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# Introduction

This contribution introduces a new use case for supporting IoT device calibration using ML.

R01:

* Add a parapgrap describing sensor drift
* Add a post-condition for substitution
* Revise a potential requirement

### -----------------------Start of change 1-------------------------------------------

## 7.x Use case #x – IoT Device Calibration using Machine Learning

### 7.x.1 Description

In the case of IoT sensors used in autonomous vehicles and smart factories, periodic inspection is required to verify that the required accuracy is continuously maintained. Many IoT sensors are difficult to calibrate and maintain regularly because their working environment is different.

Environmental factors typically influence air temperature measurement using low-cost temperature sensors, e.g., solar radiation, humidity, wind speed, and rainfall. Such environmental factors and wear of sensors are problematic for low-cost air temperature sensors, which lack a radiation shield or a forced aspiration system, exposing them to direct sunlight and condensation.

Drift is a natural phenomenon for sensors. It affects all sensors regardless of the manufacturer. It can be caused by physical changes in the sensor. The drifting of the sensor starts as soon as the sensor leaves the factory. When sensors do drift, then this is often a slow process. Drifting beyond the tolerance of the sensors can occur even before the next calibration.

In such cases, it is possible to check whether the sensor is operating normally by using the measurement values of several nearby high-accuracy reference sensors performing the same operation. For example, more data for ML training is generated by installing the same sensors redundantly in mines, farms, or machines. Periodically, it is possible to learn by using the values of the surrounding sensors, and by changing the calibration values so that the correct values are maintained continuously, it is possible to detect and prevent ageing or error conditions of the sensors.

The basic concept of this use case is to use Machine Learning in a situation where continuous IoT device calibration is required.

In order to support this use case, the IoT platform performs machine learning to generate a calibration value for an IoT device using data collected for a certain period from reference devices. The IoT platform then uses the output from Machine Learning to calibrate the target IoT device. (Optionally, the target device can download the output calibration value into its local memory and do calibration in the device)

As the IoT device requires calibration regularly or when its measurement deviates from the standard value, the IoT platform can continuously perform Machine Learning for calibration.

In order to support the concept of IoT devices calibration using ML, additional information for maintaining calibration and new behaviours to IoT platforms are required.

### 7.x.2 Source

### None

### 7.x.3 Actors

* Low cost temperature sensor: a temperature sensor that requires periodic calibration to provide accurate measurement.
* Reference temperature sensor: a temperature sensor with high accuracy for generating reference measurement.
* IoT platform: An IoT platform stores data for calibration, and performs ML to build a model for calibration.

### 7.x.4 Pre-conditions

* The low-cost weather temperature sensor and the high-accuracy weather temperature sensors for reference are registered to the IoT platform.
* The IoT platform holds device calibration information and can perform ML for calibration.

### 7.x.5 Triggers

* If the IoT platform is configured to build a calibration model regularly, for example, on the first day of every month, the time triggers the process for ML for calibration.

### 7.x.6 Normal Flow

Figure 7.2.6-1 illustrates the high-level flows of the IoT device calibration using ML, which consists of the following steps:

* Step 1: All devices are registered to the IoT Platform. These devices send their measurement to the IoT Platform continuously.
* Step 2: Either the calibration time interval reaches, or the measurement of Sensor-A deviates from the standard range.
* Step 3: Then IoT Platform starts ML using the collected training data from the reference high-accuracy temperature sensors (in this case, Sensor-B, Sensor-C and Sensor-D). The IoT platform also manages various information, such as calibration interval, calibration log, calibration results and standard range, required to perform calibration ML.
* Step 4: The IoT platform performs ML using training values from the reference devices and stores ML results for calibration.
* Step 5: The IoT platform notifies the calibration results to Sensor-A.



Figure 7.x.6-1 1 A flow for calibrating IoT devices using ML in the server IoT platform

### 7.x.7 Alternative Flow

None

### 7.x.8 Post-conditions

* The low-cost weather sensor is calibrated based on the notified calibration results from the IoT platform after performing ML using a training dataset from reference high-accuracy temperature sensors.
* The sensors with severe drafting can also be substituted with new sensors.

### 7.x.9 High Level Illustration



Figure 7.x.9-1 Conceptual diagram of low-cost weather temperature sensor calibration using ML

### 7.x.10 Potential Requirements

1. The oneM2M System shall be able to manage calibration information and training datasets for ML to eliminate or minimize measurement errors from IoT sensors .
2. The oneM2M System shall be able to perform ML using training datasets from reference IoT devices and notify calibration results to a target sensor that requires calibration.

### -----------------------End of change 1-------------------------------------------