Metrology for Sensor Networks in Asia Pacific Metrology Programme's Focus Group on Digital Transformation



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### **Table of Contents**

- About APMP-DXFG
- Related work in MSL, New Zealand
- Related work in KRISS, South Korea
- Related work in NMC, Singapore

## **About APMP-DXFG**

- Established since Nov 2021
  - In response to an APMP Executive Call for a DXFG in June 2021
  - Founding Chair: Dr Blair Hall, MSL (Nov 2021 Nov 2024)
  - Current Chair: Dr Cui Shan, NMC (Nov 2024 Nov 2027)
  - 54 members from 19 economies, including 3 RMO liaisons (EURAMET, GULFMET, COOMET)
- Objectives of APMP-DXFG:
  - To acquire the latest information on DX;
  - To identify the challenges for APMP;
  - Awareness raising, knowledge transfer and stakeholder liaison;
  - Stakeholder engagement, including industry and QI bodies;
  - Maintain alignment with the BIPM and other RMOs;
  - To help developing economy members narrow the gap.
- Some members have work related to sensor networks
  - No specific task group or collaboration project in DXFG



## **Related work in MSL**

Modelling to enhance sensor networks

Dr. Blair Hall



### Modelling to enhance sensor networks

Measurement Standards Laboratory of New Zealand

Sensor networks are a multitude of tiny measuring systems

Can sensor data be made traceable?

How can raw sensor data be transformed into traceable measured values?



When sensors are manufactured, batch properties can be characterised

Also, sensor types can be modelled to explain imperfect behaviour

So, batch parameters can be attributed to individual sensors, which are modelled

Data processing can fuse raw data from multiple sensors

Mean offset, gain, etc., and sample variability (systematic effects)

Reading variability (repeatability)

 $x_i^{\text{sensor}} = Y + O_{\text{batch-mean}} + O_{\text{batch-variation}}^{\text{sensor}} + E_{\text{rep} \cdot i}^{\text{sensor}}$ 

Unique digital IDs avoid ambiguities

 Batch characteristics tend to correlate
 sensor data, but this can be accounted for and used to enhance accuracy of certain measurements For example, a lattice of temperature sensors

Each sensor measures temperature at its location.

Can we interpolate to get the temperature at other locations, or measure a temperature gradient?

$$T[0] \approx \frac{T_{00} + T_{01} + T_{10} + T_{11}}{4}$$

$$\frac{dT[0]}{dx} \approx \frac{(T_{10} - T_{00}) + (T_{11} - T_{01})}{2}$$



#### Consider four different models for the sensors in the grid

In the different model cases, a sensor reading has:

- 1. a random error
- 2. a systematic error (common to all sensors)
- 3. a random error and a (common) systematic error
- 4. a random error and a characterised systematic error



case	$u(t[0])/^{\circ}\mathrm{C}$	$u(\frac{dt[0]}{dx})/^{\circ}C$	r(t[0],t[1])	$r(rac{dt[0]}{dx},rac{dt[1]}{dx})$
1	0.50	1.00	0.50	-0.50
2	1.00	0.00	1.00	0.00
3	0.79	0.71	0.90	-0.50
4	0.06	0.09	0.75	-0.50

#### Sensor modelling and associated data processing

- Common (systematic) and individual sensor behaviour can be represented
- Common influences produce correlated measurements: modelling captures this
- Heterogenous networks can be supported (plug-and-play)
- Light-weight digital processing in sensors (distributed processing)
- Modelling and data processing can support traceability (GUM-compliant)

Further information:

B. D. Hall, "An opportunity to enhance the value of metrological traceability in digital systems", in: proceedings of the 2019 Workshop on Metrology for Industry 4.0 and IoT (MetroInd4.0 & IoT), DOI: 10.1109/METROI4.2019.8792841.

Software: https://github.com/MSLNZ/GTC

## **Related work in KRISS**

Application of sensor network in acoustics

Dr. Wan-Ho Cho



#### Introduction

#### Type of acoustic sensor configurations

	Single node – limited range	Multi node – wide range
Non synchronized - Magnitude	Sound information only Platform: Sound level meter, Etc - Monitoring at single sampled position	Spatial distribution of sound Platform: Outdoor measurement system, Etc - Monitoring at various sampled positions
Synchronized - Magnitude + Phase	Sound & Spatial information – direction Platform: Array system - Sound localization - Spatial filtering of signal	<ul> <li>Sound &amp; Spatial information – 3D + α</li> <li>Platform: Connected sensor network</li> <li>Wide range surveillance</li> <li>Acoustic scene analysis</li> </ul>

#### Change of measurement process

	Traditional	Recent / Future
Performer/Operator	Self measurement or provided by known operator $\rightarrow$ Detailed measurement condition also known	Contribution by unknown operator & devices → Cloud of measurement data
Scalability	Limited	
Accessibility	Accessible to every step of measurement data & instruments	Not accessible to every step (even any)
		KRI은S 한국표준과학연구

#### **Research works on single node – Single sensor**

- Sensor development/validation/management
  - Development of outdoor microphone



Outdoor noise monitoring system





Development of reliable sensor

- Quality infrastructure for non-standardized devices
  - Low-cost sensor / Smart device application



Pt.	Overall SPL (Diffuse field, dBA)		
	WS2	Smart watch	
1	90.26	90	
2	90.44	90	
3	90.26	90	
4	90.07	90	
5	90.09	90	

Example of smart watch evaluation



Efficient calibration of MEMS microhpone

Validation &

qualification of sensor



DCC compatibility can be applied as a type approval requirement



#### Research works on single node – Array system

- Conventional application
  - Sound source localization

by TDoA, Beamforming, Etc...





#### Localization & tracking of moving vehecle

#### Expansion of application

- Expansion of frequency range: Ultra- & Infrasound range
- With AI & ML techniques: Low S/N ratio condition
- → Diagnosis & Inspection (e.g.) partial discharge, leakage, ...
   Wide range monitoring (e.g.) anti-drone, ...



Inspection & localization of gas leakage in noisy condition





Reconstruction of drone noise **KR** 

#### Research works on multi node application

- Conventional monitoring network
  - Environmental noise monitoring Sampled information (Time & position)
  - → Real time & constant monitoring with high density locations



<u>National noise information system</u> (https://www.noiseinfo.or.kr)

- Wide-area monitoring by distributed/dynamic network
  - Data collection by scalable sensor network
  - Application of acoustic scene analysis
- → Real-time monitoring & decision for various situations



Better Standards, Better Life

## Application of sensor network in acoustics

Future scan – Vision

Sustainable sensor network





## **Related work in NMC**

Data-driven metrology for sensor networks

Dr. Shan Cui



Metrology Centre

NMC

## **Digitalisation of Metrology**



Image credit: [1] Carmignato, S., et al. "Dimensional artefacts to achieve metrological traceability in advanced manufacturing." CIRP annals 69.2 (2020): 693-716. [2] https://www.nymail.com/index.php/blog/mail-receiving-services

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### **Data-Driven Calibration of Sensor Networks**

# Looking at measurement data point of view in digitalization of economy

- How to ensure measurement data is traceable and reliable in IoT without relying on lab-based calibration
  - Smart city/nation, smart factory, smart building, and so on
- How to ensure sensing data used by data analytics and AI is validated and reliable
  - Especially for applications that need high-reliability and safety, such as autonomous vehicles (cars, planes, trains, ships)



### Self-Diagnostic Self-Healing Sensor Health Assurance System



## SDSH to automate measurement quality assurance in sensor network with measurement traceability to the SI units

#### Impacts

- Deployed in a Green Mark Platinum building for energy efficient ventilation control and good indoor air quality
- Cost reduction in longterm maintenance of sensors by minimizing lab-based calibration
- Reliable sensing data for reliable control
- Reduced downtime
- Wide applications for IoT and IIoT sensing

#### TRL

• TRL 7

#### **Tech Features**

error and correction with

measurement traceability

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- Autonomous calibration of sensing data assisted by machine learning
- · Minimising errors in sensing data with built-in metrology

### **How SDSH Works**



#### To remotely and autonomously:

- a. Diagnose the health condition (measurement accuracy & uncertainty) of a network of sensors,
- **b. Reinstate** the health condition of sensors, when possible, through data-driven recalibration, and
- c. Isolate unhealthy sensors.

**Measurement traceability** through pilot sensors to physical references



More information: https://www.a-star.edu.sg/nmc/news-articles/news-and-articles/research-spotlight/SDSH

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### **Demonstration in Demand Controlled Ventilation (DCV)** SDSH in indoor air quality (IAQ) sensor network to provide reliable control

 ✓ Better Energy Efficiency (20% energy saving) & Better IAQ



Location of IAQ sensors

This research is supported by the National Research Foundation, Singapore, and Building and Construction Authority under its Green Buildings Innovation Cluster Programme (BCA 94.23.1.1).





# **THANK YOU**

For more information about APMP-DXFG, visit https://apmp-dxfg.github.io/

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