Sensor network metrology: Current state and future directions

Measurement: Sensors 38 (2025) 101798

Contents lists available at ScienceDirect

Measurement: Sensors

journal homepage: www.sciencedirect.com/journal/measurement-sensors

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ARTICLE INFO

Keywords:
Sensor network metrology
Digital transformation
Smart cities
Sensor networks
Traceability

ABSTRACT

This article investigates the essential role of sensor network metrology in advancing the reliability and adaptability of sensor networks through a review of the state of the art and expected trends in this field. Addressing the challenges of harmonized metrological approaches, it outlines a future roadmap for the metrological assessment of real-world non-static distributed sensor networks and underlines the importance of joint efforts for a sustainable and reliable future.

1. Introduction

The increasing ubiquity of sensor networks across various domains comes with an urgent need for advancements in Sensor Network Metrology. As these networks become more prevalent, metrology faces significant challenges to address its classical role in establishing network-level uncertainty propagation and ensuring traceability to the international system of units (SI) in this emerging field. It fundamentally limits the applicability and reliability of the data they collect. Central to this issue, the quality and trustworthiness of the data are of utmost importance for decision-making applications and similarly for the operational efficiency of methods relying on these sensors, e.g., intelligent alerting systems. As a consequence, the absence of a comprehensive understanding of data quality and metrological evaluation of real-world sensor networks restricts their full potential and their integration into critical sectors [1–5].

The urgency for advancing sensor network metrology is rooted in its potential to enhance several fields. Among all, a great potential is expected in environmental monitoring, industrial processes, smart cities, and Internet of Things (IoT), while it is well positioned to revolutionize healthcare, improve energy management, and monitor some of the grand challenges of our time, such as climate change. For instance, the deployment of sensor networks in environmental monitoring enables accurate tracking of air and water quality, which significantly contributes to environmental protection efforts by detecting pollutants and implementing corrective measures. Likewise, in the industrial domain, sensor networks facilitate digital workflow and innovation and enhance product quality. It also increases operational efficiency through condition monitoring and innovative sensing methodologies employing uncertainty-aware data fusion for manufacturing processes [6–9].

However, challenges linked to the dynamic and complex nature of real-world sensor networks, including the size, mixed quality, and volatility of data highlight the necessity for a harmonized metrological approach incorporating in-situ co-calibration methodologies. Furthermore, accessibility issues, and the high costs of onsite calibration facilities showcase such a need even further. While the integration of machine learning (ML) and statistical algorithms in calibration processes shows the potential to enhance efficiency and precision, it does necessitate exploration of associated metrological aspects such as uncertainty analysis, appropriate treatment of correlations and employment of metrological redundancy [10–15].

The significance of sensor network metrology extends beyond technological advancements to encompass legislative considerations. Legal mandates and environmental objectives propel the demand for improved sensor network metrology as EU directives illustrate the societal and environmental implications of advancing sensor network metrology. Such activities are supporting decision making, effective policy implementation, regulation, and, in particular, the sustainable advancement of technology and society. The ongoing research and developments in the field promise to redefine the landscape via enhanced precision, reliability, and interoperability. These are in turn, crucial for meeting the complex demands of modern societies, industrial processes, and environmental sustainability [16–18].

The paper unfolds by detailing the general advancements and directions in the sensor network metrology and the integration of the novel technologies. Following this, it goes through the field-specific progresses for smart grids, smart water sensor networks and smart district heating networks under smart cities in section 3, environmental and climate monitoring in section 4, and industrial monitoring in section 5. The next section then highlights other trends which include local sensor networks.

2. General advancements and directions

Historically, efforts within the European Metrology Programme for Innovation and Research (EMPIR) and its precursor, the European Metrology Research Programme (EMRP), have provided valuable insights and methodologies tailored to specific metrological needs of sensor network applications. Notably, projects like EMRP ENG63 GridSens and EMRP ENV57 MetroERM have made strides in developing algorithms for state estimation, sensor placement, and the monitoring of electrical grids. Groundbreaking work also has been done under the umbrella of projects like EMPIR 17IND12 Met4FoF and EMPIR 17IND02 SmartCom which have been instrumental in addressing calibration drift

https://doi.org/10.1016/j.measen.2024.101798

Available online 10 January 2025

and introducing preliminary methods for uncertainty propagation through ML preprocessing steps. The groundwork laid by these projects is progressing within the European Partnership on Metrology programme with projects such as EPM 22DIT02 FunSNM to tackle some of the core challenges. These advancements are comprehensively documented across references [19–40] offering a detailed account of the progress made in the field. Meanwhile [41,42],specifically illuminate the current FunSNM project framework.

A critical area that has seen limited development is the quantification of drift levels interconnected by physical or data-driven models of the observed phenomena. Projects such as EMPIR 17IND12 Met4FoF introduced preliminary methods for uncertainty propagation in sensor networks; however, achieving SI-traceability and addressing sensor drifts, especially for soft sensors, has remained a challenge [43–46].

Against this backdrop, the current research activities in Europe and further afield ambitiously seek to advance the state of the art by developing holistic and metrologically sound methods for sensor network challenges. This includes a focus on *in-situ* calibration techniques, SI-traceability, self- and co-calibration methods, and uncertainty-aware sensor fusion. One of the core objectives is to enhance the capability of the network to autonomously identify and correct malfunctioning sensors, thereby directly improving data quality [5,11,30,47,48].

Furthermore, current directions aim to tackle the metrological assessment of distributed sensor networks, an area that has been previously explored only at a cursory level. By expanding mathematical tools and data quality metrics, the unique needs and harmonized risk assessment approaches need to be identified and addressed for distributed city-wide sensor networks. As a result, this effort will provide a foundation for evaluating the trustworthiness and data quality of networks crucial for smart city infrastructure and other non-static applications planned to be in place in a couple of years [8,49,50].

Additionally, the EMPIR 17IND02 SmartCom project previously advanced formal frameworks for digital calibration certificates (DCC) and Met4FoF initiated agent-based approaches to ML implementation within sensor networks. Building on these foundations, there are plans to introduce novel data handling techniques that include machine-interpretable, metrology-aware descriptions employing semantic technologies. This initiative is expected to culminate in the development of open-source software libraries and frameworks that are adept at handling dynamic measurements in large-scale, transient sensor networks [1,6,29,47,51–56].

The literature collectively underscores exponential growth of the sensor networks and the missing role of metrology across multiple applications, widely spread from energy efficiency enhancement and sustainable urban development to the IoT ecosystems. The continuous evolution of the technologies and methodologies promises to deepen their impact. Similarly, it fosters innovations that meet the complex demands of modern societies, industrial processes, and environmental sustainability. This synthesis captures the potential role of sensor network metrology, and its significance as a key driver of trust in technological and societal transformations. Sections 3 to 6 will discuss the topic-specific advancements and their planned future directions in this regard. Some examples are accessible here: [11,40,52,57–62].

3. Smart cities

The incorporation of semantic information and multi-sensor data fusion techniques represents methodological innovations that enhance data analysis, quality, and system interoperability. In many cases, these advancements are pivotal for smart cities, where accurate and reliable data underpin automation and smart decision-making [52,61,62].

3.1. Smart grids

In smart grids, it is critical to consider matters relevant to interoperability and to have an efficient data exchange across diverse networks. Naturally, it necessitates standards and protocols for harmonized communication, ensuring data quality and reliability through well stablished metrics, e.g. synchronization and low measurement uncertainties for effective grid management [63–67].

Big data analytics, together with Artificial Intelligence (AI) algorithms, are crucial in the optimization of the distribution and its performance. This is achievable by not only aggregating the extensive data generated within the smart grids, but also through the data quality and appropriate handling of intrinsic correlations at the network level. The establishment and adherence to interoperability standards will ensure seamless communication among diverse grid components and is vital for a reliable operation of future smart grids. As grids expand, certain attention should be paid to scalability without compromising security [68–70].

In the evolution of smart grids, future trends pivot on the axis of reliability and metrology. This is expected to happen based on the integration of more sophisticated digital technologies and harmonized methodologies. A main focus is on the resilience and advanced self-healing mechanisms, which detect, diagnose, and neutralize disturbances. This is complemented by the deployment of monitoring systems, such as Phasor Measurement Units, which empower real-time operational decisions. It thus elevates the efficiency and stability of power distribution networks [63,65].

On the metrology front, the widespread adoption of smart meters and sensors facilitates precise energy usage measurement and verification. This supports accurate billing and efficient energy management. Advancements are expected in co-calibration of the meters as well as in uncertainty handling algorithms for the mixed quality sensor networks. Moreover, leveraging metrology-aware AI algorithms and big data analytics will be crucial in optimizing energy distribution and grid performance. Furthermore, effective establishment and adherence to interoperability standards will ensure seamless communication among diverse grid components. It is in particular vital for the efficient and reliable operation of future smart grids. To conclude, to be able to handle the dynamic demand of electricity in the future, these transitions towards an intelligent, adaptive, and sustainable grid infrastructure becomes ever more important [41,71,72].

3.2. Smart water sensor networks

Advancements in sensor network metrology will be of great importance for the critical issues regarding water loss and quality in the face of shortages. Current methods, including AI-driven analytics and traditional water balance techniques, demonstrate a growing focus on real-time leakage detection as well as predictive maintenance of water meters. Projects like BF SWIM, SW4EU and MetroWaMet exemplify efforts towards integrating intelligent monitoring systems and improving water management strategies. These initiatives underscore the importance of continuous and accurate monitoring, data analysis for effective water loss management, and quality control. Future efforts must concentrate on the development of reliable sensor technologies and smart tools. Future directions should also foster interdisciplinary collaboration and international standardization to enhance the sustainability of the management of water resources. Digital twins, physics-based models and data driven models serve as mathematical tools to provide a holistic network-level view as well as monitoring systems for water leak detection and can be integrated with the intelligent alerting systems that can forecast outlier data with respect to the World Health Organization (WHO) recommendations. Some of the most relevant articles are [73–83].

3.3. Smart district heating systems

The evolution of smart district heating systems, most importantly the transition towards 4th generation district heating (4GDH), stands at the forefront of enhancing urban energy sustainability and efficiency. This paradigm shift is expected through the integration of renewable energy sources effectively to optimize energy demand management. Despite considerable advancements facilitated by digital technologies for real-time monitoring, control, and the integration of green sources, as exemplified by initiatives such as RELaTED, Horizon 2020 STORM, and TEMPO projects, there remains a pressing need for further innovation. Critical to this optimization is the enhancement of sensor accuracy and the management of calibration drift, alongside improvements in data quality metrics for a comprehensive metrological assessment across such networks. In order to establish a robust metrological framework for sensor networks it is necessary to encompass computationally efficient uncertainty propagation methods, data quality, and SI-traceability. These developments are instrumental for the operational refinement of district heating networks, enabling significant reductions in energy losses and facilitating the seamless incorporation of renewable heat sources [41,84–90].

Moreover, the advancement of software frameworks for transient sensor networks to automate the application of metrological methods is found to be essential. In the strictest definition a sensor network is called transient if the network changes over time, e.g., sensors (nodes) are added or removed, or the connectivity changes. However, one could generalize that a sensor network subject to any kind of time-dependent changes can be said to have transient characteristics. Such advances will ensure the reliability, traceability, and effective employment of data for operational optimization as well as predictive maintenance. Demonstrating these metrological innovations through case studies will provide critical insights into their applicability and will be of assistance in the development of software tools tailored for the district heating sensor networks.

Looking at a close future, addressing the challenges of reliable data quality assessment and measurement uncertainty exploiting digital twins and metrological redundancy, and applying these solutions in practical contexts, will be pivotal to lowering the operating temperature and therefore heat losses. Such advancements promise substantial contributions in terms of energy savings, significant emission reductions, and urban heating infrastructure resilience. This would represent significant progress in the quest for energy sustainability [84,89,91].

4. Environmental and climate monitoring

Recent technological advancements in environmental monitoring, exemplified by Refs. [7,53,57,59,92–96], represent significant progress towards better accuracy, scalability, and cost-efficiency for environmental observations. Likewise, the reliable measurement uncertainties of the networks, particularly air temperature data found to be crucial in climate science. This significance is emphasized by key organizations like the Intergovernmental Panel on Climate Change (IPCC), International Bureau of Weights and Measures (BIPM), and particularly World Meteorological Organization (WMO) which highlight the need to address the air temperature challenges to study global warming accurately. The urgent need is also identified by the European Metrology Networks on Climate and Ocean Observation (EMN COO) and on Pollution Monitoring (EMN POLMO), for advanced sensor network metrology. At the same time, the imperative for advancing sensor network metrology in environmental monitoring is further highlighted by leveraging low-cost sensor (LCS) networks to monitor crucial environmental parameters. It is further outlined by the WMO-Global Atmosphere Watch (GAW) that monitoring is essential both on land and oceans. Furthermore, we believe that the call for harmonization of LCS measurement techniques by 2027, in relation to gases (CEN/TS 17660-1: 2021) and particulate matter (TS 17660-2), underscores the broader challenge of improving air quality via harmonized and metrologically sound LCS networks. This highlights a key area for metrological research in the very near future. Thus, a general future trend includes engagement with standardization committees for LCS characterization and their validation practices [18,97–105].

The utilization of distributed sensor networks in environmental monitoring has revolutionized the collection of data on various parameters, e.g., pollution levels, temperature, precipitation, and humidity. The introduction of large scale mixed-quality transient distributed sensor networks has already enhanced their functionality and scope. It also enables flawless integration and communication between sensors located far away from each other. Naturally, this connectivity facilitates the collection of large volumes of data. In this scenario, the most essential part that remains is the quality of the acquired data and its appropriate metrological treatment – essential for trustworthy modelling [106–113].

The integration of advanced technologies into the distributed networks has paved the way for more sophisticated techniques, e.g., leveraging AI and ML on the data. It enables the creation of metrology-aware predictive and clustering models and the detection of network-level anomalies. A good example here is the employment of the measured data as correlated random variables to assess the repeatability, reproducibility, and sensitivity of different AI model candidates. This brings an opportunity for intelligent alerting of potential environmental risks before they escalate. Such metrology-aware AI models are crucial in the context of climate change [6,114–120].

The incorporation of advanced metrological frameworks and semantic information into sensor networks signifies a strategic move towards more efficient and advanced data handling. The FunSNM project, in particular, underscores the importance of effective harmonized technologies in handling complicated data streams. While there has been notable progress in developing models for data reconstruction in meteorology and hydrology, there is a recognized need to incorporate uncertainty into these models more effectively. Modern computational techniques, e.g., machine learning and deep learning, along with various sensor data quality metrics, play a vital role in future research activities on sensor network metrology and enhancing the reliability of climate data and forecasts [40,52,121].

Furthermore, the advancement of forecasting and early warning systems for floods – as highlighted by WMO – relies on the utilization of metrologically validated data from dense networks. Consequently, sensor network metrology will play an essential role in advancing climate-science-specific intelligent alerting systems [122–127].

In the broader landscape of global trends in sensor network metrology for environmental monitoring, recent progress signals a transition towards more sophisticated hybrid sensor networks. This provides improved spatial and temporal monitoring maps. An illustrative example can be observed in air quality sensor networks, which combine stationary and mobile sensor units on vehicles to monitor a wide array of pollutants including different particulate matter sizes, CO, NO_2, and O_3. This exemplifies the move towards uncertainty-aware and high-resolution maps of air pollution. Simultaneously, efforts are focused on calibration and validation of sensor network nodes to ensure data reliability and quality; This is specifically relevant for reference-level networks, such as the GCOS Surface Reference Network, providing top quality, fully traceable and comparable data for climate monitoring.

There is a deliberate effort towards evaluating and selecting calibration strategies that are most suited for real-world application of these sensor networks. This includes the adaptation of calibration strategies customised for specific network requirements, development of computational tools for inline uncertainty assessment, and optimization of calibration setups for pre-deployment sensor node characterization [128–134].

Identifying and selecting calibration strategies that are most suited for the real-world application of these sensor networks is a key task. This includes the adaptation of calibration strategies to specific network requirements alongside development of computational tools for inline uncertainty assessment, and, obviously, optimization of calibration setups for pre-installation sensor node characterization. These initiatives would further improve the performance of the network in terms of quality and reliability [111,135–138].

5. Industrial monitoring

The integration of sensor networks in the industrial sector, through applications such as condition monitoring in the Factory of the Future and novel sensing templates using data fusion for assembly processes are examples that partially show the digital transformation crucial role in improving product quality and elevating the operational efficiency. Consequently, sensor networks for industrial applications are at the core of the realization of Industry 4.0, characterized by the convergence of evolving technologies such as the Internet of Things (IoT), Cyber-Physical Systems (CPS), and Smart Manufacturing in particular.

The literature presents a rich tapestry of interests within this domain where reliability and the application of rigorous metrology to ensure the robust performance of these systems are essential. Likewise, cybersecurity emerges as a significant concern; Ashibani and Mahmoud emphasise the need for secure frameworks to protect CPS from evolving threats. The integration of IoT with sensor networks, as reviewed by Landaluce et al., brings to light the challenges together with potential solutions for ensuring reliable sensing applications within vast networks. Similarly, research by Sharma and Prakash focuses on the reliability of communication in sensor networks within hazardous environments like coal mines, highlighting the role of relay nodes in enhancing network integrity [2,26,58,139–142].

The quest for reliability is also evident in studies examining the application of wireless sensor networks (WSNs) in urban areas by Rashid and Rehmani, who surveyed the potential of WSNs to transform urban living. This is complemented by Tandale et al., who critically assess IoT application layer protocols, an aspect central to the functionality and dependability of IoT devices [143,144].

Research interests further extend to digital twins in industrial applications, which serve as a bridge between physical and virtual worlds, offering unique approaches such as that offered by Farsi et al. In addition, Majeed and Rupasinghe elaborated on IoT-embedded supply chains and elaborated the impact by the reliability of the networks. The potential role of data mining for quality improvement in the context of Industry 4.0 is a research avenue explored by Oliff and Liu; This work provides a link between data quality and the reliability and effectiveness of manufacturing processes which might be of interest for metrological assessments [145–147].

Kumar et al. provide a comprehensive survey of industrial requirements for WSNs. It outlines the protocols and challenges in ensuring network performance that meets the requirements set by each industrial application. This has been further advanced by Osterrieder et al., who underscore the critical nature of the smart factory within Industry 4.0, which inherently relies on the trustworthiness and precision of networks. The literature also reflects a clear interest in advanced metrological methods to improve the reliability and functionality of local and distributed sensor networks in industrial settings, e.g., malfunctioning and drift detection algorithms. Concerning future directions in metrology for smart industry, demand is high for high data quality, uncertainty aware sensor fusion, and soft sensor applications. Researchers will therefore focus on developing methods to ensure data from sensor networks is not only reliable but also adheres to metrological practices [148,149].

6. Other trends

Besides all the main streams in the field of sensor network metrology mentioned in the previous sections, applications of sensor networks span diverse domains. Some examples are structural health monitoring sensor networks and medical sensor networks, each having a key role and great demand for highly reliable data. The application of sensor networks in structural health monitoring, for instance, in museum environments, emphasizes their importance in preserving cultural heritage and ensuring the integrity and safety considerations. Likewise, in healthcare, the precision and reliability provided by advanced sensor network metrology facilitate breakthroughs in remote patient monitoring and personalized medicine; this highlights the potential for sensor networks to revolutionize healthcare by enabling early detection of health issues. However, more rigorous reliability assessment practices are needed, having metrology as an anchor of reliability [59,60].

The term ‘sensor network’ fundamentally refers to a collection of spatially distributed (or otherwise distinct) sensing devices tasked with measuring one or more physical quantities. However, this can be realized at any scale, from micro to macro, where a holistic network-level measurand is of interest. The field is also witnessing progress in applications that require high levels of accuracy and reliability in local sensor networks. Innovations in uncertainty-aware sensor fusion, co-calibration, self-calibration, blind calibration, and drift detection are crucial for the advancement of local networks in the same manner. Examples of these developments include the network of Coulomb Blockade Thermometers for quantum computer applications, and other applications at cryogenic temperatures up to 25 K, where network level sensor fusion is instrumental in minimizing uncertainty components propagated by the fabrication inhomogeneities. Moreover, photonic microring resonators can also be realized as local temperature sensor networks, where holistic network-level signal processing and uncertainty aware data fusion will leverage their reliability and further reduce the measurement uncertainty. A significant breakthrough is expected in the coming years under the umbrella of the EPM 23FUN01 PhoQuS-T project. On the other hand, MEMS, i.e., Micro-Electro-Mechanical Systems, sensor networks will be of great interest in the near future, while conventional calibration methods are significantly time consuming. Bayesian-based virtual calibrations are identified as one of the future research directions in this industry. Another promising direction in the field of local sensor network metrology is established for multiwire thermocouples in the field of thermal metrology in which data-driven and physics-based drift detection plays a pivotal role in *in-situ* detection of drift. These technologies demonstrate the field’s commitment to addressing the challenges of measurement accuracy and reliability not only in city-wide sensor networks but also at the micro scale. Background work for such advancements is presented here [46,150–152].

One of the challenges in sensor networks is the impact of network topology. As discussed in this paper, many applications where we can see sensor network implementations work with sensors/devices that have a limited lifetime, but the processes outlined in Sections 3-5 go beyond the active operation of a single or individual element. This fact affects the measurement result and the information we want to know at a certain time interval if we need to rely on all elements of the sensor network. This brings us to the fact that in certain processes the sensor network topology can be dynamic, which imposes new challenges for metrology such as changing the number of branches, and the time of delivery of measured data for processing [15].

7. Conclusion

The increasing prevalence of sensor networks places sensor network metrology in the spotlight to ensure their reliability and applicability. Adoption of machine learning algorithms, and semantic technologies as well as best use of digital calibration certificates in sensor networks will be of great importance in improving the data quality, providing SI-traceability, applicability, and interoperability. For instance, the use of uncertainty-aware machine learning can predict sensor failure and drifts in IoT scenarios or predict changes in the quality of water in distribution networks. Semantic technologies can enable seamless data aggregation in complex environmental monitoring sensor networks for online decision-making applications. Digital calibration certificates ensure that sensor data in pharmaceutical manufacturing applications remain reliable and traceable, meeting rigorous industry standards for accuracy and compliance.

As a consequence, more sophisticated metrological approaches are needed to catch up with the dynamic, intricate and diverse nature of real-world sensor networks. Such integration aims to enhance operational efficiency and decision-making, emphasizing the vital role of sensor network metrology in addressing global challenges, e.g., climate change, energy sustainability, and water management.

Looking forward, the roadmap for sensor network metrology is clear yet challenging; it involves not only the refinement of existing methodologies and technologies but also development of novel harmonized tools for distributed, transient, mixed-quality, and hybrid sensor networks. The integration of harmonized metrological practices into the fabric of these trends across sectors – to ensure the trustworthiness, reliability, and traceability of data to SI – is an ambitious goal for the coming years. The advancements in sensor network metrology are key to addressing the biggest challenges of our time and are expected to pave the way for a more reliable sustainable and connected world.

Funding statement

The project (22DIT02 FunSNM) has received funding from the European Partnership on Metrology, co-financed from the European Union's Horizon Europe Research and Innovation Programme and by the Participating States.

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