize the loss and improve the network's predictions.

These two steps, forward pass and backpropagation, work together in a cycle. Each data point (or a small batch of data points) goes through the forward pass and then the backpropagation. This cycle repeats for the entire training set, and the entire process is often run over multiple epochs (complete passes through the training data). Essentially, the network iteratively refines its predictions by comparing them to the desired outputs and adjusts its internal parameters (weights and biases) to get closer to the target values.

4.2 Calibration using Optimization Algorithm

In this case, an algorithm for calibration with EES was developed. The algorithm follows a similar logic as the ML model, but is less robust and requires a programming process step by step. The algorithm is shown in Fig. 10.

The calibration process starts with two key components, input data and determination of correction/calibration function:

1. **Input Data**: Sensor measurements that require calibration, along with the corresponding reference device readings (LTHC values in this case), are necessary. Both sets of data are crucial for identifying discrepancies between the sensor and the reference.
2. **Correction Function**: This is where the challenge lies. The type and form of this function depend on the patterns observed in the measured data. Here's what influences the choice of function:

- **Calibration Direction**: Does the calibration aim to increase or decrease sensor readings, or both? A function that can adjust values in both directions is necessary for two-way calibration.
- **Number of Parameters**: The correction function typically has two to four parameters that control the magnitude and direction of the adjustments.
- **Dependence**: The function might depend solely on temperature, solely on relative humidity, or on a combination of both, depending on the observed trends in the data.

Choosing the right correction function is crucial for achieving accurate calibration results.

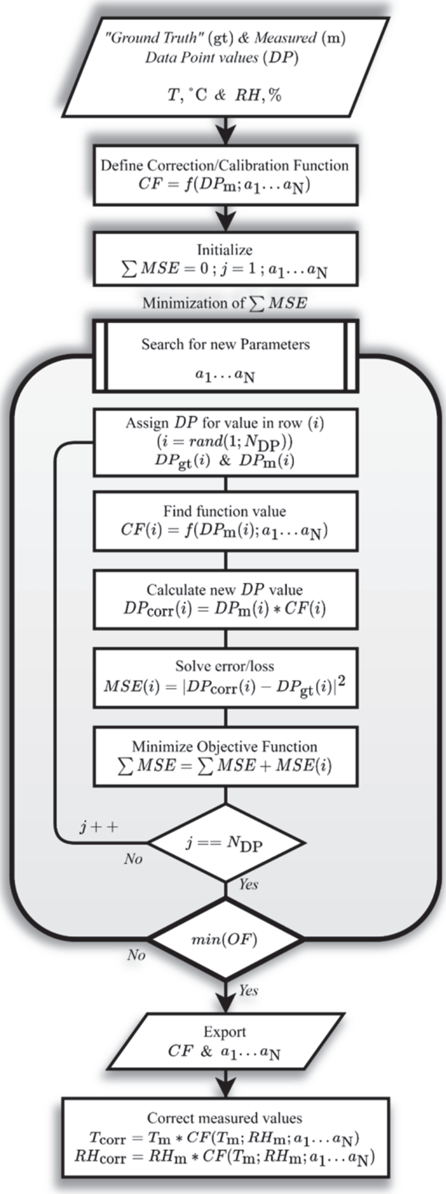

Figure 10 Optimization algorithm for the general and specific use case calibration of data points values

Before the actual optimization of the calculation, the rest of the mathematical model must be set up according to the algorithm and the data initialized. The size of the data set for the optimization is also chosen, usually 80% of the total data, to avoid overfitting. At the beginning of each iteration, the algorithm randomly selects the parameters from a_1 to a_N or uses the method to determine the starting value of the selected optimization method to determine them. In each optimization step, a random subset of the data is selected for optimization. This subset consists of the values of the calibration data and the corresponding values of the ground truth. For this data and the parameters a1 to an, the value of the correction function (CF) is determined to adjust the parameter value. The error or loss function is then evaluated and added to the total error, which, in this case, is the sum of the mean square errors (∑MSE). This sum represents the objective function.

This process is repeated until the entire data set or 80% of it has been processed. If the target function is fulfilled, i.e. the minimum total MSE has been found, the algorithm is finished. If this is not the case, a new set of parameters from a_1 to a_N is selected based on the algorithm built into the software. In this particular case, it is a genetic algorithm or one of the three multivariable optimization methods (Conjugate Directions Method, Variable Metric Method or Nelder-Mead Simplex Method). As soon as the optimum or minimum of the objective function is found, the process ends and leads to a correction function with corresponding parameters. This can then be integrated into the Smart Sticker or data acquisition device to enable real-time correction of the measured values.

4.3 Comparison of Methods

Both methods differ considerably in the implementation of the mathematical model and the approach to finding solutions. A small part of the implementation, in particular code snippets, can be found in Tab. 4. For the ML method, the definition of the PyTorch NN regression model is shown, while for the optimization algorithm, the definition of the whole algorithm in EES is presented.

Table 4 Comparison of the code snippets for the ML Python "PyTorch NN Regression model" on the left and the implemented "optimization algorithm" in EES on the right

ML Python "PyTorch NN Regression model"

```
class RegressionModel(nn.Module):
    def __init__(self, input_size, hidden_sizes, output_size, dropout_prob=0.0):
        super(RegressionModel, self).__init__()
        layers = []

        # Add input layer to the list of layers
        layers.append(nn.Linear(input_size, hidden_sizes[0]))
        layers.append(nn.ReLU())
        layers.append(nn.Dropout(p=dropout_prob))

        # Add hidden layers to the list of layers
        for i in range(len(hidden_sizes)-1):
            layers.append(nn.Linear(hidden_sizes[i], hidden_sizes[i+1]))
            layers.append(nn.ReLU())
            layers.append(nn.Dropout(p=dropout_prob))

        # Add output layer to the list of layers
        layers.append(nn.Linear(hidden_sizes[-1], output_size))
        self.model = nn.Sequential(*layers)

    def forward(self, x):
        return self.model(x)
```

EES "Optimization algorithm"

```
procedure OptimizationAlgorithm(LT$; start; N_DP; a_1; a_i; ... ; a_n : min)
  j = start
  min = 0

  repeat
    i = Round(Random(1; N_DP))

    DP_m[i]=Lookup(LT$; i; 'DP_m')
    DP_gt[i]=Lookup(LT$; i; 'DP_gt')

    "Correction function:"
    CF=f(DP_m[i]; a1; a2; a3; a4)
    DP_corr[i]=DP_gt[i]*CF

    "Sum MSE:"
    MSE=Abs(DP_corr[i]-DP_gt[i])^2
    min=min+MSE
    j=j+1

  until(j>N_DP)
END
```

The complexity of implementation, abstraction, and understanding of the mathematical model are definite drawbacks of ML. However, both methods have their own advantages and disadvantages, some of which are presented in Tab. 5. While one method is more suitable for a smaller amount of input data, the other requires a significantly larger dataset to achieve satisfactory results.

A significant advantage of ML is its high precision and speed of calibration, especially with multidimensional data. In this case, the accuracy of relative humidity measurements is highly dependent on the temperature at which they are measured. A disadvantage, however, is that the data must be processed after acquisition, which means that the calibration results cannot be seen in real time. The quality of the input data has a significant impact on the final result, but ML allows for easy implementation of outlier and noise filtering, which is often not the case with optimization methods, as this task must be performed separately with other software solutions.

ML models excel at capturing complex patterns, but can also act as a "black box". On the other hand, traditional optimization methods offer interpretability, but can struggle with complex relationships and high-dimensional variables.

Table 5 Advantages and disadvantages of ML Python "PyTorch NN Regression model" and implemented "optimization algorithm" in EES

Advantages		Disadvantages	
Machine learning Regression model	Optimization Algorithm	Machine learning Regression model	Optimization Algorithm
Capable of learning complex, non-linear relationships autonomously	Produces interpretable models with explicit mathematical functions	High initial knowledge for setup and high-end infrastructure requirements	Limited flexibility for complex, non-linear relationships
Handles high-dimensional data with many features effectively	Provides analytical solutions and closed-form expressions	Hyperparameter tuning is resource-intensive and complex	Manual parameter tuning, sensitive to outliers and noise
Captures intricate patterns and feature interactions	Conceptually intuitive and straightforward to implement	Computationally demanding for very large datasets	Susceptible to local optima in non-convex problems
Utilizes transfer learning for pre-trained model adaptation	Efficient for small to medium-sized datasets	Often a "black-box" model, reducing interpretability	Significantly slower for larger datasets
Maintains consistent performance with proper regularization	Supports diverse optimization algorithms (e.g., Genetic Algorithm)	Performance heavily depends on data quality and representation	Trial-and-error process for selecting appropriate correction/calibration functions
Highly scalable for large datasets with parallel computing	Suitable for real-time predictions or embedded systems	Prone to overfitting without proper regularization techniques	Struggles with high-dimensional data and feature interactions
Open-source implementations in languages like Python	Flexible for incorporating domain-specific constraints	Requires substantial training data for generalization	Advanced techniques may require proprietary software

One of the most important advantages of the optimization algorithm is the real-time prediction of measurement data. This allows the mathematical model to be implemented on measurement devices, such as the smart label in this case. When a real-time data retrieval system is implemented over Wi-Fi, it is crucial that the data can be processed in real-time on the smart label or the device that collects the data.

Nowadays, even the problem of real-time processing with ML can be circumvented by using additional resources, such as a Raspberry Pi device on which a regression model can be implemented to process data in real time. However, this requires additional effort and architecture that is often outside the scope of the problem, as in this case. The smart label needs to be a standalone product, very small and cost-effective for mass production.

Both methods require measurement and monitoring of data under controlled conditions before implementation, which is generally required for any type of sensor before integration into the final product. One advantage of the smart label is its compactness, which allows calibration even after the sensors have been installed. Problems arise when a sensor is of very poor quality or limited to a maximum theoretical value, as is the case with the BME280 relative humidity and temperature sensor implemented on the Smart Sticker. Fortunately, the product is equipped with several sensors, so that usually only the necessary sensor is used, mainly to save space on the data memory. In the future development of the Smart Sticker, only sensors that can be calibrated quickly and easily will be used, and at an acceptable price, as affordability is one of the main features of the Smart Sticker.

5 RESULTS AND DISCUSSION

Calibrations with both methods have proven to be simple procedures to achieve the desired result, i.e. corrected measured values with low-budget, low-accuracy sensors. Despite the advantages and disadvantages of both methods, the calibration results are comparable. They are shown in Fig. 11 near a temperature of 45 °C.

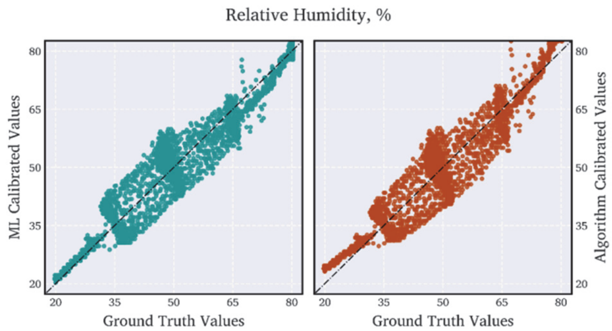

Figure 11 Comparison between values calibrated using Machine Learning method and Optimization Algorithms in EES around temperature of 45 °C

The ML approach achieved slightly better calibration results, particularly in the lower (20-35%) and higher (around 80%) relative humidity ranges. While the difference between the two methods is minimal in the mid-range (35-65% relative humidity), a significant advantage of the ML method lies in its speed. Both methods were trained using the same amount of data (approximately 32000 data points), with 80% allocated for training or optimization. However, the classical method (likely using a genetic algorithm) took considerably longer to find the optimal solution. While reducing data and using simpler optimization algorithms could improve speed, such techniques might not always guarantee the best possible results (finding the global minimum).

Once a correction function is established, regardless of the method, calibration of new data becomes a real-time process and can be seamlessly integrated into various applications. However, in this case, considering the performance and efficiency trade-off, the focus in further analysis will be on the calibration procedure using the Machine Learning model with PyTorch in Python. Fig. 12 visually represents the calibration solution. It compares the raw sensor data (input data), the reference LTHC measurements (target results - "Ground truth" values), and the predictions made by the ML model (predicted results).

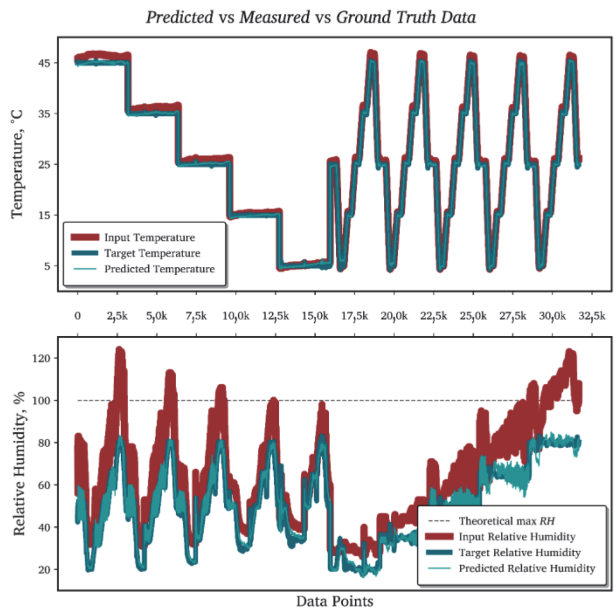

Figure 12 Comparison of the predicted, measured and "ground truth" values for temperature (top) and relative humidity (bottom)

Since the input data for the relative humidity measurement is almost unusable and exceeds the theoretical maximum relative humidity of 100%, it is very difficult to calibrate this data. It is also noted that the measurement exhibits a high dependence on the sensor temperature. This phenomenon can be seen especially in the right part of the graph, where the measurement at "constant" relative humidity resembles a temperature change, especially at higher temperatures and relative humidities. This is a characteristic of the HTS221TR sensor and it was possible to correct the measurements as can be seen in the graph. There is some deviation, but often an accurate measurement is not necessary, and measurements that deviate within 5% in absolute terms are satisfactory. On average, the deviation of the measured data was ±13,4%, while for the calibrated measurements, it decreased below the target deviation of ±5% to ±2,5%.

The performance of the machine learning model can be further refined by adjusting hyperparameters like the number of hidden layers, neurons, learning rate, dropout probability, epochs, and batch size. However, this optimization process requires a balancing act. While fine-tuning can potentially reduce the error further, it also increases the risk of overfitting. An overfitted model performs well on the specific training data but might not generalize well to unseen data. Therefore, it is crucial to find the optimal balance between error reduction and generalizability.

Interestingly, the sensor exhibits high accuracy in temperature measurement even without calibration. Despite this, including temperature as an input parameter significantly improves the calibration of relative humidity. This highlights the strong influence of temperature on humidity measurements, making it essential for both the ML and optimization-based approaches. In fact, excluding temperature as an input would render the calibration invalid.

While temperature is a crucial input for accurate humidity calibration, it can be optionally excluded as an output parameter (as shown in Fig. 13). This can be a strategic choice to expedite the training process and optimization of hyperparameters. However, it is important to acknowledge this trade-off between efficiency and comprehensiveness. Excluding temperature calibration might be suitable for scenarios where only humidity accuracy is critical.

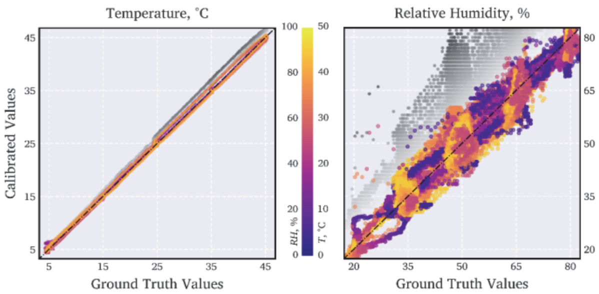

Figure 13 Comparison of the predicted, measured and "ground truth" values for temperature (left) and relative humidity (right)

Fig. 13 shows four sets of data points, visualized as gray and colored points on the graph. The gray points represent the raw, uncalibrated measurements: temperature on the left side and relative humidity on the right side of the graph.The other two data sets, colored according to the legend, represent the calibrated values.

The plot demonstrates the effect of calibration on both temperature and relative humidity. Observations include:

- **Temperature Calibration**: The calibrated temperature values (colored points) closely match the "ground truth" actual values, indicating successful temperature calibration.
- **Relative Humidity Calibration**: The calibration process primarily targets and corrects significant deviations in relative humidity measurements, particularly those observed at temperatures above 35°C. While some deviation persists, the calibrated relative humidity values (colored points) are now centered around the diagonal line (representing perfect agreement), and their spread (standard deviation) is noticeably reduced as shown in Fig. 14.

While calibration has demonstrably improved the data, it is crucial to acknowledge the presence of outliers and measurement noise. These factors can potentially impact calibration results. To mitigate their influence, pre-processing steps like outlier detection and removal might be necessary before calibration.

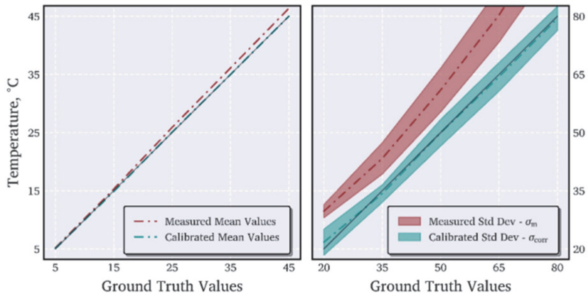

Figure 14 Comparison of the measured and calibrated values, including mean values and standard deviation, with the "ground truth" values for temperature (left) and relative humidity (right)

The effectiveness of calibration is evident in Fig. 13 and Fig. 14. Here, the mean values for both temperature and relative humidity (after calibration) closely align with the diagonal identity line ($y = x$), signifying a significant reduction in deviation. The standard deviation, a measure of data spread, has also noticeably decreased.

However, it is important to consider the generalizability of these results. While the model performs well on the training data it was trained on, real-world applications might present unforeseen challenges. Fig. 15 explores how the trained model performs on actual, unseen data.

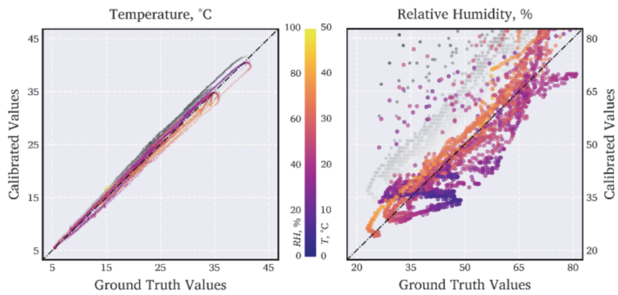

Figure 15 Correlation between calibrated and "ground truth" values for temperature (left) and relative humidity (right) using ML calibrated model on real life use case data points

The analysis revealed an adequate match for temperature values, although the model tends to underestimate the data in both scenarios. This is manifested as a slight downward correction.

One potential explanation for this underestimation lies in the inherent behavior of the HTS221TR sensor. Realistically, the sensor tends to overestimate data values during readings. The model, however, is weighted towards reducing these values, leading to the observed underestimation. This behavior might be driven by the influence of data points with the most significant deviations, typically those at higher temperatures and relative humidities. These outliers might have 'artificially' forced the model to adopt this underestimating tendency.

To address this underestimation, two approaches can be considered: hyperparameter tuning or targeted data training on a new set of data points with better distribution. By implementing one or both of these strategies, the underestimation issue can potentially be mitigated, leading to a more accurate calibration process.

6 CONCLUSIONS

Calibrating low-voltage, low-budget sensors for temperature and relative humidity measurements is a necessary but time-consuming task. It requires a substantial amount of data for both sensor readings and training a machine learning model, or for finding the correction function through optimization algorithms.

When a device incorporates multiple sensors for the same purpose (like temperature and humidity in this case), they can be used as additional inputs during calibration. Alternatively, they can be used independently for direct readings. Given the Smart Sticker's reliance on battery power, a low-cost and energy-efficient approach was prioritized. This led to using just the HTS221TR sensor for calibration.

The HTS221TR sensor, while enabling relative humidity calibration, offered the least accurate temperature measurement among the three available sensors. Combining the LPS22HBTR sensor (dedicated for accurate temperature) with the HTS221TR (for humidity) could achieve a good balance between power consumption and the overall cost of the Smart Sticker. Therefore, it is possible to conclude the following:

1. The study confirms that cheap sensors, such as the HTS221TR, are not always very accurate, especially when measuring relative humidity, where values often exceed the theoretical maximum of 100%.
2. Temperature and relative humidity are closely linked, with sensor readings showing a disproportionate increase in relative humidity values, particularly at higher temperatures. So, temperature is a critical parameter in both calibration methods, greatly affecting relative humidity calibration, and without it as an input parameter, valid calibration would not be possible.
3. Both calibration methods (ML and Optimization algorithms) proved to be simple procedures to obtain corrected values from low-budget sensors with low accuracy, with comparable results.
4. The ML method showed slightly better results in lower (20-35%) and higher (around 80%) ranges of relative humidity, while the differences between 35-65% relative humidity was negligible.
5. The optimization algorithm proved to be a more reliable approach for real-time reading and correction.
6. Calibration significantly enhanced the accuracy of the sensors. Specifically, for relative humidity, the average deviation reduced drastically from ±13,4% to just ±2,5% after calibration. Additionally, it aligned mean values along the identity line.

Acknowledgements

This study was supported by the European Union through the European Regional Development Fund, under the project "Smart Sticker for Measuring and Monitoring Storage and Transportation Conditions of Products" KK.01.1.1.04.0116.

7 REFERENCES

[1] Paull, R. E. (1999). Effect of temperature and relative humidity on fresh commodity quality. *Postharvest Biology and Technology*, *15*(3), 263-277. https://doi.org/10.1016/S0925-5214(98)00090-8

[2] Aung, M. M. & Chang, Y. S. (2023). *Cold Chain Management*. Springer International Publishing.

[3] Rodríguez-Bermejo, J., Barreiro, P., Robla, J. I., & Ruiz-García, L. (2007). Thermal study of a transport container. *Journal of Food Engineering*, *80*(2), 517-527. https://doi.org/10.1016/j.jfoodeng.2006.06.010

[4] Carullo, A., Corbellini, S., Parvis, M., & Vallan, A. (2009). A wireless sensor network for cold-chain monitoring. *IEEE Transactions on Instrumentation and Measurement*, *58*(5), 1405-1411. https://doi.org/10.1109/TIM.2008.2009186

[5] Matić, T., Zidar, J., Aleksi, I., & Žagar, D. (2022). Smart Sticker Ultra-Low-Power Shock Detection in the Supply Chain. *Sensors*, *22*(11). https://doi.org/10.3390/s22114003

[6] Chen, G., Li, X., & Fang, K. (2013). The humidity and temperature control of immersion cycle corrosion test chamber. *Advanced Materials Research*, *634-638*(1), 3870-3874. https://doi.org/10.4028/www.scientific.net/AMR.634-638.3870

[7] Lerma-Carrillo, A., Díaz-Ramírez, J., & Gajewska, T. (2021). Analysis of temperature and humidity in cold transport services. *Proceedings of the International Conference on Industrial Engineering and Operations Management*, *January*, 1298-1309. https://doi.org/10.46254/an11.20210255

[8] Nechifor, S., Petrescu, A., Damian, D., Puiu, D., & Târnaucă, B. (2014). Predictive analytics based on CEP for logistic of sensitive goods. *2014 International Conference on Optimization of Electrical and Electronic Equipment, OPTIM 2014*, 817-822. https://doi.org/10.1109/OPTIM.2014.6850965

[9] Zidar, J., Matić, T., Aleksi, I., & Sušac, F. (2022). Low Power Embedded System Sensor Selection for Environmental Condition Monitoring in Supply Chain. *International Journal of Electrical and Computer Engineering Systems*, *13*(2), 99-107. https://doi.org/10.32985/IJECES.13.2.2

[10] Mensah, K. & Choi, J. M. (2017). Energy consumption and stability investigation of constant temperature and humidity test chamber. *International Journal of Air-Conditioning and Refrigeration*, *25*(1), 1-11. https://doi.org/10.1142/S2010132517500109

[11] González Rivero, R. A., Morera Hernández, L. E., Schalm, O., Hernández Rodríguez, E., Alejo Sánchez, D., Morales Pérez, M. C., Nuñez Caraballo, V., Jacobs, W., & Martinez Laguardia, A. (2023). A Low-Cost Calibration Method for Temperature, Relative Humidity, and Carbon Dioxide Sensors Used in Air Quality Monitoring Systems. *Atmosphere*, *14*(2). https://doi.org/10.3390/atmos14020191

[12] Cardona Gil, J. A., Pazos Urrea, J. P., Osorio, M., & Hincapié, C. A. (2015). Humidity and temperature control applied to a controlled environment chamber. *ASME International Mechanical Engineering Congress and Exposition, Proceedings (IMECE)*, *5-2015*, 1-7. https://doi.org/10.1115/IMECE2015-52979

[13] Heinonen, M. (1999). Humidity generator with a test chamber system. *Measurement: Journal of the International Measurement Confederation*, *25*(4), 307-313. https://doi.org/10.1016/S0263-2241(99)00016-0

[14] Salminen, J., Sairanen, H., Grahn, P., Högström, R., Lakka, A., & Heinonen, M. (2017). Characterization of the Humidity Calibration Chamber by Numerical Simulations. *International Journal of Thermophysics*, *38*(6). https://doi.org/10.1007/s10765-017-2221-y

[15] Galović, A. (2007). *Termodinamika II* (IV). Fakultet

strojarstva i brodogradnje.
[16] Industrial Quick Search (IQS). (n.d.). *Humidity Chambers*. IQS Directory. https://www.iqsdirectory.com/articles/environmental-chamber/humidity-chamber.html
[17] Labtron. (n.d.). *Temperature and Humidity Test Chamber LTHC-A10*. www.Labtron.com
[18] Vajs, I., Drajic, D., Gligoric, N., Radovanovic, I., & Popovic, I. (2021). Developing relative humidity and temperature corrections for low-cost sensors using machine learning. *Sensors*, *21*(10), 1-22. https://doi.org/10.3390/s21103338
[19] Živić, M., Galović, A., Avsec, J., & Barac, A. (2019). Application of gas condensing boilers in domestic heating. *Tehnicki Vjesnik*, *26*(3). https://doi.org/10.17559/TV-20180831125929
[20] Wang, L. & Zhu, Z. (2020). Research on Temperature and Humidity Decoupling Control of Constant Temperature and Humidity Test Chamber. *IOP Conference Series: Materials Science and Engineering*, *711*(1). https://doi.org/10.1088/1757-899X/711/1/012104

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