FINAL PUBLISHABLE REPORT

Grant Agreement number:	17IND12
Project short name:	Met4FoF
Project full title:	Metrology for the factory of the future

Project start date and duration:		June 2018, 40 months
Coordinator: Sascha Eichstädt, PTB Tel: +49 30 3481 9400 E-mail: sascha.eichstaedt@ptb.de Project website address: https://www.ptb.de/empir2018/met4fof/home/		
Internal Funded Partners: 1. PTB, Germany 2. CEM, Spain 3. IMBIH, Bosnia and Herzegovina 4. INRIM, Italy 5. IPQ, Portugal 6. LNE, France 7. NPL, UK 8. TUBITAK, Turkey 9. VSL, Netherlands	External Funded Partners: 10. SPEA, Italy 11. STRATH, UK 12. TU-IL, Germany 13. UCAM, UK 14. ZEMA, Germany	Unfunded Partners: 15. ITRI, Taiwan
RMG1: IMBiH, Bosnia and Herzegovina (Employing organisation); PTB, Germany (Guestworking organisation)		
RMG2: IMBiH, Bosnia and Herzegovina (Employing organisation); PTB, Germany (Guestworking organisation)		

TABLE OF CONTENTS

1 Overview

The "Factory of the Future" (FoF) as an inter-connected production environment with an autonomous flow of information and decision-making constitutes the digital transformation of manufacturing to improve efficiency and competitiveness. Transparency, comparability and sustainable quality all require reliable measured data, processing methods and results. This project established a metrological framework for the complete lifecycle of measured data in industrial applications, including calibration capabilities for individual sensors with digital pre-processed output and uncertainty quantification associated with machine learning (ML) in industrial sensor networks. The project focused on two very common challenges in manufacturing; (i) process optimisation and (ii) predictive maintenance; which were represented by the 3 different testbeds chosen for the project's demonstrators. The project successfully implemented its outputs in the 3 different testbeds (using different types of sensor networks in each) in order to demonstrate the practical applicability of the outputs and to promote future up-take by industry.

2 Need

Traceable calibrations, harmonised treatment of measurement uncertainties, and industrial standards and guidelines are the major components of a comprehensive metrological infrastructure that has enabled globalised manufacturing and international trade. Digitalisation and data science are rapidly changing almost all aspects of this landscape: e.g. sensors are becoming smart, large networks of sensors are being used together with ML algorithms to make automated decisions and manage production processes. The combination of these technological elements constitutes the FoF, a paradigm that is evolving rapidly worldwide.

According to the 2016 UK "Workshop on Data Metrology" and other similar surveys, one of the top priority industrial needs in the FoF is data quality. This project addressed the need for data quality by focussing on the measurement uncertainty framework supporting such a metrological infrastructure. In order to address the complete flow of information this infrastructure needed to cover the traceable calibration of smart sensors whilst taking into account dynamic effects, the metrological treatment of complex sensor networks, uncertainty evaluation for the data aggregation and decision-making methods. Previous projects have developed the foundation of some of these aspects: EMRP IND09 established a metrological infrastructure for analogue dynamic measurement of mechanical quantities; EMPIR 14SIP08 implemented the mathematical methods from EMRP IND09 into software tools and guidelines for industrial end users; and EMRP ENG63 developed mathematical methods for sensor network metrology focusing on electrical power grids.

However, the outputs from these preceding projects (and hence calibration facilities) needed further work to include digital-only sensors, which required this project to develop new concepts to deal with the internal time keeping of sensors. Cost-efficient traceable calibration of Micro Electro Mechanical Systems (MEMS) sensors for ambient conditions is also needed to associate their output with reliable uncertainties. Further to this, methods for sensor network metrology needed to be extended and uncertainty-aware ML methods need to be developed to address uncertainty evaluation in industrial sensor networks.

3 Objectives

The overall goal of this project was to establish the metrological infrastructure required for quality assurance and traceability in the FoF by taking into account measurement uncertainty from the traceable calibration of individual sensors through to ML data aggregation methods. The objectives of the project were:

1. To develop calibration methods for industrial sensors of dynamic measurements such as acceleration, force and pressure with digital data output (data streams) and internal digital pre-processing, including the extrapolation of the measurement uncertainty from individually calibrated sensors to other individuals of the same type by means of co-calibration and statistical modelling.
2. To develop and demonstrate methods enabling digital sensors to provide uncertainty and/or data quality information together with the measurement data.
3. To develop a cost-efficient in-situ calibration framework for MEMS sensors measuring ambient temperature for their integration into an industrial sensor network with metrological quality infrastructure.

4. To develop and assess data aggregation methods for industrial sensor networks based on machine learning and efficient software architectures, addressing synchronisation of measurements, making use of redundancies of measurements, taking into account uncertainty from calibration and network communication issues, including strategies for balancing cost versus uncertainty and explore methods to identify the measurement coverage and accuracy required for process output targets.
5. To improve existing industry-like testbeds for sensor networks in manufacturing environments towards the implementation of a metrological quality infrastructure and to facilitate the take up of the project outputs by the stakeholders, especially the manufacturing industry.

As part of Objective 5, the project used 3 different testbeds with different types of sensor networks:

1. The SPEA Automatic Test Equipment (ATE) for MEMS temperature sensor testing uses a network of reference temperature sensors, where the optimal implementation and usage of this sensor network determines the efficiency and reliability of the ATE results.
2. The STRATH testbed considers radial forging using pre-heated metallic material and vibrating hammers. The testbed will be used to try and optimise the heating and forming process based on a range of different sensors in order to improve the production output quality.
3. The ZEMA testbed uses a range of sensors measuring different quantities for end-of-line tests and condition monitoring methods for electromagnetic cylinders.

For all three testbeds, uncertainty in the whole flow of information, from the individual sensors to the data analysis output, was consistently considered.

4 Results

4.1 To develop calibration methods for industrial sensors of dynamic measurements such as acceleration, force and pressure with digital data output (data streams) and internal digital pre-processing, including the extrapolation of the measurement uncertainty from individually calibrated sensors to other individuals of the same type by means of co-calibration and statistical modelling.

Traceable dynamic calibration has been used predominantly for motion quantities like acceleration, and with mechanical quantities like force or pressure (derived from acceleration). In the metrology, the primary dynamic calibration of sensors for such quantities has been restricted to analogue systems; composed of a data acquisition module for a voltage output device under calibration that is synchronously sampled with a reference data channel. The latter could be a voltage measurement of a reference transducer or an optical measurement of a laser interferometer. Such analogue systems are well established and standardised for acceleration. For example, an outcome of the former EMRP IND09 "Dynamic" project was the development of such analogue systems for derived mechanical quantities at several metrology institutes.

A fundamental challenge in dynamic calibration is the direct link between reference samples for a varying quantity with the resulting output samples of the sensor to be calibrated. Whilst this challenge can be solved by the synchronisation of measurement channels in conventional calibration systems, this solution is unfeasible for digital output sensors, due to their autonomous (uncontrolled) internal sampling. In addition, conventional calibration systems are usually unable to acquire measurement data via a digital interface.

To overcome these issues, PTB developed a complementary hardware module, called digital acquisition unit (DAU). This DAU module, based on a state-of-the-art microcontroller, is able to handle the data acquisition or reception from the digital output sensor. To gain the necessary accurate timing information, the DAU module contains an internal clock algorithm, which is "GPS-disciplined", i.e., it is aligned to universal coordinated time (UTC) by using the "pulse per second" signal distributed by global positioning system (GPS) satellites. The design of the DAU microcontroller has been developed such that, if GPS is unavailable, another precise source of a pulse per second signal can be used.

To link this autonomous time-base to the associated calibration system, an additional voltage signal is sampled by the DAU with its on-board analogue to digital converter. This synchronisation signal is generated and sampled simultaneously by the conventional calibration system on its free measuring channel (i.e., the channel that would otherwise be used for the sensor to be calibrated). For some conventional calibration systems, a synchronisation signal can be provided by a dedicated constant output linear amplitude (COLA) signal, for other calibration systems the drive signal can be used to control the electromechanical shaker. As the synchronisation signal is identical for both components (i.e., conventional calibration system and DAU), although sampled at differing times, it allows for the precise association of the signal phases of the reference in the conventional system and the digital output of the sensor at the DAU.

For the first time ever, this newly developed DAU hardware module and the corresponding software allows NMIs to perform the primary phase calibration of digital output accelerometers using laser interferometry. The design and algorithms for the DAU were made available in the public domain by the project using GitHub repositories.

The project successfully demonstrated the applicability of the components and methods within the existing registered measurement capabilities (CMCs) of CEM and PTB through a comparison calibration of the same digital accelerometer at CEM and PTB with different conventional calibration systems as a reference. Figure 4.4.1 depicts a photograph of the digital accelerometer and DAU system mounted on the national standard calibration device of PTB.

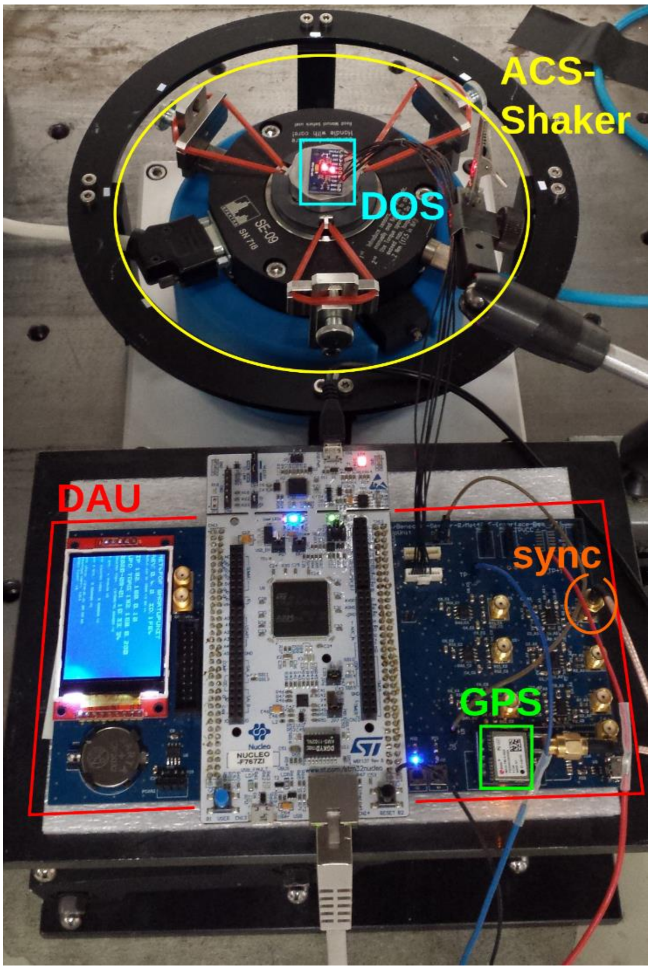

Figure 4.1.1 Digital Acquisition Unit (DAU) and digital accelerometer (DOS) mounted on the primary calibration system of PTB for the CMC comparison.

Both partners (CEM and PTB) calibrated an MPU9250 digital-output sensor (accelerometer) and provided the results of their conventional calibration (CMC) together with a stream recording of the data received by the newly developed DAU.

In subsequent analysis of the calibration data by partners PTB and IMBIH, including the ISO- 16063-11 (Methods for the calibration of vibration and shock transducers — Part 11: Primary vibration calibration by laser interferometry) and a conformal sine-approximation of the digital data, the complex sensitivity of the accelerometer was calculated.

Further comparison analysis was also performed by PTB and IMBIH and followed the typical procedures for CMC and international key comparisons. The consistency of the results between CEM and PTB is clearly visible in Figure 4.1.2.

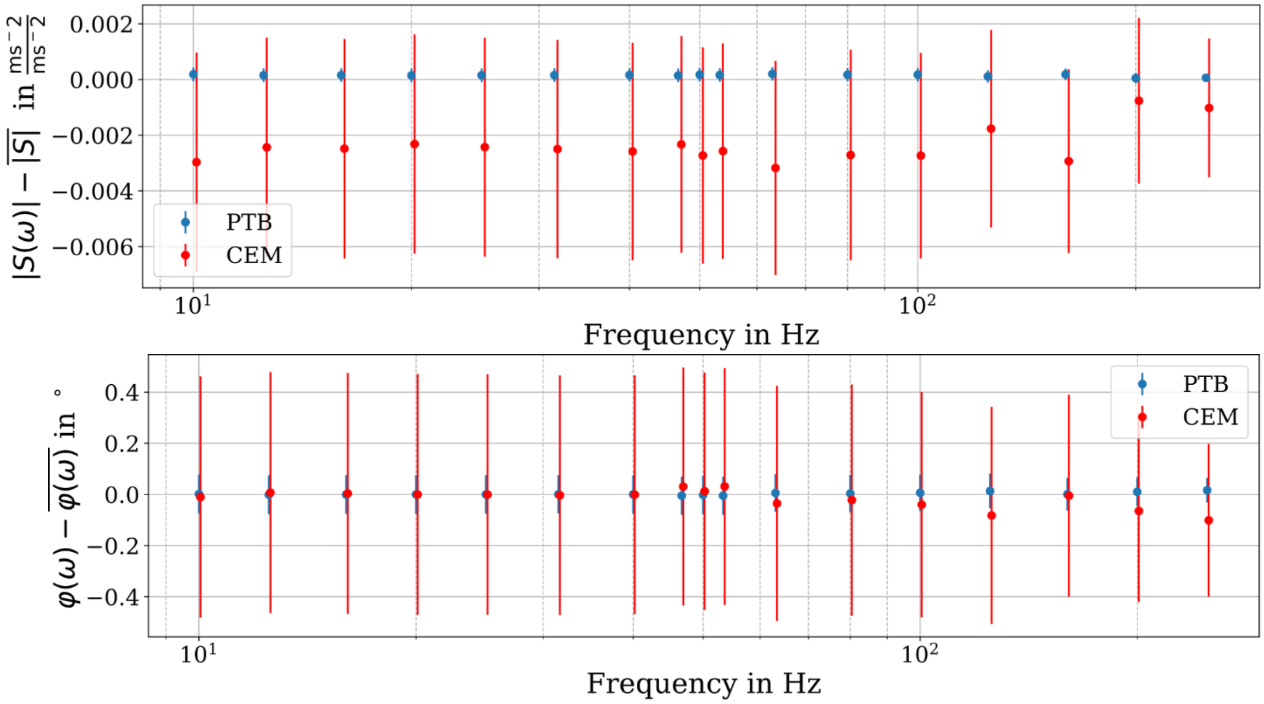

Figure 4.1.2 Comparison of calibration results of CEM and PTB for the magnitude (top) and phase (bottom) of the complex sensitivity in the frequency range from 10 Hz to 250 Hz. The error bars indicate the best CMC of each institute registered for the calibration of analogue accelerometers.

It should be emphasised that the whole calibration system (including the newly developed DAU) is not limited to motion quantities, as due to the generic design, it can also be applied to dynamic force, torque, or pressure calibration systems, if they operate on a sample-by-sample basis.

The project also investigated digital output force or pressure sensors and found that in such fields analogue sensors are usually complemented with small highly integrated digitiser modules, also known as digital transducer interface (DTI). In typical industrial applications, such as automotive crash testing, combinations of an analogue sensor and DTI digitiser module are used in a block-wise sampling mode. In such cases, a start trigger is provided from the application and subsequently the DTI digitiser module samples a large number of measurement values into an internal buffer which is later provided to the data acquisition unit. Thus, timestamping of each sample similar to the previously described project's DAU is impossible. Nevertheless, it seemed a clear aim for the project to try and address this and make industrial standards accessible for dynamic calibration.

For precise timing during calibration, the synchronisation signal, which provides the time reference for conventional calibration systems, is used to generate the necessary start trigger for the DTI-based system. This start trigger can be accomplished by a simple rising edge triggering on the sinusoidal sync signal. Such a set-up was tested at PTB and subsequently deployed to TUBITAK for dynamic shock pressure calibration measurements with TUBITAK's drop-mass calibration device. After careful set-up and adaptation successful dynamic shock pressure calibration measurements were performed. Figure 4.1.3 shows a photograph of the calibration set-up in the dynamic pressure lab of TUBITAK.

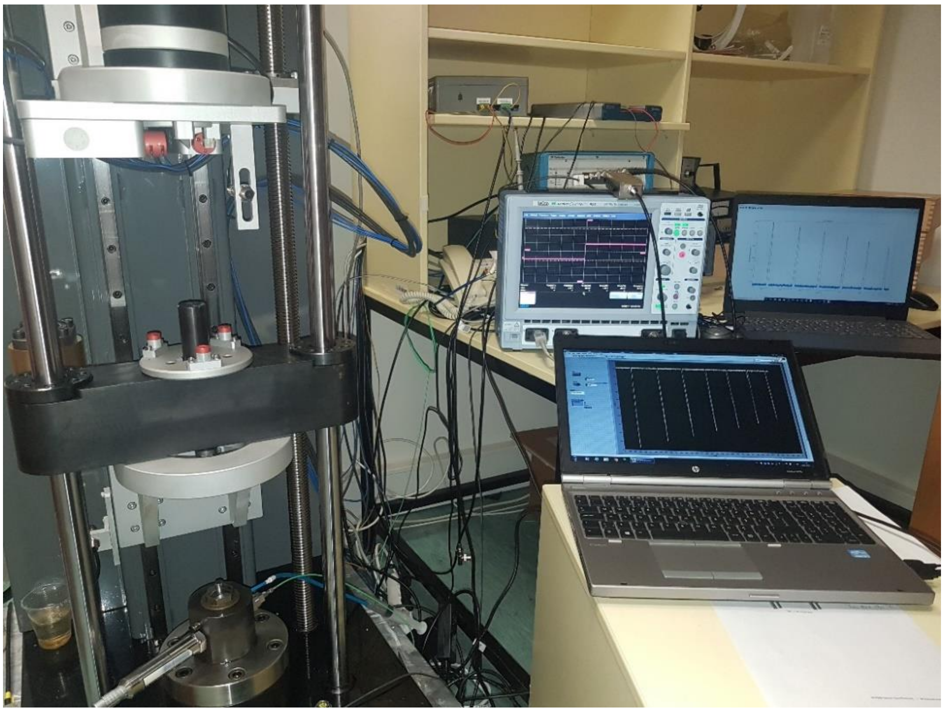

Figure 4.1.3 Shock pressure calibration set-up at TUBITAK as used for the dynamic calibration measurements of a DTI-based digital pressure measuring chain.

An impression of the synchronously acquired analogue data from the reference pressure sensor and the calibrated digital measuring chain is given in Figure 4.1.4.

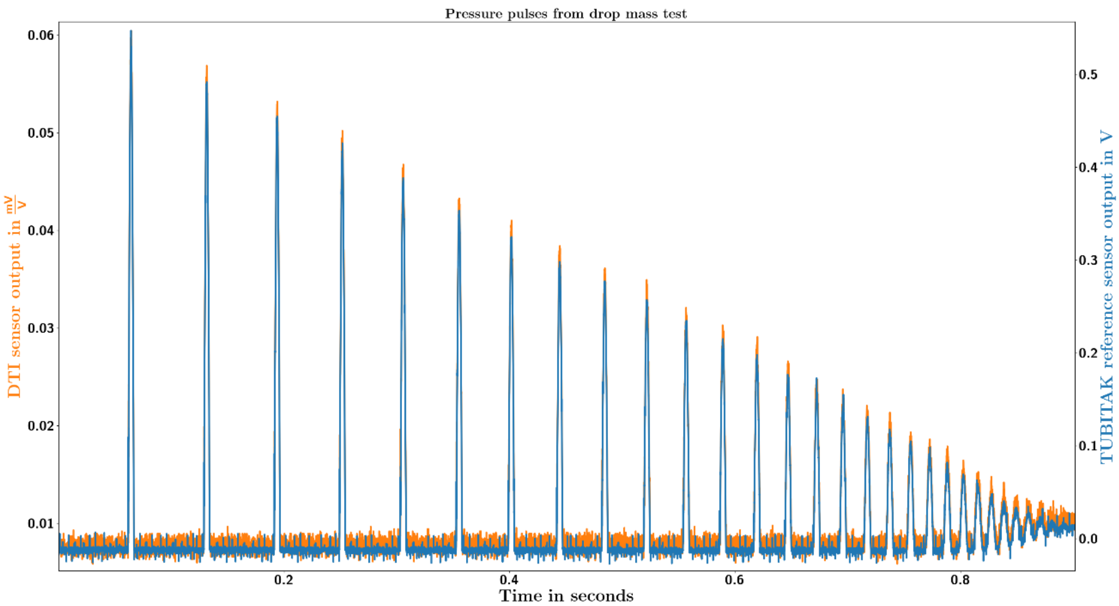

Figure 4.1.4 Picture of the decaying repetitive pressure shock pulses as measured by the reference sensor of TUBITAK and the DTI-based pressure measuring chain.

Unfortunately, a second dynamic pressure calibration was unable to be realised during the project’s lifetime and, therefore validation by comparison calibration could not be carried out.

Further to the dynamic shock pressure calibration measurements, PTB performed sinusoidal force calibration measurements on its primary vibration calibration system. The digital output sensor used, was comprised of a conventional strain gauge force transducer combined with a DTI module and was successfully calibrated at PTB. The sinusoidal force calibration results were also consistent with results for the conventional calibration of the same force transducer.

The overall outcome of these project developments was a complementary method that used commercial electronics (the project's DTI module) and methods implemented in software to enable the use of conventional calibration systems to SI traceability and dynamically calibrate magnitude and phase (timing) of the complex transfer function of digital output sensors.

In addition to this, by developing methods for the dynamic calibration of digital output sensors, the project produced other important outcomes such as the GPS-disciplined DAU; and the synchronisation of the DTI module brought insights into the internal timing characteristics of digital sensors and was able to characterise the quality of their internal sampling units. Figure 4.1.5 demonstrates the distribution of sample time intervals for two of the investigated digital output accelerometers. It is clearly visible that the distribution is far from the usually assumed Gaussian or rectangular distribution.

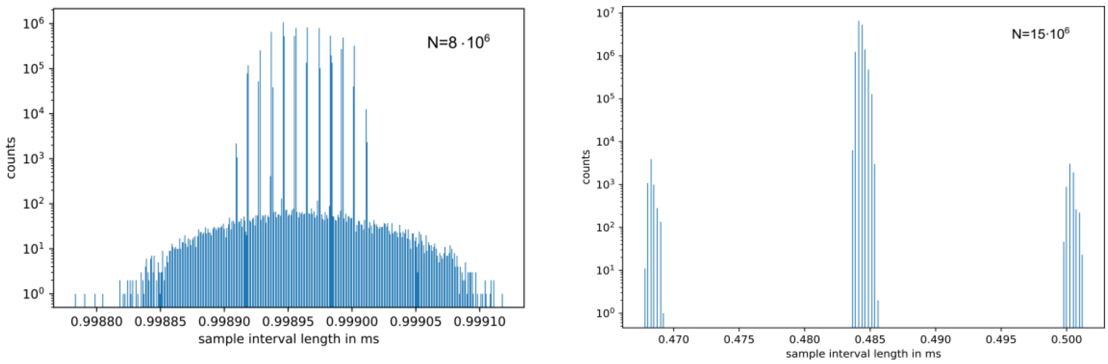

Figure 4.1.5 Histograms of the distribution of sample interval lengths for two investigated digital output accelerometers (MPU9250 left, BMA280 right) during measurements in the lab.

In addition, the project's thermal tests demonstrated a strong dependency of the internal sampler to environmental conditions, which are typically not expected by the user or currently documented in data sheets. This strong dependency could only be detected and quantified with the appropriate precise timestamping or synchronisation with the reference calibration system, DAU or DIT module respectively.

Summary

The project achieved Objective 1; to develop calibration methods for industrial sensors of dynamic measurements and internal digital pre-processing, including the extrapolation of the measurement uncertainty from individually calibrated sensors to other individuals of the same type by means of co-calibration and statistical modelling. The project did this by extending existing calibration facilities based on a novel micro-controller (µC) board, which allows the association of the digital sensor signal with traceable timestamps.

The project's µC board can hold digital sensors and provide time-stamping traceable to the SI. A communication interface based on Protobuf-Messages connects the µC board to upstream systems, that are running the ABF software also developed within the project. The project's ABF was developed to enable easy integration with data analysis methods and can also provide the measurement information in a large range of protocols for end users. For example, the ABF has been successfully used with OPC-Unified Architecture (a widely used machine to machine communication protocol for industrial automation) to provide data streams from the project's µC board to connected PCs.

The newly developed hardware was successfully tested in a dynamic calibration as part of an extension to the existing acceleration calibration facilities at PTB. A second test application of the hardware was via the integration of calibrated MEMS sensors for temperature and acceleration into the testbeds at ZEMA and STRATH. The successful integration in the two testbeds enabled them to include calibrated digital sensors for additional applications and data analyses.

4.2 *To develop and demonstrate methods enabling digital sensors to provide uncertainty and/or data quality information together with the measurement data.*

The DAU in Objective 1 complements a digital output sensor with a microprocessor. This microprocessor uses the digital output sensor's interface to collect measured data whenever available and transmits it to a host PC connected to the DAU via Ethernet. This architecture can be used not only for dynamic calibration, but with adapted firmware, it can also be used with a sensor in a larger network of sensors such as in the Internet of Things (IoT). This resulted in a proof-of-concept "Smart Traceability" sensor that could provide measured values together with their associated uncertainty and other relevant data quality information. The project did this by extending a conventional sensor with a "Smart-up Unit". In addition, the project further developed the software from EMPIR project 14SIP08 by extending the corresponding software library PyDynamic to include a continuous integration (CI) workflow for automated software quality assurance. The central software repository on GitHub connects PyDynamic and the other software developments from this project to an implementation of the ABF developed in Objective 1.

In order to provide identification information and meaningful machine-interpretable information, a new data protocol was designed by PTB in collaboration with the EMPIR project 17IND02 SmartCom. The new data protocol combines measurement data with information about the measurement in a stateless efficient fashion. This meta information describes the sensor as well as the channels provided by the sensor, and includes:

- A serial number as identifier either from the sensor or (if that is non-existent) from the DAU
- The quantity measured by each sensor channel
- The measurement range of each channel
- The measurement unit for to interpret the range information
- The resolution provided for each channel.

Key	Data	Data
ID	123	123
Samplenumber	100	101
Unix time	1594224567	1594224567
Unix time nsecs	123456000	12356012
Time uncertainty	155	156
Data_01	0.234	0.235
Data_02	0.125	0.127
Data_03	9.634	9.602
Data_04	0.005	0.004
Data_05	0.006	0.007
Data_06	-0.005	-0.007
Data_07	-50.62	-50.42
Data_08	10.12	10.02
Data_09	2.35	2.00
Data_10	23.54	23.55

Key	Description	Description	Description	Description	Description
ID	123	123	123	123	123
Type	PHYSICAL_QUANTITY	UNIT	RESOLUTION	MIN_SCALE	MAX_SCALE
Description_01	X Acceleration	\metre\second\tothe{-2}	65536	-156914	156909
Description_02	Y Acceleration	\metre\second\tothe{-2}	65536	-156914	156909
Description_03	Z Acceleration	\metre\second\tothe{-2}	65536	-156914	156909
Description_04	X Angular velocity	\radian\second\tothe{-1}	65536	-34907	34906
Description_05	Y Angular velocity	\radian\second\tothe{-1}	65536	-34907	34906
Description_06	Z Angular velocity	\radian\second\tothe{-1}	65536	-34907	34906
Description_07	X Magnetic flux density	\micro\tesla	65520	-5775.43	5775.43
Description_08	Y Magnetic flux density	\micro\tesla	65520	-5775.43	5775.43
Description_09	Z Magnetic flux density	\micro\tesla	65520	-5775.43	5775.43
Description_10	Temperature	\degreecelsius	65536	-77.208	119.080

Figure 4.2.1 *Schematic representation of the data format and streaming protocol used for transmission of measurement data in SI-units and sensor meta-data from the DAU to the agent-based software in the connected network*

The project's original concept was to use the digital output sensor or the DAU to provide comprehensive measurement uncertainty information associated with the measured data. However, it became clear early in the development (and was confirmed by the project's testbed operators SPEA, STRATH and ZEMA), that a main component of measurement uncertainty was related to the conditions in the testbed, such as the mounting of sensors or environmental conditions. Therefore, the project decided not to include the measurement uncertainty calculation methodology in the DAU. Instead, the measurement uncertainty calculation method was performed via a dedicated agent in the agent-based framework, see Section 4.4

The DAU with the respective data streaming protocol is capable of delivering measurement uncertainty information associated with a calibration to an agent as a contribution to the combined uncertainty calculation performed within the testbed. The agent-based framework then keeps track of the additional contributions (meta data) associated with each calibration situation and the application of the digital output sensor. The DAU and the agent-based software were successfully demonstrated by partners PTB and ZEMA, supported by software modules developed by UCAM and PTB at the testbed at ZEMA. Moreover, the calibration setup developed for Objective 1 used the DAU together with the aforementioned data protocols for the calibration.

Summary

In summary the project achieved Objective 2; to develop and demonstrate methods enabling digital sensors to provide uncertainty and/or data quality information together with the measurement data. The project achieved this by extending the setup developed for Objective 1 with the ability to communicate calibration information and measurement uncertainty using standard data protocols.

The project did this by extending a conventional sensor with a “Smart-up Unit”. In addition, the project further developed the software from EMPIR project 14SIP08 by extending the corresponding software library PyDynamic such that measurement data communication from the Smart-up Unit to a connected PC can be processed in a data streaming environment.

The project equipped the testbed at ZEMA with digital-only sensors for acceleration and temperature with the Smart-up Unit. The digital sensors were calibrated at PTB and INRIM with support from SPEA, and they provided their data via the µC board (from Objective 1) to the data acquisition system (of ZEMA). A similar installation of calibrated, digital-only sensors for acceleration and temperature with a Smart-up Unit was also carried out for the testbed at STRATH. Both testbeds are now able to produce data sets from digital sensors together with reliable uncertainty statements. The project’s GitHub repository also contains examples on how to use the ABF and methods from the extended PyDynamic library for the analysis of this data.

4.3 To develop a cost-efficient in-situ calibration framework for MEMS sensors measuring ambient temperature for their integration into an industrial sensor network with metrological quality infrastructure

In many Industrial Internet of Things (IIoT) environments, MEMS are used for measuring ambient conditions due to their flexibility and low cost. However, to be able to incorporate such information into a quality ensured FoF, reliable calibration information for MEMS is required.

Regular post-production testing of MEMS is typically carried out using an ATE. However, prior to the start of this project measurement traceability for MEMS calibration services was lacking for the whole metrology chain, i.e. at the NMI level of NMI, in accredited calibration services and, consequently, at the industrial and end-user level. This issue was a consequence of the lack of adequate technical set-ups and procedures as well as normative standards for MEMS calibration. Therefore, the challenge for MEMS calibration was the establishment of a robust, cost-effective, SI traceability route whilst maintaining the overall efficiency of high-volume testing usually found in ATE.

This project aimed to address this challenge by enabling ATE systems to test a batch of MEMS under specified, controlled and traceable temperature conditions. Under such conditions the measurement traceability for the MEMS should then be able to be promptly transferred from the applied conditions (generated by the ATE thermal stimulus, as depicted in Figure 4.3.1) to the measurements performed by the units under test, i.e., the MEMS, once the latter is embedded into an IoT device.

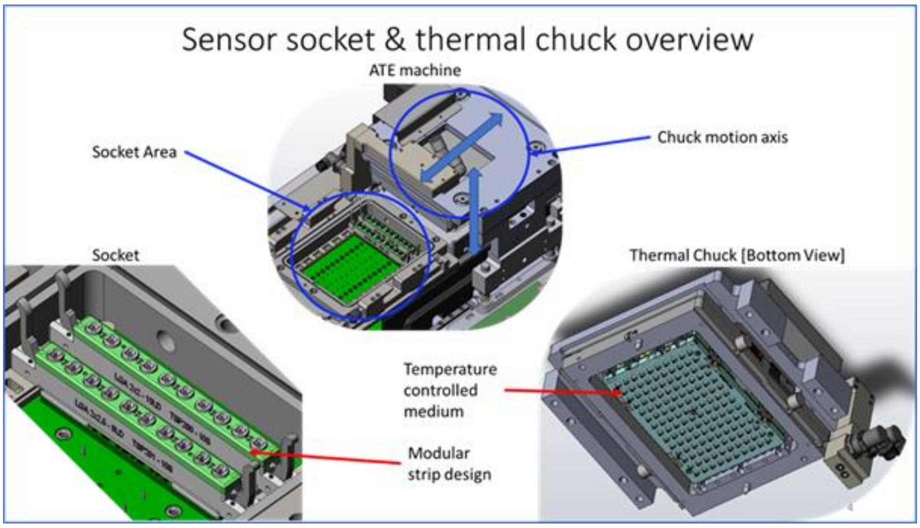

Figure 4.3.1: The core of an ATE for MEMS temperature sensors is made of three parts: a frame to host several sensor socket strips; an array of individual socket strips which host the devices under test and provide the electrical interface; a sliding cover, the so-called thermal chuck, which provide the thermal stimulus to each MEMS under test.

INRIM and SPEA successfully established such a SI traceability route by developing a sensor network capable of performing in-situ MEMS sensors calibration in an ATE (i) at the rate required by customers, (ii) with the specified accuracy and (iii) with minimal modifications to an existing ATE platform.

The development process had two steps to reach the desired goals:

1. a minimalist approach, in which an ATE reference fixture was developed
2. a paradigm shift to embed a “metrology layer” in a retrofitted system.

The minimalist approach (step 1) entailed a temperature sensor network and was developed to overcome the intrinsic constraints of in-situ calibration in industrial settings. At the same time, step 2 defined a calibration framework to provide robust measurement traceability for MEMS temperature sensors calibrated in an ATE.

As part of the in-situ calibration framework for MEMS sensors, the reference fixture sensor developed by INRIM and SPEA consists of a series of sensor socket strips equipped with calibrated reference sensors as shown in Figure 4.3.2. Each replaceable sensor strip was designed to accommodate specific temperature sensors (e.g., platinum thermometers, digital IC temperature sensors or golden devices).

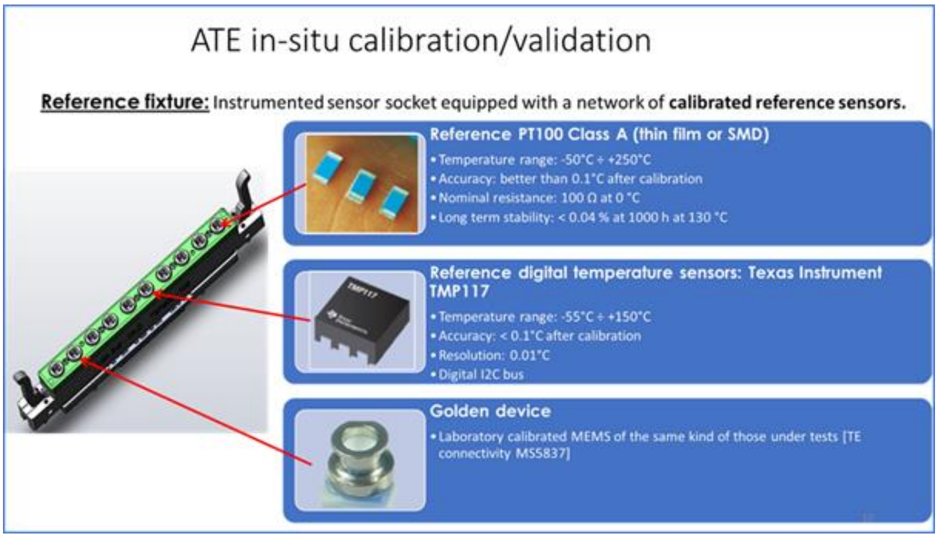

Figure 4.3.2: A reference fixture based on an instrumented sensor socket strip was developed for a host of reference temperature sensors.

Before using the reference fixture sensor with ATE in an industrial setting, the sensors were calibrated against laboratory temperature standards. To do this, INRIM and SPEA developed a water-proof capsule (shown in Figure 4.3.3) suitable of hosting a single sensor socket strip, populated with suitable sensors, which were calibrated by comparison to a standard platinum thermometer in a precision temperature bath.

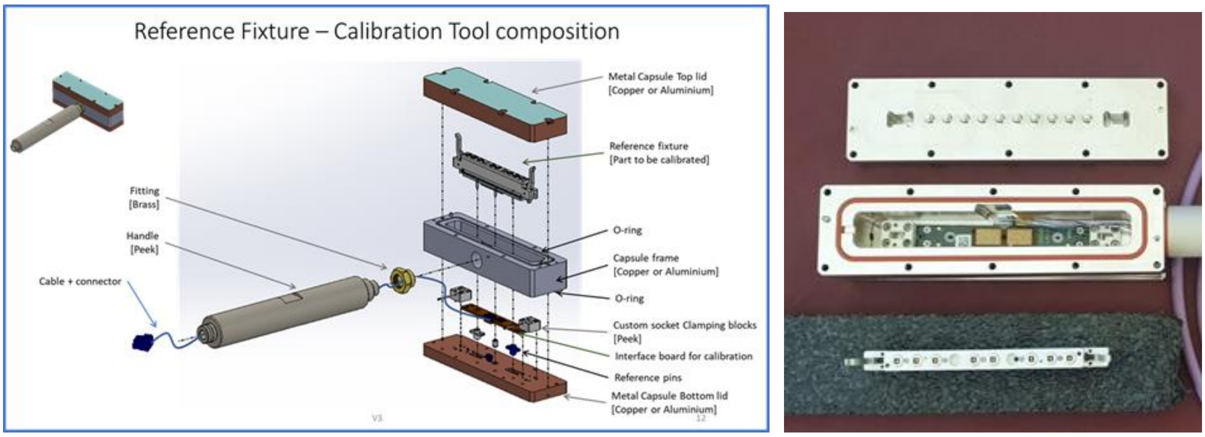

Figure 4.3.3: The calibration tool developed for comparison calibration of the reference fixture sensors against a standard platinum thermometer in the temperature range from –20 °C to 95 °C.

To validate the thermal behaviour of the in-situ calibration framework for MEMS sensors, partner IPQ developed a simulation to model the thermal chuck. Using this simulation, IPQ could gather information on the temperature distribution so that a decision on the optimum number of sensors, and its distribution, could be properly implemented and justified. INRIM and SPEA made several experiments on the SPEA testbed to assess the performance of the in-situ calibration framework for MEMS sensors, while the IPQ thermal modelling provided useful insights of the interplay between MEMS under testing and the ATE thermal stimulus. An example of the temperature distribution modelling of the SPEA testbed is depicted in Figure 4.3.4.

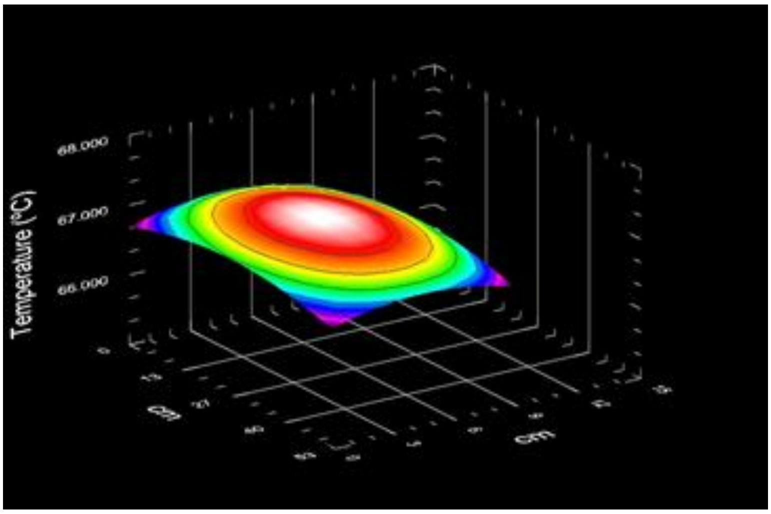

Figure 4.3.4: Thermal modelling showed that at about 67 °C the cooling effect from the surroundings is noticeable, lowering temperatures slightly in a concentric or ring shape that decreases from the centre to the borders. The 3D graph allows for an immediate perception of the shape and grade of temperature variations.

The development of the reference fixture sensor and its calibration tool allowed a detailed investigation, under traceable conditions, of the temperature homogeneity over the ATE thermal chuck, its temperature stability and the difference between the mean temperature and the set point.

Such a study has never been done before and its findings shed a new light on ATE thermal operation and demonstrate that a metrology enabled ATE can be developed (with major improvements) compared to current ATE. The project's findings also delivered a cost-efficient in-situ calibration framework for MEMS sensors measuring temperature for their integration into an industrial sensor network with a metrological quality infrastructure. Unfortunately, the project's challenging target of 0.2 °C uncertainty could not be achieved using the minimalist approach. However, it provided a solid scientific knowledge for future design improvements for in-situ calibration framework for MEMS sensors.

Summary

In summary the project achieved Objective 3; to develop a cost-efficient in-situ calibration framework for MEMS sensors measuring ambient temperature for their integration into an industrial sensor network with metrological quality infrastructure. The project did this by developing a novel ATE at the SPEA testbed for the traceable in- situ calibration of MEMS temperature sensors using a network of reference sensors in an automated industrial test environment. The new ATE setup was first designed and then implemented in the SPEA testbed so that it could be used to provide traceable calibration of on-board temperature sensors for a reference fixture.

Traceability of the novel ATE calibration setup was achieved by a calibration of the reference fixture at INRIM, which can now be offered as a novel calibration service. Manufacturers of MEMS temperature sensors can use the ATE calibration setup with a calibrated reference fixture to provide calibrated sensors to their customers. These customers can then integrate the calibrated MEMS sensors into their sensor network, including statements for traceability. Using methods from Objective 2, this information can be used to achieve uncertainty-aware data processing and machine learning such industrial sensor networks.

4.4 To develop and assess data aggregation methods for industrial sensor networks based on machine learning and efficient software architectures, addressing synchronisation of measurements, making use of redundancies of measurements, taking into account uncertainty from calibration and network communication issues, including strategies for balancing cost versus uncertainty and explore methods to identify the measurement coverage and accuracy required for process output targets

Artificial intelligence, robotics and condition monitoring are just some of the key enablers for the FoF, which will push quality control and assurance towards greater automation and higher accuracy. Industrial sensor networks and the associated data processing pipelines are the infrastructure underlying these capabilities or the FoF. Benefitting from the advancement of digital technologies, sensor networks have already been used to advance many manufacturing sites and have motivated the associated progress in research and development.

Compared to small-scale sensor networks, the processing of measured data is extremely challenging for a large sensor network or for a structurally complicated network of sensors with an unknown number of latent variables and possible high levels of interaction between the sensors. However, industrial sensor networks are often large and/or structurally complicated and have such properties. Thus, traditional mathematical modelling approaches, which require an understanding of the physical principles of the system, are impractical.

ML methods, also known as data-driven methods, provide a feasible alternative and have recently received considerable attention. Instead of requiring explicit knowledge of the system, ML methods can be regarded as a black-box approach. The word ‘learning’ refers to the capability of a ML method to learn from training data, which is typically achieved by optimising an objective cost function. Then depending on whether the training data includes labels, ML methods are categorised as supervised or unsupervised. In supervised learning, a ML model provides mapping between input sensor data and the output target variable (considered as a label) by learning from the training data. In unsupervised learning, the ML model provides the underlying structural properties of the input sensor data. There are advantages and disadvantages associated with the use of ML. For example, one advantage is the adaptive nature of ML methods as this removes the need to explicitly model the physical system. In contrast a disadvantage can be a lack of ‘interpretability’ of the model and the difficulty in evaluating associated uncertainty information.

Uncertainty evaluation is essential for the processing of measured data, and it underpins metrological traceability and quality-assurance. The “Guide to the expression of uncertainty in measurement” (GUM) provides a standard framework for evaluating measurement uncertainty that is both model-based and probabilistic. The focus of the GUM is on uncertainty propagation for a linear system or an approximately linearised system in the case where a system is mildly nonlinear. When a linear approximation is not acceptable, the GUM permits “other analytical or numerical methods” for uncertainty propagation, such as a Monte Carlo method. But it is well-known that nonlinearity is one of the distinguishing features of ML models. This is especially true for ML models based on complicated structures, where various forms of nonlinearity are embedded within the ML models and make standard uncertainty evaluation approaches difficult.

All this means that the aggregation of data from different sensors is an essential but challenging task in the FoF. To try and address this, this project, investigated data aggregation methods at specific testbeds and extended them to incorporate metrological aspects. More specifically, data aggregation methods for ML were developed and tested for the ZEMA testbed for lifetime estimation and at the STRATH testbed for product quality optimisation. Using these two testbeds (SRATH and ZEMA) a variety of scenarios and typical data defects were studied during the project including:

- timing and synchronisation issues,
- redundancy,
- mixed quality networks and
- application of typical digital signal processing methods.

As a starting point for the analysis, the project considered mathematical modelling for the FoF data analysis. Mathematical modelling is widely used to support metrology and applications dependent on measurement. It is used to (i) inform the design of sensors and measuring systems, (ii) to make inferences and predictions about quantities of interest, and (iii) to increase our understanding of real-world systems or processes for which a model provides an abstract representation, albeit one that is necessarily approximate.

The transformation towards the FoF also presents a number of modelling challenges. For example, the absence of physical models is compensated by the availability of large volumes of sensor data leading to a dependence on data-driven models, in particular those using ML and deep learning.

The metrological treatment of sensor networks differs from the treatment of single measuring instruments in several ways, i.e., the quantity of interest, the measurand, can be a distributed quantity (e.g., a temperature field) or aggregated quantity (e.g., health status of a machine), and traceability of the measurand to the SI may be impossible. In addition, data analysis in the FoF is typically (semi-)automated and deals with time-dependent measurands. This is a consequence of the amounts of data being acquired, the complexity of the sensor networks themselves, and the way that the sensors are used. Therefore, partners NPL, PTB, INRIM, ZEMA, STRATH, SPEA, TU-IL, UCAM, VSL, ITRI, IMBIH and LNE considered modelling and data aggregation for practical testbed situations as well as flexible implementations of the corresponding modelling and data analysis methods.

For example, in the presence of jitter effect and measurement noise, a Bayesian approach for removing the effects of jitter and noise was developed in the project. The Bayesian approach estimates the true signal along with its associated uncertainty as follows:

Let denote $s(t)$ the true data, η as measurement error with variance ω^2, and ξ as the timing error with variance τ^2. Assume η and ξ are samples drawn independently from Gaussian distributions that are independent of time and of the signal and of each other. The measured signal is modelled as

$$v(t) = s(t + \xi) + \eta$$

A cubic polynomial $p(t; \boldsymbol{a})$ is used to approximate the underlying data in a short window, where $\boldsymbol{a}$ contains the parameters of the cubic polynomial function.

The success of the proposed approach depends on the adequate representation of the underlying signal by the cubic polynomial function. This is achieved by minimising the weighted residual sum of square difference between $v(t)$ and the cubic polynomial representation in a moving window approach. For the parameter estimation, Bayesian methods were suggested. The likelihood function is written as

$$h(v|\boldsymbol{a}, \tau^2, \omega^2) = \prod_{j=k-n}^{k+n} h(v_j|\boldsymbol{a}, \tau^2, \omega^2).$$

Consider prior knowledge for $\boldsymbol{a}$ is captured by an uninformative, uniform distribution, viz., $g(\boldsymbol{a}) \propto 1$. The prior distribution chosen for τ^2 and ω^2 is the inverse-gamma distribution due to the reason of conjugate prior. Applying Bayes' theorem, the posterior distribution for $\boldsymbol{a}$, τ^2 and ω^2 is then given by

$$g(\boldsymbol{a}, \tau^2, \omega^2|\boldsymbol{v}) \propto h(\boldsymbol{v}|\boldsymbol{a}, \tau^2, \omega^2) g(\boldsymbol{a}) g(\tau^2) g(\omega^2).$$

A Markov-Chain Monte-Carlo method, based on a random-walk Metropolis-Hastings algorithm, is suggested to obtain samples from the posterior distribution in terms of which estimates of $\boldsymbol{a}$, τ^2 and ω^2 and uncertainties associated with the estimates are evaluated.

The proposed algorithm was tested with a simulated signal

$$s(t) = ae^{-bt} \sin 2\pi f t \qquad 0 \le t \le 1$$

with $a = 10$, $b = 2$ and $f = 2$. The signal was sampled with a uniform timing spacing of 0.01 s corresponding to a sampling frequency of 100 Hz, and the jitter and noise levels were set as $\tau = 0.002$ and $\omega = 0.005$, respectively. The simulation results shown in Figure 4.4.1 demonstrate the prior distributions for τ^2 and ω^2 in the form of inverse-gamma distributions with the posterior distributions provided by a Markov-Chain Monte- Carlo sampling algorithm using 100 chains each of length 10,000 and a burn-in of 1,000 samples.

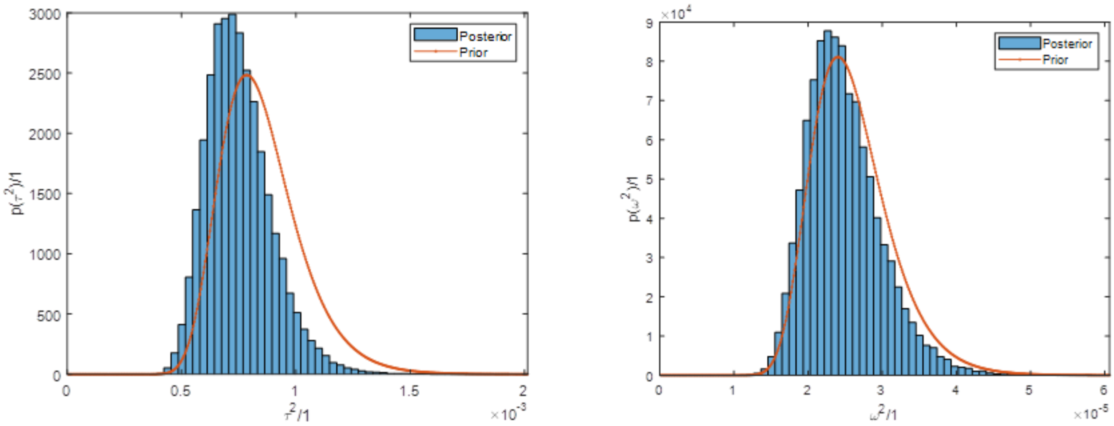

Figure 4.4.1: The prior and posterior distributions from the Bayesian analysis of data within a time window of length $N = 15$*. (Left): Estimated probability density of* τ^2*. (Right): Estimated probability density of* ω^2*.*

Another important aspect in sensor networks is measurement coverage and redundancy evaluation. One aspect of measurement coverage is the amount of metrological redundancy in the industrial sensor network. Assessing the amount of redundancy can be done based on physical reasoning or can be data driven, and different outcomes are possible.

Note that there are different ways of deriving the value of the measurand from the set of measured sensor values, quantified by a notion of gradual uncertainty increase when sensors fail or are removed. In the project, the following concepts and evaluation criterions were proposed by partners NPL and VSL (i) the concept of sensor relevance and (ii) the definition of metrological network redundancy.

Sensor relevance states how much the quantity X_i measured by sensor i contributes to knowing the value and uncertainty of the measurand Y. Possible metrics for quantifying the sensor relevance are:

- Rel-SensCoef(X_i, Y): calculate the sensitivity coefficient $c_i = dy/dx_i$ and evaluate $|c_i|u(x_i)/u(y_i)$.
- Rel-PearCor(X_i, Y): calculate the Pearson correlation coefficient between known values of Y and corresponding measurement data X_i of sensor i.

Metrological network redundancy can be derived in multiple, independent (or rather not fully correlated) ways from the sensor data and can be quantified by the following metrics:

- Red-Excess (X, Y, u): Number of sensors present in the network in excess of the minimum number necessary to determine values of the measurand with at most uncertainty u. Here, if Red-Excess $(X, Y, u) = m$, then any *m* arbitrary sensors can be removed from *X*, and it is still possible to determine Y, with $u(Y) \leq u$.
- The metric Redunc(X, Y, m) denotes the maximum uncertainty increase in *Y* where *m* arbitrary sensors are removed from the set of sensors given by *X*, compared to the case of using all sensors.

The above concepts were applied in both the ZEMA and the STRATH testbed. In the STRATH testbed, the metric Rel-PearCor was used. With the 99 sensors in the STRATH testbed, the project found it to be beneficial to quantify the relevance of each sensor for the part dimensions using the Pearson correlation coefficient and a particular feature of the data. In the ZEMA testbed the Red-Excess metric showed that in principle 1 sensor would suffice to estimate the measurand (expected remaining lifetime), but that uncertainty increases significantly when using less than 7 sensors. The Redunc metric applied to the ZEMA testbed further confirmed this finding.

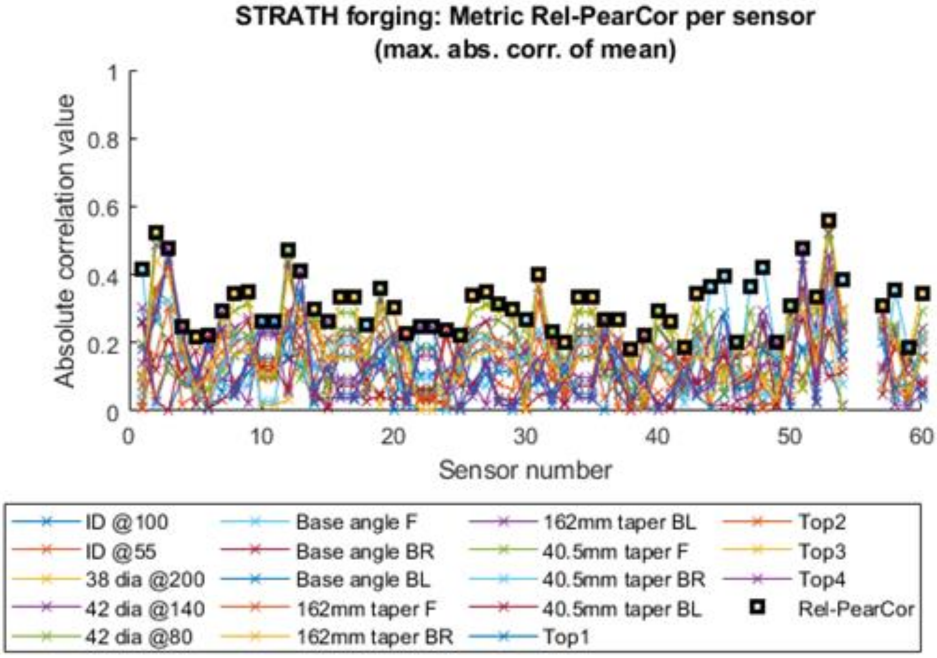

Figure 4.4.2: Metric Rel-PearCor applied to sensors in the STRATH testbed.

To investigate the issue of varying sensor quality within an industrial sensor network, the project considered a Relevance Vector Machine (RVM) and its extension to Relevant Group Selector (RGS). The RVM and RGS were used to select relevant sensors and the relevant features. The RVM and RGS algorithms are hierarchical Bayesian formulations that allow grouping (features from different sensor will correspond to a different group) and to simultaneously perform feature selection within groups in order to reduce over-fitting of data. To account for the uncertainty from varying sensor quality within a network, the feature vector $\phi(X_i)$ extracted from the sensor input X_i is modelled as $\phi(X_i) \sim N_d(\phi(X_i), \Sigma_\phi)$, where Σ_ϕ is a diagonal matrix with the diagonal elements representing the level of uncertainty.

ML methods are commonly applied in the FoF and similar environments. In the project, an existing automated ML toolbox was extended to consider measurement uncertainty. This extended, automated ML toolbox consisted of (i) feature extraction, (ii) feature selection and (iii) classification as shown in Figure 4.4.3.

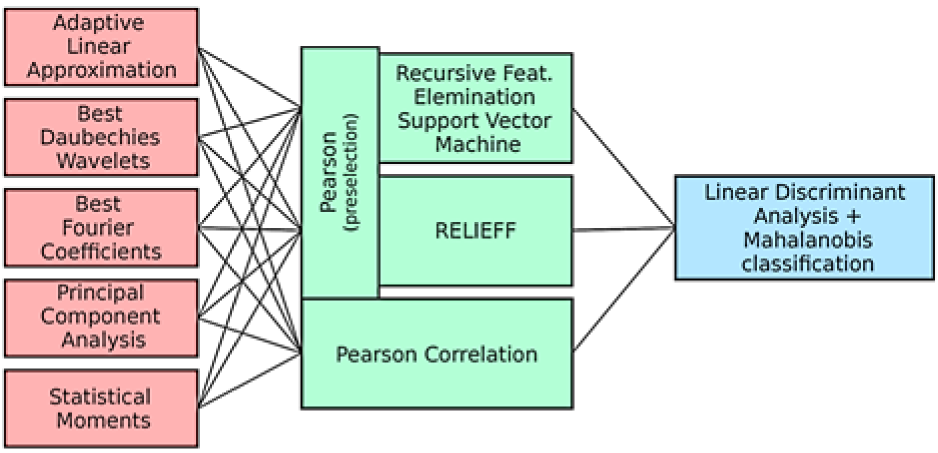

Figure 4.4.3: Toolbox scheme with feature extraction (red), selection (green) and classification (blue).

The first step in the extension of the automated ML toolbox was the feature extraction. This consists of five complementary methods that extract features from time, frequency and the time-frequency domain. Four of the five feature extraction methods were extended with uncertainty propagation according to the *GUM*: the exception being the Principal Component Analysis (PCA). For example, the uncertainty propagation through the Adaptive Linear Approximation (ALA) is shown in Figure 4.4.4 where a Naphthalene concentration measurement *X* together with its ALA reconstruction. *X'* is calculated by using 18 features – nine mean values and nine slopes. Calculating the sensitivity coefficients for mean value and slope of every linear section leads to the definition of the sensitivity matrix as a block matrix.

$$J_{\overline{y},b} = (\mathbf{C}, \mathbf{D})^T \quad \in \; \mathbb{R}^{2l \times n}$$

where **C** and **D** denote the matrix with the sensitivity coefficients for the mean values and the slopes, respectively. This results in the following uncertainty matrix for the ALA features:

$$U_F = J_{\overline{y},b} \cdot U_X \cdot J_{\overline{y},b}^T = \begin{pmatrix} \boldsymbol{CU_X C^T} & \boldsymbol{CU_X D^T} \\ (\boldsymbol{CU_X D^T})^{\boldsymbol{T}} & \boldsymbol{DU_X D^T} \end{pmatrix}$$

where $\mathbf{U_X}$ denotes the covariance matrix of the sensors' signals. The root of the diagonal entries of $\mathbf{U_F}$ are the values, that are shown as error bars in Figure 4.4.5.

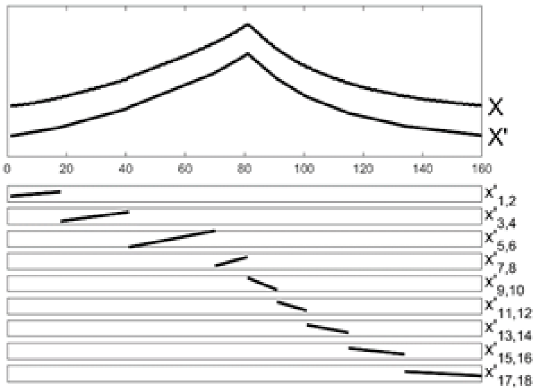

Figure 4.4.4: X is the electric conductance of a Naphthalene concentration measurement. X' (only shifted for better visibility) denotes the reconstruction with Adaptive Linear Approximation (ALA) with nine linear sections and 18 features (mean values and slopes).

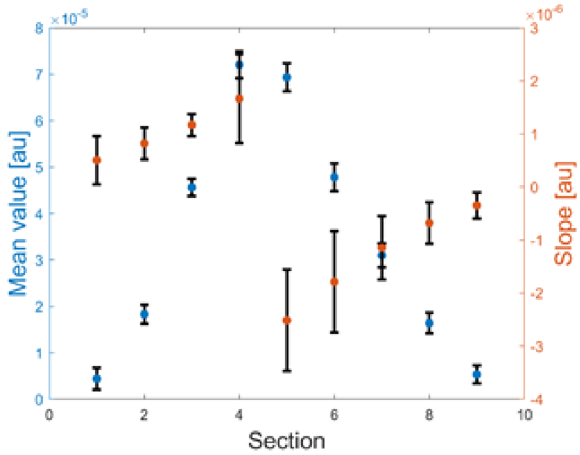

Figure 4.4.5: Features extracted with ALA mean values (blue) and slopes (red) for the Naphthalene concentration measurement with their uncertainty values shown as error bars.

The second step in the extension of the automated ML toolbox was the feature selection. The Pearson correlation was extended to a weighted Pearson correlation algorithm where the uncertainty values of the features are used as weights. Recursive Feature Elimination Support Vector Machine (RFESVM) and ReliefF were extended with uncertainty propagation according to the GUM and, two further filter methods with uncertainties as weights were implemented – a weighted Spearman correlation and χ^2.

The classification was the last step in the extension of the automated ML toolbox. A Linear Discriminant Analysis (LDA) was performed to reduce the dimensionality, and the uncertainty propagation was carried out according to the Supplement 2 of the GUM. In Figure 4.4.6, an LDA plot together with test data and its uncertainty values are shown. Figure 4.4.7 shows a corresponding prediction plot.

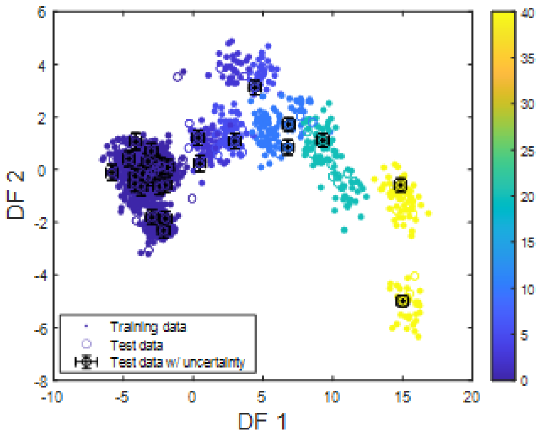

Figure 4.4.6: LDA with training data and test data with uncertainty values.

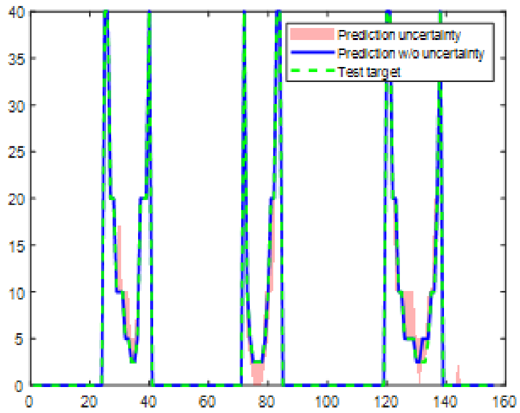

Figure 4.4.7: Prediction without and with uncertainty consideration.

Sensors and their networks are formed in all sorts of environments industrial applications. Therefore, data analysis methods for FoF environments must be extremely flexible and versatile, due to frequent changes in the sensor network topology, the used sensors and data analysis aims. A flexible framework for the implementation of the corresponding data analysis is needed and an excellent way to represent such networks is a multi-agent system (MAS), where independent software modules (agents) encapsulate properties and functionalities. In the project, the framework agentMet4FoF was developed as an interactive and flexible open-source implementation of such a MAS. The software engineering process was driven by several industry-oriented use cases from partners ZEMA and UCAM; so as to increase the end user applicability of the work. This led to a framework agentMet4FoF that is specialised in representing heterogeneous sensor networks.

The project's work focussed on supporting metrological treatment of sensor streaming data; included the consideration of measurement uncertainties during data analysis and processing as well as propagating the metadata alongside the data itself. Hence, the project's development considered how metrological input can be incorporated into an agent-based framework for addressing the uncertainty of ML in future manufacturing.

Some notable features of the framework agentMet4FoF are:

- Modular agent classes for metrological data streams and analytics
- A built-in buffering mechanism to decouple transmission, processing and visualisation of data
- Easy connection among software agents to send and receive data
- Backends for *Osbrain* for simulating as well as handling real distributed systems running Python connected via a TCP network, and
- *Mesa* for local simulations of distributed systems, debugging and more high-performance execution

A significant benefit of the framework agentMet4FoF for end users is an interactive and customisable dashboard to (i) visualise and change agent-network topologies, (ii) visualise groups of cooperative agents as coalitions, (iii) view and change the agents' parameters, and (iv) view the agents' outputs, see Figure 4.4.8.

To demonstrate the suitability of the framework agentMet4FoF for use in industry-like environments, real sensor data was processed by partners UCAM, NPL, VSL, LNE and PTB in several use cases provided by partners ZEMA and STRATH.

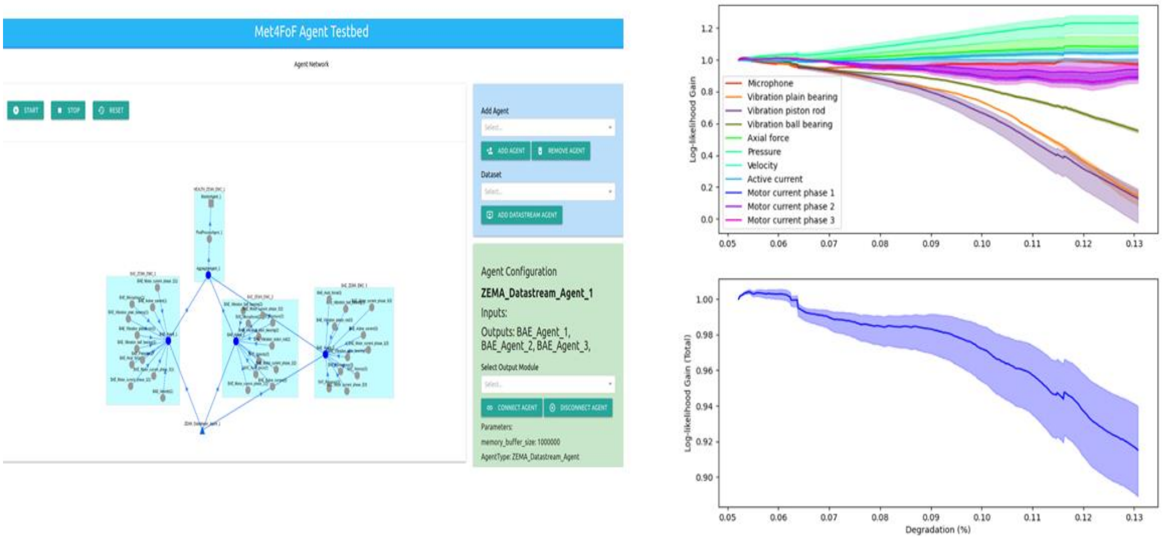

Figure 4.4.8 (left) Dashboard of agentMet4FoF with groups of sensors (as coalitions), connections between agents and controls to change agents' parameters. (right) Example output data streams from agentMet4FoF.

A connection was also successfully established with the virtual twin of the SmartUp unit (see Objective 5), in order to further process and visualise the generated data. Real recorded sensor data was sent to the driver of the SmartUp unit as if recorded in real time and from there the data was transferred to an agent of agentMet4FoF. The network connection consists of an ordinary TCP/IP connection as required.

All software from the project was provided as open source on GitHub. For the framework agentMet4FoF documented examples, screencasts and use cases are available on the project's website.

Summary

In summary the project achieved Objective 4; to develop and assess data aggregation methods for industrial sensor networks based on ML and efficient software architectures, addressing synchronisation of measurements, making use of redundancies of measurements, taking into account uncertainty from calibration and network communication issues, including strategies for balancing cost versus uncertainty and explore methods to identify the measurement coverage and accuracy required for process output targets.

The project did this by investigating and developing generic mathematical models and uncertainty evaluation approaches for industrial sensor networks based on ML. The project also derived several approaches for the assessment and exploitation of redundancy in sensor networks and applied the approaches to testbed data sets from Objectives 1 & 2. The developed methods were implemented in the project's ABF software library in order to allow flexible use of a variety of sensor networks. The project's ABF contains a comprehensive set of tools for simulation and analysis of heterogeneous sensor networks.

The project results showed that, in principle, the integration of measurement uncertainty in the factory of the future is possible. For the ZEMA testbed uncertainty propagation for the feature extraction as the first step of ML was developed and implemented in the extended PyDynamic library (Objective 2). Novel Bayesian feature selection methods as well as uncertainty propagation for the existing methods at the ZEMA testbed were also successfully tested. Finally, classification – the last step of ML at the ZEMA testbed – was extended with an uncertainty propagation. Hence, for the whole data lifetime at the ZEMA testbed uncertainties associated with the data can be made available.

The same feature extraction methods with uncertainty propagation were applied to the STRATH testbed data. For the subsequent ML regression, a variety of Bayes ML methods were investigated. However, more research is needed for the STRATH testbed to identify a suitable sensor setup and ML pipeline combination in order to achieve a sufficient regression result.

4.5 To improve existing industry-like testbeds for sensor networks in manufacturing environments towards the implementation of a metrological quality infrastructure and to facilitate the take up of the project outputs by the stakeholders, especially the manufacturing industry

As part of Objective 5, the project used 3 different testbeds with different types of sensor networks:

3. The SPEA ATE for MEMS temperature sensor testing uses a network of reference temperature sensors, where the optimal implementation and usage of this sensor network determines the efficiency and reliability of the ATE results.
4. The STRATH testbed considers radial forging using pre-heated metallic material and vibrating hammers. The testbed will be used to try and optimise the heating and forming process based on a range of different sensors in order to improve the production output quality.
5. The ZEMA testbed uses a range of sensors measuring different quantities for end-of-line tests and condition monitoring methods for electromagnetic cylinders.

ZEMA testbed

The ZEMA testbed for lifetime tests of electromechanical cylinders (EMCs) was developed in a former project for condition monitoring, lifetime prognoses and end-of-line tests of EMCs with a spindle drive. At the ZEMA testbed long-term, high load and speed driving tests are carried out until a position error of the EMC occurs. The device under test is an EMC, widely used in applications that require a high repetition accuracy and high forces. The spindle drive as a passive mechanical component of an EMC which converts the rotary movement of the driving servo motor into linear stroke of the piston rod. The ZEMA testbed is equipped with eleven different sensors at multiple positions that provide data which is sampled equidistantly:

- three accelerometers with 100 kHz sampling rate attached at the plain and the ball bearing as well as at the piston rod,
- one microphone with a sampling rate of 100 kHz,
- three electrical motor current sensors with 1 MHz sampling rate each, and
- four process sensors (active current of the EMC motor, axial force, pneumatic pressure, and velocity) with 10 kHz sampling rate each

A PXI system is used to control the cylinder movement and data acquisition for the ZEMA testbed (i.e. ZEMA DAQ). The PXI system reads the measured values of the already existing analog sensors (e.g. a Kistler 8712A5M1) and stores the measured values of 50 cycles in an HDF5 file.

To test the project’s DAU developed in Objective 1, three digital sensors connected to the DAU were added to the ZEMA set-up by mounting a carrier clasp to the tested cylinder. In this way, the original ZEMA DAQ remained unchanged, and the additional digital sensors were used the DAU. In the data processing step, the data from the ZEMA DAQ and the project’s DAU were combined. The three additional sensors measured a total of 16 variables and were:

1. TDK InvenSense MPU9250 (XYZ acceleration, XYZ angular velocity, XYZ magnetic flux density and temperature; data rate 1 kHz)
2. Bosch BMA280 (XYZ acceleration, temperature; data rate 2 kHz)
3. TE connectivity MS5837-02BA (temperature and air pressure; data rate 1 Hz)

The three additional sensors were attached to a sensor (carrier) clasp using epoxy resin, the entire sensor (carrier) clasp was then calibrated on PTB’s 3-component vibration acceleration device. A picture of the carrier clasp is shown in Figure 4.5.1. The SmartUp unit shown in Figure 4.5.2 complements the DAU with the communication of machine-readable information on the sensors as part of the data streams as described above.

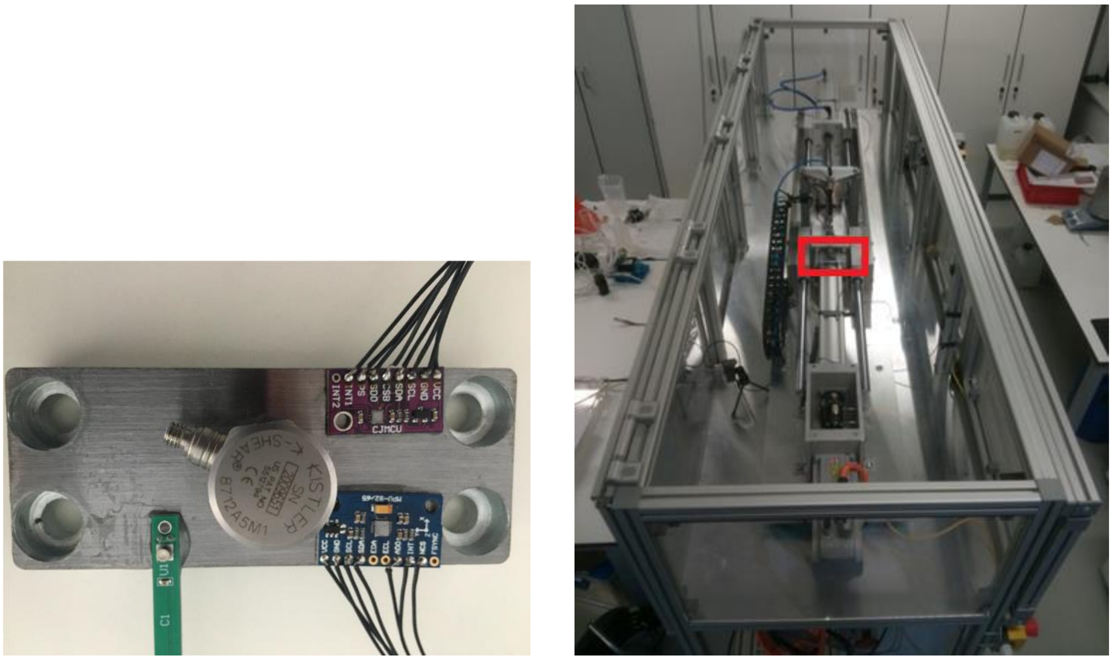

Figure 4.5.1 Photograph of the carrier clasp for mounting of three digital and sensors (and one analog accelerometer in the centre) left and of the ZEMA-teststand with the mounting location of the carrier clasp marked be the red frame, on the right.

The SmartUp unit was equipped with the Bosch BMA280 (purple), the TDK InvenSense MPU9250 (blue), and the TE Connectivity MS5837 (green) sensors as it is shown in Figure 4.5.3. The sensors of the SmartUp unit were placed on the same sensor holder as the acceleration sensor Kistler 8712A5M1 (grey) on the ZEMA testbed. In Figure 4.5.4 the installation at the ZEMA testbed is shown.

Figure 4.5.2: SmartUp Unit developed in the project Met4FoF.

Figure 4.5.3: Sensor holder with the three sensors of the SmartUp unit and one sensor of the ZEMA DAQ (in the middle of the holder).

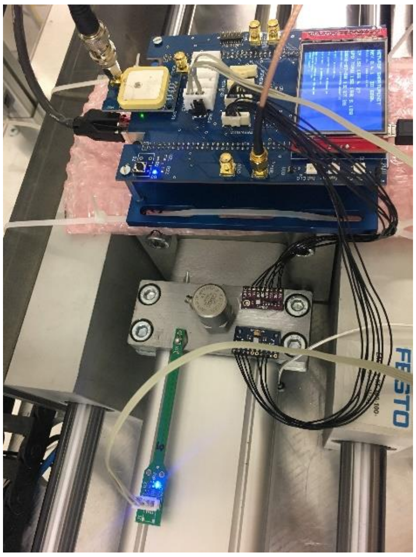

Figure 4.5.4: Installation of the SmartUp Unit and their sensors at the ZEMA testbed.

Figure 4.5.5 shows the sensors of the SmartUp unit (purple dots) and the sensors of the ZEMA DAQ unit (red dots) and their location with respect to the EMC. The green triangle symbolises the trigger signal of the ZEMA testbed which was recorded by the SmartUp unit and hence was the link between both units. The MS5837 sensor is missing in this figure as this sensor had a defect after installation at the ZEMA testbed.

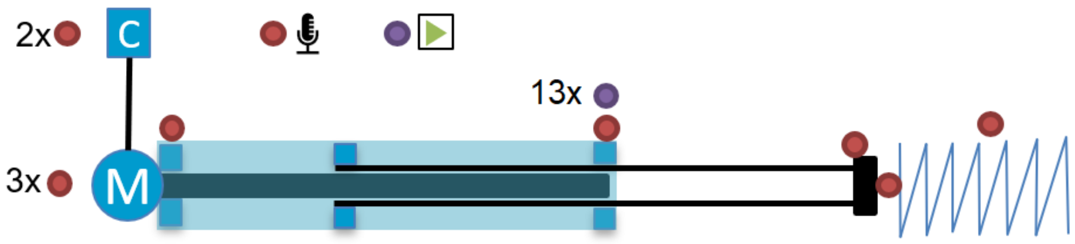

Figure 4.5.5: Sensors of the ZEMA DAQ unit (red) and the SmartUp Unit (purple).

The goal of installing the SmartUp unit was to replace the high cost ZEMA DAQ unit with a more cost-effective system whilst still being able to obtain the same quality of ML results for the lifetime prediction of an EMC.

The ZEMA DAQ unit records the data cycle-wise, meaning that after receiving a trigger signal denoting the beginning of a working cycle, a cycle of exactly 2.8 s is recorded and then no data is gathered until the next trigger signal for the next working cycle is recognised. In contrast, the SmartUp unit records data continuously but therefore non-equidistantly and the data is GPS timestamped meaning that there is no interruption between two working cycles.

To be able to use both datasets with the automated ML toolbox, extended with measurement uncertainty evaluation (Objective 4), as one complete dataset, it was important to extract cycles from the continuous signal to get a cycle-centric representation of the SmartUp unit data. Hence, the only link between both systems was the trigger signal of the ZEMA DAQ unit which was GPS timestamped by the SmartUp unit.

Using the GPS timestamped ZEMA testbed trigger signal, the SmartUp unit data set was divided into cycles of approx. 2.9 s. Between each working cycle of the ZEMA testbed, there was a small unspecific waiting time when the ZEMA DAQ unit did not record data, but during which the continuous data stream of the SmartUp unit is still ongoing.

For the ML, only 1 s, beginning after 1.7 s of the working cycle was used. This 1 s could be easily extracted from the SmartUp unit data and therefore, the data from the SmartUp unit and the ZEMA DAQ unit was aligned to the same time axis. Hence, it is necessary to interpolate the SmartUp unit data at the same equidistant ZEMA DAQ specific time values.

Figure 4.5.6 shows the continuous data stream from the SmartUp unit for the MPU9250 acceleration in z- direction together with the trigger signal at the top. As an example, the extracted 151 st cycle is shown in the middle and its cubic interpolation at the bottom. Using the extended, automated ML toolbox produced nearly the same classification results for cubic, previous, and linear interpolated data. But for the next and nearest interpolation of the SmartUp unit data, the results of the classification were worse.

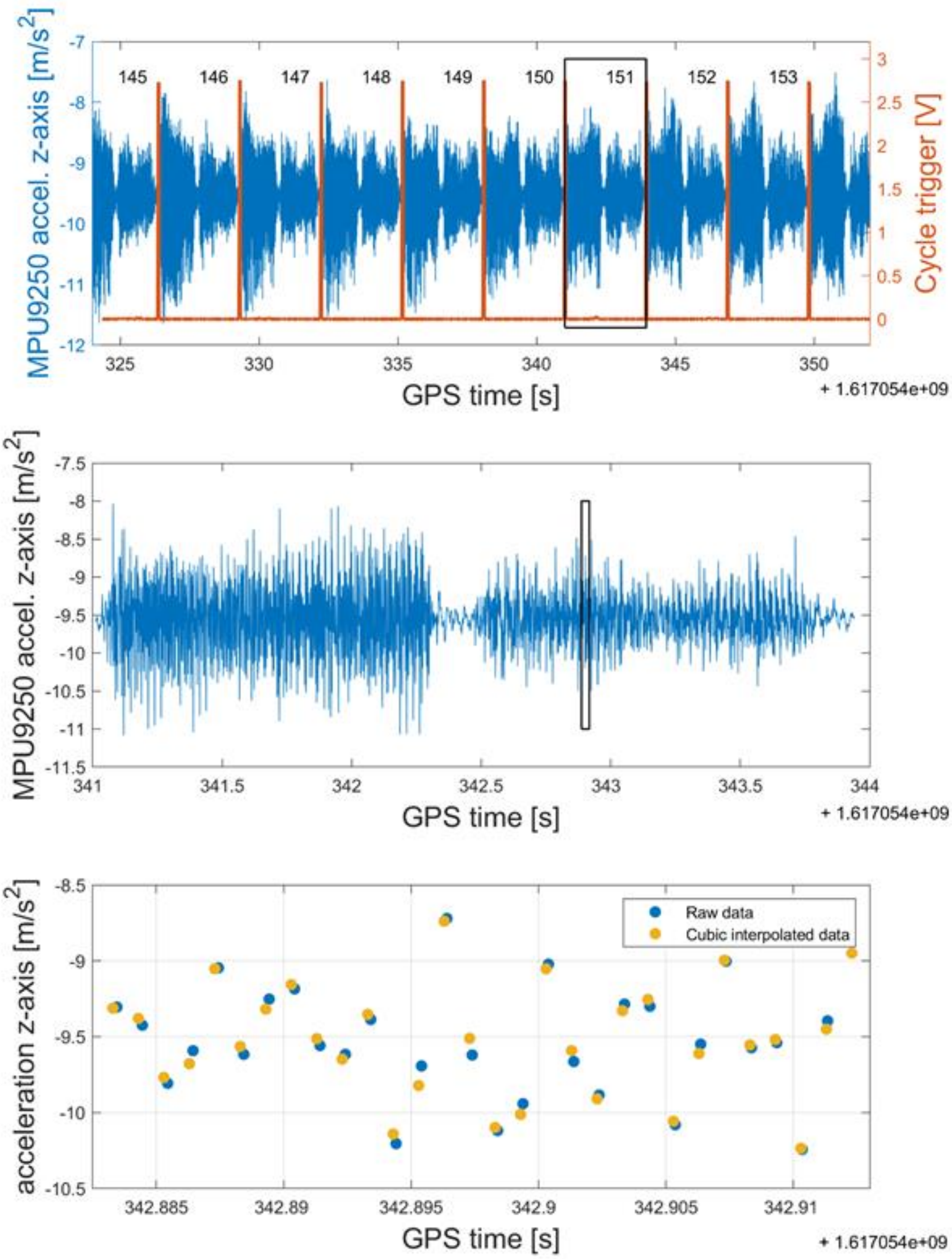

Figure 4.5.6: Top: Continuous data stream of the acceleration in z-direction (MPU9250). Middle: 151 st cycle of the lifetime test. Bottom: Interpolation of the 151 st cycle at the equidistant ZEMA DAQ time axis points.

To show the prediction quality, the ML target lifetime was overlayed with the ML prediction lifetime for cycles for the duration of the experiment. Data that was used for ML training, was not used for testing and vice-versa, which meant that the results were cross validated.

The ML prediction was robust for the high cost ZEMA DAQ and testbed measurement system with a target resolution of 1 %. As can be seen in Figure 4.5.7, the ML prediction with data from the low-cost DAU/Smart-Up unit system was less accurate for the remaining lifetime values between 50 % to 90 % than the high-cost set-up, but comparably of the same quality for values below 50 % lifetime.

However, if the requirement for the resolution of the target classes was reduced from 1 % (3.7 hr lifetime) to 10 % (37 hr lifetime) increments, it was still possible to achieve useable and insightful results from the lower cost Smart-Up unit (see Figure 4.5.7). Therefore, depending on the application, the lower cost SmartUp unit may be detailed enough to be used as a replacement for the high cost ZEMA measurement system.

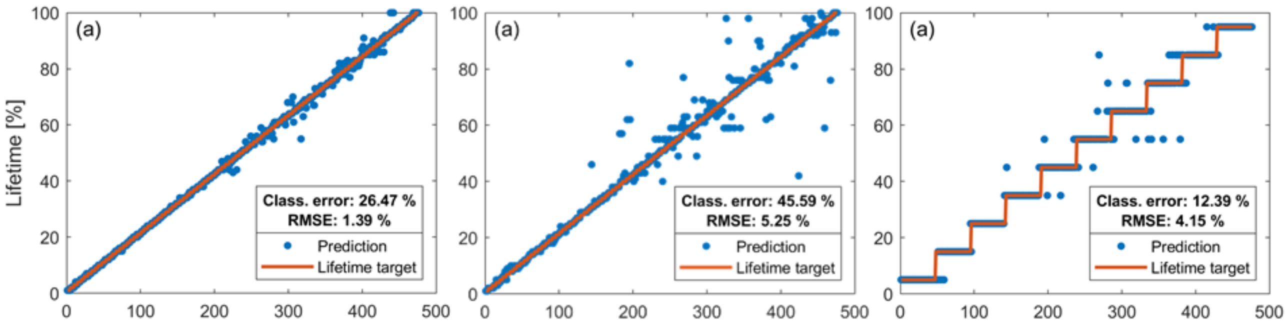

Figure 4.5.7: Left: High cost ZEMA testbed measurement system with 1 % target steps. Middle: Lower cost Smart-Up unit measurement system with 1 % target steps. Right: Lower cost SmartUp unit measurement system with 10 % target steps.

To promote the up-take and further use of the project's results with the extended ZEMA testbed, partner ZEMA published several data sets on the repository at Zenodo. RMG1 and RMG2 developed and published tutorials to illustrate the data and the application of ML methods.

Partner ITRI also investigated the application of a model-based approach for the lifetime estimation, instead of a data-driven ML method. The analysis showed that in principle such an approach was application, but would require further adjustments in the measurement system.

STRATH testbed

The STRATH testbed is a General Forging Machine (GFM) Radial Forge (SKK10-R). Radial forging is widely used in sectors such as aerospace, rail, and medical manufacturing. The STRATH testbed forge is a four-hammer machine, the hammers being concave to match product specification with a maximum forging force of 1,500 kN and hammer speed of 1,200 strokes/min. The part rotational speed is approximately 44 rpm within a programmable range of 40-70 rpm. The STRATH testbed is equipped with approx 100 sensors monitoring the forging process at a sampling interval of 1 ms. The range of sensors are segmented both to process output and for machine control. The four hammers are aggregated into two sensor diagnostics (left and right) that record hammer force, position and speed with pyrometers to record temperature at various locations e.g. in the forging box.

The table below shows key characteristics of the STRATH GFM SKK10-R Radial Forge

Key Features	
Max. forging force	1,500 kN
Max starting diameter blank	125 mm
Min diameter	20 mm
Min length of blank	70 mm
Max length of forged part	950 mm
Max workpiece weight	25-30 kg

The STRATH radial forge is capable of processing parts either at room temperature (cold forging) or elevated temperatures up to 1200 °C (hot forging). For many applications temperatures of approx 800°C is typical. Heating is provided by either a furnace or 1 of 2 induction coils located within the forging cell. The forging cell is fully automated as parts are transferred between stations using a robotic arm. A typical cycle is:

1. manually place the preform into a loading tray
2. the robot arm picks up the part and places it into a holder in an induction coil
3. the part is heated to the desired temperature in the induction coil
4. the robot arm picks up the part and places it into the chuck jaws
5. the chuck jaws close and securely hold the part
6. the part is moved into the forging box and forged to the desired geometry
7. on completion of the forging cycle the robot arm removes the part from the chuck jaws and places the part onto an unload tray

Radial forging is a popular alternative to conventional machining for the following reasons: the first, and possibly most important, is material usage. The forging process is regarded as “net shape” or “near net shape” and very little material is wasted. The processing time in radial forging is also a major advantage compared with conventional machining, e.g., a typical forging cycle is measure in minutes compared to hours for conventional machining.

In the STRATH testbed, ML is used to derive predictions about the dimensional accuracy of the parts produced from data generated during the forging process. The DAU (from Objective 1) and two sensors (MPU9250 and BMA280) were installed as additional sensors in the STRATH testbed facility. The two sensors were attached to the massive steel housing of the forge near the forging hammers by magnets bonded to the circuit boards. The GPS time stamped data from the digital sensors was stored as CSV files on a PC and subsequently converted to HDF5 files.

In the STRATH testbed, data-driven ML methods were used to predict the part dimensions measured by a coordinate measuring machine (CMM). There were 99 sensors in the STRATH testbed and three datasets were obtained, corresponding to a first datasets of a validation run with no changes to machine settings and two (second and third) datasets from designed experiments.

In the first dataset, 81 parts were forged. It takes roughly 3 minutes to forge each part and so, with a sampling interval of 10 ms, a time series of roughly 18,000 samples was provided by each sensor and for each forged part or experiment.

The second and third datasets contain experimental data for 50 and 46 parts, respectively, with three controlled variations, namely of billet temperature at the entry to the forge, chuck head axial feed speed and hammer radial feed speed. The second and third datasets were of moderate size for the ML tasks and high accuracy in prediction was expected. The aim of applying such controlled variations was to mimic a larger range of input conditions in the STRATH testbed.

Figure 4.5.8: (left) The radial forge housed at STRATH, UK). (right) Part before (preform) and after forging.

Following the installation of the DAU (Objective 1), a problem was observed with the synchronisation between the DAU and the other embedded sensors in the STRATH testbed. Indeed, concerns about synchronisation arose in the early stage of segmentation in the data processing pipeline.

The whole forging process for the STRATH testbed was segmented into three working phases, (i) heating, (ii) pick-up and (iii) forging. To automate the segmentation process, sensor signals were used to mark the start and end of each of the three-working phase. The on/off state of power for the induction coil was used to signal the start and the end of the heating phase. The forging phase is where the measured forging force is larger than zero. The pick-up phase is then the time between end of heating and start of forging phase.

For the forging phase, several sensor signals were compared, such as the sensor for force applied to the part, the position sensors which recording the nominal and actual positions of the chuck head axes, the speed of the chuck head in certain axis and the pyrometer measuring the temperature of the part in and out of the forging box. Although all these sensor indicators are valid when combined with logical knowledge of the forging process, analysis showed the presence of uncertainty for determining the forging duration. Therefore, the position sensors were used for segmentation as the result it was shown to provide the least uncertainty.

To promote the up-take and further use of the project's results with the extended STRATH testbed, STRATH published several data sets on the repository at Zenodo. RMG1 and RMG2 developed and published tutorials to illustrate the data and the application of ML methods.

SPEA testbed

The SPEA testbed was used as part of Objective 3 to develop an in-situ calibration framework for MEMS sensors measuring ambient temperature and for their integration into an industrial sensor network with metrological infrastructure that supports metrology enabled ATE. Due to current industrial developments in the growing MEMS market, SPEA decided not to use a minimalist approach and incrementally improve its ATE for MEMS sensors testing. Instead SPEA decided to develop a new and improved thermal chuck that could overcome the intrinsic limits of their original thermal chuck as well as addressing the requirements for critical testing of novel and advanced MEMS sensors.

The new and improved thermal chuck (part of SPEA's ATE) was designed and manufactured with additive manufacturing technology. This technology allowed more effective design and realisation of the cooling channels, resulting in more efficient and uniform thermal conditioning for the thermal chuck. The new and improved thermal chuck can test a batch of 196 sensors at time and includes a board with 64 digital reference temperature sensors for temperature measurement and control. This digital reference temperature sensor network/board forms an additional embedded metrology layer compared to the original thermal chuck design and can be considered an "on-board" reference fixture.

Id_Sensors Row	Site1	Site2	Site3	Site4	Site5	Site6	Site7	Site8
8_TMP	4,95	4,91	5,02	5,05	5,06	4,98	4,88	4,92
7_TMP	5,01	4,98	5,03	5,09	5,07	4,98	4,92	5,02
6_TMP	5,03	5,01	5,04	5,05	5,09	5	4,99	5,09
5_TMP	5,06	5	4,98	5,03	5,02	5,02	4,97	5,14
4_TMP	5	4,97	4,92	4,96	4,97	4,94	4,94	5,2
3_TMP	4,93	4,9	4,88	4,91	4,91	4,84	4,88	4,97
2_TMP	4,88	4,9	4,9	4,91	4,91	4,85	4,88	5,02
1_TMP	5,01	4,92	4,91	4,96	4,93	4,92	4,91	5

Id_Sensors Row	Site1	Site2	Site3	Site4	Site5	Site6	Site7	Site8
8_TMP	35,02	34,97	35,01	34,99	34,98	34,98	34,97	35,03
7_TMP	35,01	35,02	35,02	35,02	35,02	34,99	34,98	35,02
6_TMP	35,01	34,99	35,03	35	35,02	34,98	34,96	35,05
5_TMP	34,98	34,99	34,98	35,02	34,99	35	34,97	35,05
4_TMP	35,01	35,01	34,96	35	35,01	35	34,98	34,97
3_TMP	34,98	35,01	35	35,02	35	34,97	35,01	35,05
2_TMP	34,98	35,03	35	34,99	35,01	34,99	35	35,01
1_TMP	35,02	35,02	34,96	35,01	35	34,98	35,02	34,99

Figure 4.5.9: The experimental data from the improved thermal chuck and sensor network showed significantly improved performance with respect to the original thermal chuck as SPEA and used for ATE temperature testing.

INRIM and SPEA developed a novel calibration tool; a waterproof sensor capsule concept (see Figure 4.5.10) which was used for the calibration of SPEA's ATE 64 digital reference temperature sensor board against a reference platinum thermometer traceable to ITS-90.

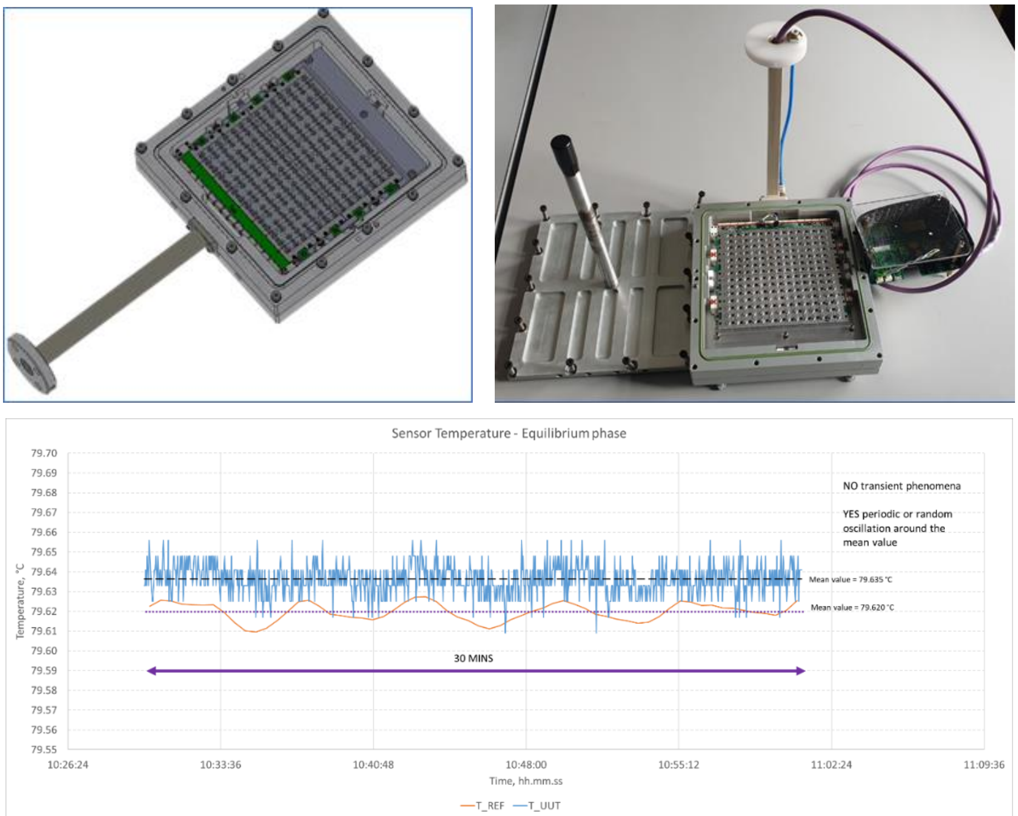

Figure 4.5.10: the waterproof sensor capsule concept used for laboratory calibration of the ATE reference sensors board. Comparison between the reference platinum thermometer reading and a digital temperature sensor reading was performed during a thermal equilibrium phase.

The SPEA testbed was also used as part of the project's successful collaboration with EMPIR project 17IND02 SmartCom. The collaboration enabled the implementation of a so-called "one-touch calibration" feature. A special function which used the developed digital calibration certificate (DCC) from project 17IND02 with a sensor network to automatically apply calibration corrections to digital reference sensors (without human intervention).

The "one-touch calibration" was made available through a calibration provider, acting as a DCC issuer. The DCC issuer (INRIM) after sensor calibration, issued the DCCs according to a standardised XML code developed in project 17IND02 SmartCom and made them available on a cloud service accessed by the DCC User (SPEA). Once the DCC was available on a cloud service, SPEA launched the "one-touch calibration" feature using its testbed and ATE system.

This joint demonstration between both projects showed how the DCC and calibration corrections developed in 17IND02 could be applied to an instrument/sensor in an industrial environment as part of this project. Thus, demonstrating their future use in IoT sensors networks, the digital transformation of industry and the FoF.

<u>Summary</u>

In summary the project achieved Objective 5; to improve existing industry-like testbeds for sensor networks in manufacturing environments towards the implementation of a metrological quality infrastructure and to facilitate the take up of the project outputs by the stakeholders, especially the manufacturing industry. The project achieved this by integrating the DAU (Objective 1) and Smart-Up unit (Objective 2) together with the mathematical methods (Objective 4) into the testbeds provided by STRATH and ZEMA, and by further developing the testbed provided by SPEA with the outcomes from Objective 3.

The project equipped the testbed at ZEMA with digital-only sensors for acceleration and temperature with the Smart-up Unit. The digital sensors were calibrated at PTB and INRIM with support from SPEA, and they provided their data via the µC board (from Objective 1) to the data acquisition system (of ZEMA). A similar installation of calibrated, digital-only sensors for acceleration and temperature with a Smart-up Unit was also carried out for the testbed at STRATH. Both testbeds are now able to produce data sets from digital sensors together with reliable uncertainty statements. The project's GitHub repository also contains examples on how to use the ABF and methods from the extended PyDynamic library for the analysis of this data.

The project developed and validated the first ever ATE at the SPEA testbed for traceable in-situ calibration of MEMS temperature sensors using an optimised network of reference sensors in an automated test environment. As part of this work a so-called reference fixture, which contains several reference sensors, was calibrated in a laboratory traceable to the SI. This fixture was then used to provide traceable batch calibration of MEMS sensors, by mounting the fixture on the ATE machine. The setup was then validated and further optimised based on simulation analyses.

Moreover, the project made available selected data sets generated by these testbeds in order to support the development of ML in metrology.

5 Impact

This project had a joint stakeholder advisory board (SAB) together with the project 17IND02 SmartCom. The SAB included 10 partners from industry, academia and standardisation, such as INESC-MN (a Portuguese public research organisation in the field of microsystems and nanotechnology), MESAP (an Italian Innovation Cluster with 267 Members, active in manufacturing, automotive and aerospace), SPEKTRA (a German company that designs, manufactures and sells calibration systems as well as measuring and test equipment for vibration sensors), TNO (the Netherlands Organisation for Applied Scientific Research), the University of Sarajevo and VDI/VDE (VDI = Association of German Engineers and VDE = Association for Electrical, Electronic and Information Technologies). Input from the SAB has helped to decide the most suitable sensors and interfaces for the project and helped to ensure that the project's outputs are relevant for end users. Together with the SAB member TNO, the project presented a joint publication at the 2019 IMEKO TC10 conference, about the implementation of continuous quality concepts in research.

To increase the uptake of the mathematical methods developed in the project, a public GitHub repository was launched (https://github.com/Met4FoF). This repository connects the software developments from the project and uses modern software quality principles with CI technologies. All partners involved in developing software code regularly added to this repository, and it was recently presented at "deRSE19 - Conference for Research Software Engineers in Germany" in June 2019 in order to promote its uptake by end users.

Impact on industrial and other user communities

This project's outcomes will impact industries that use sensor networks, in particular those using digital sensors for monitoring mechanical quantities such as acceleration, force and pressure. They will support the provision of sensor manufacturers with the traceability needed for sustainable and reliable smart factories and enable them to meet the increasing demand for the provision of measurement capabilities with internal pre-processing. The "Smart Traceability" sensors (Objective 2) developed in this project are also applicable to other sensor types and data post-processing tasks and can be used to support the use of calibration information and measurement uncertainty evaluation (Objective 4) into the post-processing data element of a "Smart Sensor". To support this impact, all software written by the project for the Smart-up Unit (Objective 2) has been made available as open source.

Due to their cost-efficiency and versatility, MEMS are increasingly used in the IIoT, and the in-situ calibration framework for MEMS temperature sensors developed in this project (Objectives 1 & 3) were successfully demonstrated in industrial testbeds to support industrial end-user use. The novel possibilities for using ATEs for batch calibration of MEMS temperature can now be offered by partner SPEA as a commercial product. The first interested customers have already approached SPEA during the project, and more are expected to follow. Moreover, the calibration framework for temperature measurements (Objective 3) will be transferrable to humidity measurements as well as to the testing of other MEMS sensors regarding their temperature and humidity dependence. To support this work, the project's SAB included an expert in MEMS sensors; the Institute for Systems and Computer Engineering, Technology and Science -Microsystems and Nanotechnology (INESC-MN).

The large amounts of data that are gathered in inter-connected manufacturing environments can only be analysed usefully by automated application of ML methods for feature extraction and information aggregation. However, in order to gain trust in the automated data analysis routines, data quality has to be taken into account. Therefore, the methods developed in this project (Objective 4) will support reliable uncertainty assessment together with data measurements, as well as simplified data management with in-situ sensor identification and sensor data communication. For example, the measurement data communicated from Smart-up Units to connected PCs was combined by this project with *PyDynamic* routines adapted to work in a data streaming environment (Objective 2).

With the combination of metrology for digital sensors, industrial sensor networks and the respective data analysis, the whole traceability chain can become digitally enabled. Practical demonstrations of this project's approaches were shown by their implementation in the SPEA, ZEMA and STRATH industrial testbeds. This project and the project 17IND02 SmartCom also developed a demonstrator based on the Smart-up Unit (Objective 2), the 17IND02 SmartCom digital communication guidelines and this project's data analysis methods (Objective 4). The demonstrator was an enriched data set from the ZEMA testbed, extended with the Smart-up Unit (Objective 2). Enrichment of the data set was carried out using the 17IND02 SmartCom digital communication guidelines to achieve a fully machine-readable metadata of the data set, including machine-readable representation of units of measurements.

Further to this, PTB is collaborating in two nationally funded research projects in Germany to combine metrology for sensor networks with asset administration shell approaches, standardised as “RAMI4.0”, and with quality of data semantics in industry 4.0, respectively. The nationally funded projects “AAS-based modelling for the analysis of variable CPS” (BMBF FAMOUS) and “Secure and robust calibrated measuring systems for the digital transformation” (BMWi GEMIMEG-II) will implement several developments from this project (in particular from Objective 4) in additional industrial testbeds.

Impact on the metrology and scientific communities

In many applications, use of several low-quality sensors combined with intelligent data analysis is preferred to a small number of high-quality sensors, e.g. to reduce cost or increase robustness through redundancy. The results of this project on taking into account the uncertainty associated with individual sensor’s data (Objective 4) in the data analysis will help to balance costs versus quality and increase the uptake of metrological principles in FoF networks. Moreover, the methods developed for the calibration of MEMS sensors (Objective 3) will provide new approaches for traceable in-situ calibration of low-cost sensors. To support this, the project has already successfully demonstrated the use of its Smart-up Units (Objective 2) concept as a basis for a simple implementation of MEMS sensors in the ZEMA and STRATH testbeds.

ML development relies on the availability of realistic and well-documented data. Therefore, test data sets (Objectives 1, 2 & 3) from the 3 testbeds used in this project were used for further developments for uncertainty evaluation in ML. Guidelines and training courses on this work were produced by the project to increase the application of ML in metrology by the scientific community. For example, the project’s training courses included (i) Machine learning tutorials for the ZeMA dataset (July 2019), (ii) Data analysis and machine learning for ZEMA data sets and Data analysis and machine learning for STRATH data sets (both October 2019), (iii) Machine learning workshop with ZeMA machine learning toolbox (March 2021) and ZEMA/STRATH Testbed Workshop (September 2021).

The project has also been presented to the metrology and scientific communities 26 times at conferences e.g. Congres International de Metrologie (CIM 2019), the International Conference on Machine Learning (ICML 2020), Advanced Mathematical and Computational Tools in Metrology and Testing International Conference (AMCTM 2020 & 2021), Sensor and Measurement Science International (SMSI 2021), Mathematical and Statistical Methods for Metrology (MSMM 2021), IMEKO 2021 World Congress, and the European Centre for Mathematics and Statistics in Metrology (MATHMET).

Finally, the project has produced 9 open access proceedings, contributions to books and publications in journals such as the Journal of Sensors and Sensor Systems (JSSS) and Sensors

Impact on relevant standards

Existing standards for calibration of sensors, e.g. ISO 16063 for the calibration of vibration and shock sensors, need to be revised to account for digital output data streams. Therefore, the project has promoted the results of its metrological framework for digital sensors within the standardisation community and provided input to relevant standardisation groups, such as ISO/TC 108 Mechanical vibration, shock and condition monitoring WG34 dealing with acceleration, force and pressure.

Project partners involved in relevant standardisation bodies have also presented the project’s outputs to BIPM Consultative Committee for Thermometry Task Group for Emerging Technologies (BIPM CCT TG- CTh- ET) and BIPM Consultative Committee for Acoustics, Ultrasound and Vibration (CCAUV), the NEN Committee on Interconnection of information technology equipment, DKD Technical Committee on Force and Acceleration, CEN TC 264 Air quality and IEC SC65B on Measurement and control devices.

Longer-term economic, social and environmental impacts

A recent Accenture study highlighted a potential reduction in costs and improvement in resource efficiency of up to 90 % and approx. 30 %. growth in productivity due to the future implementation of the IIoT, The outcomes from this project will support this implementation and foster the long-term development of a metrological infrastructure for the digital age by providing ready-to-use templates for the dynamic calibration of digital sensors and validated data analysis procedures for the IIoT. Moreover, sensor networks are widely used in weather prediction and for monitoring environmental conditions such as air pollution and water quality. Hence, they are subject to the same problems addressed in this project and the methods we have developed could bring long term benefits to these sectors too.

6 List of publications

1. “Primary calibration of mechanical sensors with digital output for dynamic applications” Seeger, B. and Thomas, B., Acta IMEKO 10 (2021), 177 – 184 http://dx.doi.org/10.21014/acta_imeko.v10i3.1075
2. “Influence of synchronization within a sensor network on machine learning results” Dorst, T., Robin, Y., Eichstädt, S., Schütze, A. and Schneider, T., Journal of Sensors and Sensor Systems 10 (2021), 233-245 https://doi.org/10.5194/jsss-10-233-2021
3. “E2.3 Propagation of uncertainty for an Adaptive Linear Approximation algorithm” Dorst, T. and Eichsädt, S., AMA SMSI 2020 E2 Future (2020), 366 – 367 https://doi.org/10.5162/SMSI2020/E2.3
4. “E3.4 Calibration of Digital Dynamic Pressure Sensors” Yilmaz, R., Durgut, Y. and Hamarat, A., SMSI 2020 Conference – Sensor and Measurement Science International SMSI 2020 (2020), 376-377 https://doi.org/10.5162/SMSI2020/E3.4
5. “Toward smart traceability for digital sensors and the industrial Internet of Things” Eichstädt, S., Gruber, M., Vedurmudi, A. P., Seeger, B., Bruns, Th. and Kok, G. MDPI Sensors, 21/6), 2021 https://doi.org/10.3390/s21062019
6. “D1.1 GUM2ALA – Uncertainty propagation algorithm for the Adaptive Linear Approximation according to the GUM” Dorst, T., Schneider, T., Schütze, A. and Eichstädt, S. SMSI 2021 Conference – Sensor and Measurement Science International SMSI 2021, 314-315 https://doi.org/10.5162/SMSI2021/D1.1
7. “Optimization of sensor distribution using Gaussian Processes” A. Forbes, K Jagan, J Donlevy, J Alves e Sousa, Measurement: Sensors/Acta IMEKO 18 (2021), 100128, https://doi.org/10.1016/j.measen.2021.100128
8. “Metrology for the Factory of the Future” Eichstädt, S. "Research Outreach (2021) DOI: 10.32907/RO-126-1869538673

This list is also available here: https://www.euramet.org/repository/research-publications-repository-link/

7 Contact details

Sascha Eichstädt, PTB

E-mail: sascha.eichstaedt@ptb.de