

A Comparative Study on Measurement Accuracy: Wireless Sensor Networks vs. Conventional Systems for the Measurement of Large-Scale Geometric Structures

Lars-Michel Bretthauer¹, Ralf Heynicke¹, Gerd Scholl¹

¹Helmut Schmidt University, Holstenhofweg 85, Hamburg (Germany)

Abstract

Fast and highly precise geometric shape acquisition for in-process control poses a significant challenge for all kind of measurement systems, particularly in the context of large-scale structures. Conventional systems like laser trackers or photogrammetric setups are commonly employed for this purpose. However, these instruments do not provide real-time measurements, and their limitations become increasingly pronounced as the object size grows. Real-time capability, in contrast, offers substantial advantages for closed control loop forming processes in industries such as aerospace and wind energy. This requirement is addressed by our approach employing a dense network of wireless sensor probes that determine the shape of the object through the measurement of surface normal relative probe positions. Within this architecture, all measurement data is aggregated and processed in a central unit at a fixed sampling interval that remains independent of the network size. As a result, the overall measurement time stays constant, even for large-scale structures. In this work, we compare the measurement accuracy and repeatability of this novel wireless sensor network with the conventional approaches referenced above, following the procedures defined in DIN ISO 22514.

Keywords: Sensor Network, Wireless, Uncertainty Prediction

Introduction

The evaluation of new measurement systems is curial to assess the performance and measurement accuracy to existing systems. Therefore, in this work we compare the measurement accuracy and repeatability of a wireless sensor network for measuring shapes of large structures with the conventional approaches, following the procedures defined in DIN ISO 22514 and VDA Vol. 5 [1], [2]. For this purpose, an appropriate experimental setup was developed, as shown in Fig.1. The measurement object is a fiber-reinforced composite panel with rough dimensions of 1.8 m x 2.6 m. The goal is to capture the shape of the measurement object with a sensor network, which consists of 22 equally distributed sensor probes and compare it to laser tracker and photogrammetry systems. In order to obtain a variety of measurements in accordance with the above-mentioned standards, a controlled deformation is introduced using two linear motors, primarily to assess the repeatability of the measurement under varying deformation states. In addition, positional uncertainties of the sensor probes are compared with analytically and simulated uncertainty values, which were obtained in accordance with the “Guide to the expression of uncertainty in measurement” (GUM) framework [3], [4], [5].

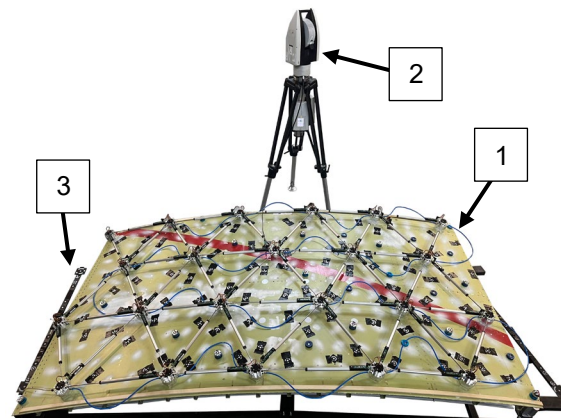


Fig. 1: Comparative measurement setup panel with applied sensor network (1) and the reference systems laser-tracker (2) and photogrammetric system (3).

Conventional Measurement Approaches for Large-Scale Structures

Laser trackers and photogrammetry have established themselves as common measurement systems in industry for measuring large components with outer dimensions greater than 0.5 m, for example in the aerospace and wind power industries [6]. A laser tracker uses a laser interferometer to measure distances with a retroreflective sphere, generating a point cloud (PC) along the surface

of a measurement object, which is often done manually. The resulting offset from the sphere must be compensated along the surface normal of the object. A photogrammetric system reconstructs a 3D point cloud from multiple photographs with different viewing angles on the measurement object. In each photograph, coded markers are detected and then converted into a point cloud using bundle adjustment. In most cases, reference scales are placed around the measurement object in order to achieve accurate results. The Leica AT 960-LR laser tracker is used for comparative measurements with the sensor network as well as the Aicon DPA Pro photogrammetry system. The performance values of the two systems are presented in Tab. 1. In order to combine the measurement data from both systems in one coordinate system, several measuring points are used, which are detected by both systems. This allows the point clouds to be seamlessly aligned with each other.

Tab. 1: Specifications of the conventional measurement systems

	Laser tracker AT 960-LR	Photogrammetry Aicon DPA Pro
Measuring range	80m	30m
Measurement accuracy	$\pm(15\mu\text{m} + 6\mu\text{m}/\text{m})$	$\pm 10\mu\text{m}/\text{m}$

Wireless Sensor Network Measurement System

The sensor network (SN) consists of distributed wireless sensor probes interconnected via mechanical links, forming a scalable architecture. Each probe operates within its own local coordinate system and provides measurements of surface stress and deformation in its immediate vicinity. These measurements are obtained by evaluating data from sensors integrated within the probe, as well as from its directly connected neighboring probes. To determine the surface stress and deformation across the entire component, the locally acquired information must be transformed into a global component coordinate system. This global coordinate system is defined by a set of reference probes with precisely known positions, denoted as S_{Ref}^C , where the superscript indicates the coordinate system in which the position is expressed. In this notation, the superscript "C" refers to the global component coordinate system. The position of a sensor j with respect to the local coordinate system of sensor i is denoted as S_j^i , as illustrated in Fig. 2. This position, expressed in the local coordinate system of probe i , can be transformed into the global coordinate system

as S_j^C by applying the transformation from the local coordinate system of probe i to the global frame, i.e., by mapping S_j^i into the global coordinate system. Consequently, the positions of all sensor probes in the global component coordinate system are obtained through successive transformations of positions defined in local coordinate systems.

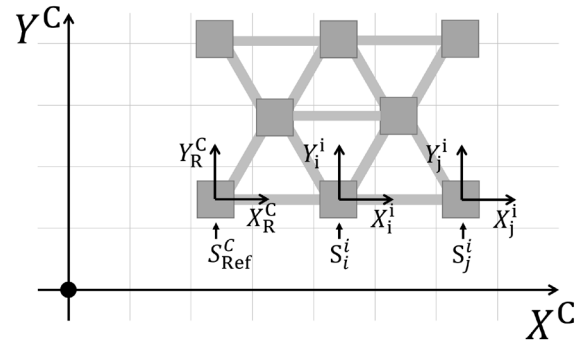


Fig. 2: Definition of the coordinate systems.

To determine the local position S_j^i , each sensor probe estimates the surface normal at its location using a 3D inclinometer. Furthermore, the mechanical links between adjacent probes are instrumented with inclinometers to measure the inclination δ_{i-j} , while the distance k_{i-j} between probes is obtained using linear displacement sensors. All inclinometer measurements are realized using MEMS-based acceleration sensors. The mechanical connections between probes are implemented using spherical ball bearings, enabling rotational flexibility while preserving mechanical stability. By combining the measured inclination angles and inter-probe distances, and considering the underlying geometric constraints, the positions of all probes within the local coordinate system can be reconstructed [5], [7].

Measurement System Analysis (MSA)

A measurement system analysis (MSA) is required to evaluate the suitability of a measurement system for industrial applications. This analysis provides information on the reliability, accuracy, and repeatability of the system with respect to a specified tolerance T . Two closely related approaches are commonly applied: VDA Volume 5 and DIN ISO 22514-7, both of which focus on the evaluation of measurement uncertainty and statistical testing in accordance with the Guide to the Expression of Uncertainty in Measurement [1], [2]. The classical MSA approach further defines the short-term capability of a measurement system using the indices C_g and C_{gk} , where the measurement system is required to utilize no

more than 20% of the tolerance range T_R up with its measurement uncertainty. The C_g factor primarily refers to the variance of the measurement system in relation to the tolerance range, while the C_{gk} value also accounts for systematic deviation in the measurement. These indices can be determined using the tolerance range T_R , the coverage factor k , the sample standard deviation s and sample mean $\hat{\mu}$ from repeated measurements against a normal or reference value with

$$C_g = \frac{0.2 \cdot T_R}{k \cdot s}, \quad (1)$$

$$C_{gk} = \frac{0.1 \cdot T_R - |\hat{\mu} - T_M|}{0.5 \cdot k \cdot s}. \quad (2)$$

Values greater than 1.33 are generally considered acceptable for both indices, values between 1.00 and 1.33 are regarded as conditionally acceptable, and values below 1.00 indicate that the measurement system is not suitable for the intended application. Within the norm approach, a distinction is made between the capability of a measurement system and that of a measurement process. In a first step, the uncertainty of the measurement system must be evaluated with a normal or reference measurement based on

$$u_{ms} = \sqrt{u_{cal}^2 + u_{lin}^2 + u_{bi}^2 + u_{ev}^2}. \quad (3)$$

- u_{cal}^2 = Calibration of the standard or workpiece
- u_{lin}^2 = Deviations from linearity
- u_{bi}^2 = Bias offset
- u_{ev}^2 = Repeatability on standards or workpiece

From this, the uncertainty of the measurement process can be determined based on the evaluated measurement system uncertainty and a repeated measurement in an operating environment with multiple operators with

$$u_{mp} = \sqrt{u_{ms}^2 + u_{gv}^2 + u_{stab}^2 + u_{av}^2}. \quad (4)$$

- u_{ms}^2 = Measurement system
- u_{gv}^2 = Reproducibility of the measuring system
- u_{stab}^2 = Reproducibility over time
- u_{av}^2 = Reproducibility of the operator

Based on the measurement system and process uncertainties, a capability index can then be calculated accordingly

$$C_{ms} = \frac{0.2 \cdot T_R}{k \cdot u_{ms}}, \quad (5)$$

$$C_{mp} = \frac{0.4 \cdot T_R}{k \cdot u_{mp}}. \quad (6)$$

For these indices, the same threshold values as for short-term capability must be achieved in order to be considered suitable. However, the measurement process uncertainty is permitted to utilize up to 40% of the tolerance range, as it accounts for additional statistical influences affecting the measurements. If a measurement system meets these criteria, it can be used reliably in an industrial environment.

Experimental Setup and Evaluation Method

For the measurement setup, the panel is fixed within a steel frame to provide a rigid substructure. The short side of the component is connected to the outer structure by a fixed clamp, while the opposite side is connected to two linear motors, as shown in Fig. 3.

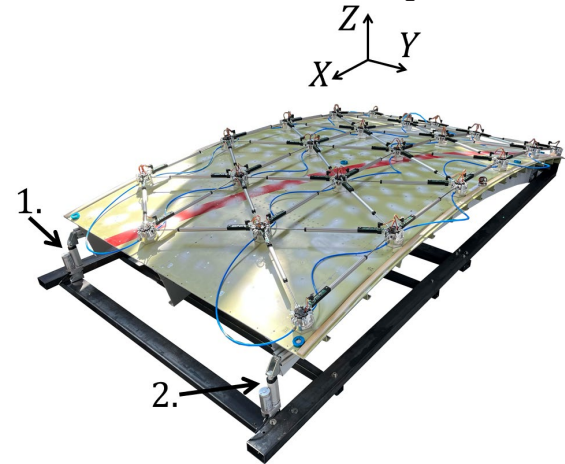


Fig. 3: Measurement setup of the panel with applied sensor network and linear motors on the left (1) and right (2) side.

The motors are designed to deform the component under multidimensional stress, with a maximum extension length of approximately 50 mm. The objective is to demonstrate that the sensor network is capable of detecting this type of deformation. According to ISO 22514-7, multiple measurement objects, operators, and repeated measurements are typically required. Since the present study is conducted on a single panel, the different deformation states are treated as individual measurement objects. These states are generated using the full extension of the linear motors and are summarized in Table 2. The poses are cycled

sequentially from 1 to 3 to obtain repeatable measurements from the same panel, while the fourth pose serves as a control measurement. A reliable assessment of system repeatability requires more than 30 repeated measurements [2]. This criterion is fulfilled in the present study, with a total of 58 measurements conducted. Furthermore, to showcase the systems measurement stability, the measurement takes place over a two-day duration.

Tab. 2: Linear motor positions for poses 1 to 4, retracted = 0, extended = 1

	Left Linear Motor Position	Right Linear Motor Position	Number of Repeated Measurements
Pose 1	0	0	20
Pose 2	1	0	19
Pose 3	0	1	17
Pose 4	1	1	2
	Sum		58

For the comparison of the point clouds, each measurement dataset is transformed into a global coordinate system. In this case, the origin of the global coordinate system is defined by the position of sensor probe #22. To achieve an initial alignment, the point clouds of the reference systems are registered using the previously measured positions of probes #22 and #11, as depicted in Fig. 4. Also, the sensor network is adjusted to the surface of the component using the reference systems to eliminate offsets from the setup of the sensor network.

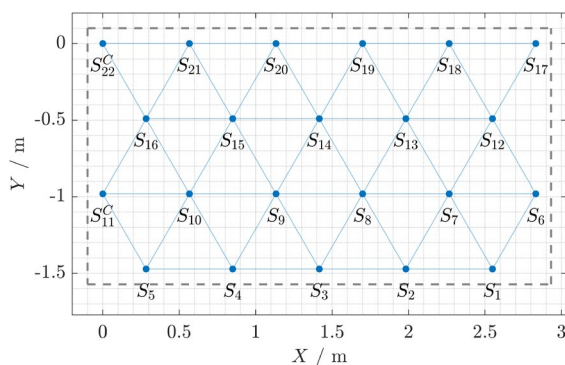


Fig. 4: Network structure of the SN with the reference probes #11 and #22.

During the subsequent fine alignment, a surface fit is generated from the point clouds to provide additional support points and, if necessary, to reduce the influence of outliers. The support points derived from the fitted surface are then used for fine alignment based on the Iterative Closest Point (ICP) algorithm [8]. The overall process for point cloud alignment and evaluation is illustrated in Fig. 5.

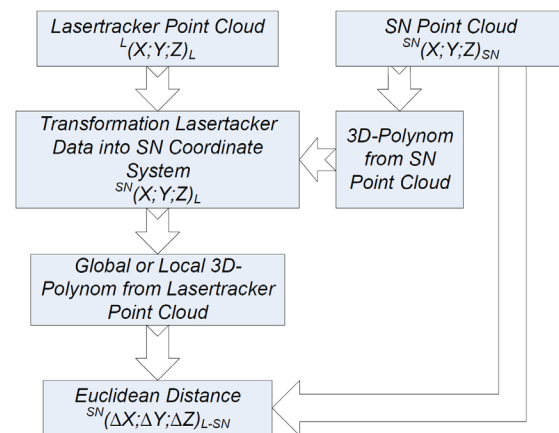


Fig. 5: Alignment procedure of the point clouds and evaluation.

The alignment process enables the calculation of deviations between the sensor network and the aligned reference data. Since the positions of the sensor probes cannot be measured directly with the reference systems, but only points in their vicinity are captured, interpolation between these points is required. Two interpolation approaches are applied. The first approach is based on a global surface fit using all measurement data, taking advantage of the regular geometry of the object. This method is suitable for evaluating the overall shape profile and is comparable to a direct comparison with a CAD model, but it does not account for local deformations. The second approach uses a local surface fit, where only points within a defined radius around each measurement probe are considered. This method allows the assessment of the waviness profile of the object up to a certain wavelength. In both cases, the surfaces are determined using weighted least-squares fitting. The two approaches are exemplarily presented for the laser tracker measurement in pose 1 at sensor probe #1 in Fig. 6.

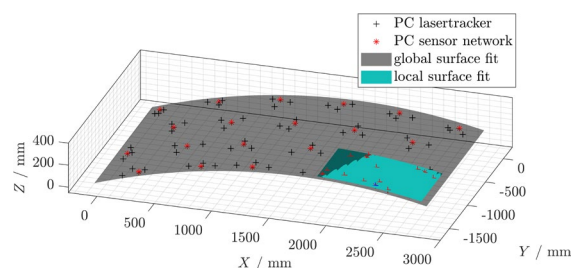


Fig. 6: Comparison of the laser tracker and sensor network point clouds (PC) with the global and local surface fit for probe #1.

To further enhance measurement accuracy, a surface fit can also be applied to the sensor network PC, enabling the extraction of the

underlying surface shape and correct the PC. This method is only applicable on the global evaluation, since it requires from the data to be globally representable with a polynomial expression. For the evaluation of the sensor network, the mean deviation is used to assess systematic errors (bias), while the standard deviation is considered to evaluate repeatability. Furthermore, these results are incorporated into the MSA to assess the capability of the system for deployment in an industrial environment. Since, this measurement setup resembles more a measurement process an expansion of the allowable usage of the tolerance band is 30%. For the tolerance T a value of ± 1.5 mm is used, since this is a commonly used tolerance in the large structure industry.

Uncertainty Estimation of the Sensor Network

As a general statement on the measurement uncertainty of the sensor network is not feasible. Since, it strongly depends on the specific measurement task, its determination in advance is essential to assess whether the achievable uncertainty is suitable for the intended application. An estimation of the measurement uncertainty can be performed in accordance with the Guide to the Expression of Uncertainty in Measurement (GUM) using either analytical or simulation-based approaches. Due to the complex structure of the sensor network, it is advantageous to decompose the system into subsystems and evaluate them individually, as described in [4]. Based on this approach, an overall uncertainty for the positions of the measurement probes can be derived. In the present work, a Monte Carlo method is employed to estimate these uncertainties, using a number of trials of $M = 10^5$ in order to obtain statistically robust results in accordance with the GUM framework [9]. The resulting absolute measurement uncertainty for each sensor is shown in Fig. 7, alongside the correct data from the surface fit.

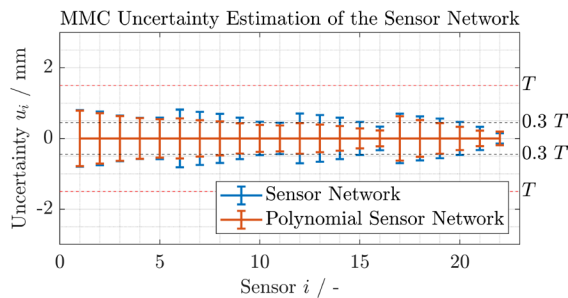


Fig. 7: Estimated uncertainty of each sensor probes position with corrected data from the surface fit correction

Since the position uncertainty propagates through the network and increases proportionally to the square root of the number of connections,

$$u_i \propto \sqrt{M_i}. \quad (5)$$

Thus, the uncertainties for the distant measurement probes relative to the reference probe are greater. This effect can be seen in the stair-step-like rise and fall of the measurement uncertainty, with reference probe #22 exhibiting the smallest uncertainty, which is primarily caused by the reference system. The probe #1 has the largest uncertainty with an uncertainty of $u_1 = 0.9$ mm with a distance $M_1 = 6$. The surface fit corrected measurement points showed a decrease of up to 15% in the measurement uncertainty. This method showed close to no improvement for the sensor probes on the outer edge of the panel.

Results

The local comparison should be evaluated as a first result, since this comparison gives a statement of the systems performance for non-regular shapes. The mean deviation between the sensor network the reference systems with a 1σ error bar is illustrated in Fig. 8. A slight bias is visible in all measurement probes, but it is significantly greater in probes #22 and #11. This is primarily due to the poor coverage of the measurement points at the outer locations by the reference systems. Generally, the sensor network performed better in the comparison to the laser tracker measurements. This can also be attributed to the system's higher sampling rate at the measuring probes.

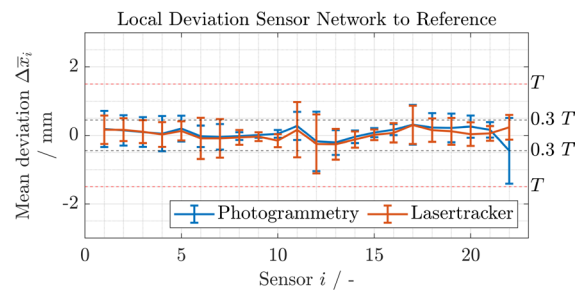


Fig. 8: Local deviation of the sensor network to the two reference measurement systems with error bars of 1σ .

In the global comparison the sensor network performed similarly to the bias deviation from the local comparison. This indicates, that the measurement object can be represented by globally fitted surface polynomial. In Fig. 9 the global deviation from the sensor network to the laser tracker is presented with the surface fit

corrected network. The corrected data showed a great improvement by reducing the average standard deviation $\bar{s}_G$ by 45%.

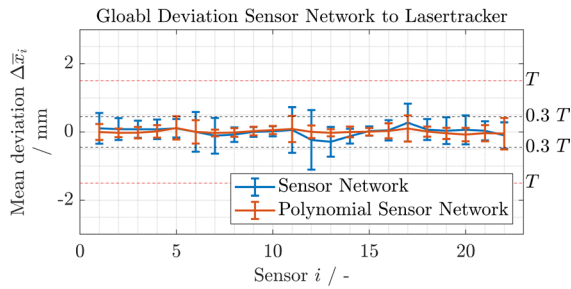


Fig. 9: Global deviation of the sensor network to the laser tracker data with error bars of 1σ .

Figure 10 presents the global deviations of the reference systems with respect to the sensor network. The shape of these curves closely resembles that shown in Fig. 9, indicating that both reference systems capture these deviations consistently. In both systems, outliers such as sensor probes #12 and #17 exhibit increased standard deviation and mean deviation. This behavior can be attributed to their large distance from the reference probe as well as their external positioning. However, the deviations of these probes can be significantly reduced by applying a surface fit correction.

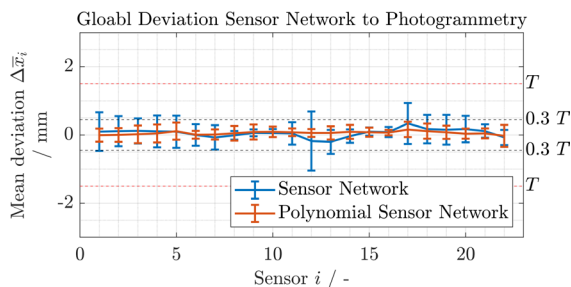


Fig. 10: Global deviation of the sensor network to the photogrammetry data with error bars of 1σ .

In order to provide a better comparison of the methods and systems, the mean deviation and standard deviation of the measurement probes are presented in Table 3. It can be observed that the system shows comparable values for the mean standard deviations $\bar{s}_L$ and $\bar{s}_G$ for both the local and global evaluation methods. In addition, a slight reduction in the mean deviation from the local to the global method is visible. The most significant improvement is observed in the corrected sensor network data, with an enhancement of approximately 45%, accompanied by a slight increase in the average deviation across all sensor probes.

Tab. 3: Linear motor positions for poses 1 to 4, retracted = 0, extended = 1

		Laser tracker		Photogrammetry	
		SN	Poly SN	SN	Poly SN
Local	$\hat{\mu}_L$ / mm	0.032	-	0.067	-
	$\bar{s}_L$ / mm	0.383	-	0.379	-
Global	$\hat{\mu}_G$ / mm	0.006	0.006	0.056	0.056
	$\bar{s}_G$ / mm	0.371	0.211	0.346	0.189

Compared to the calculated uncertainties, the network showed lower values, indicating that the individual sources of uncertainty had been overestimated. However, the outliers in measurement probes #11 and #17 show good agreement with the MMC. Therefore, the simulated uncertainties can be used to predict the factors in future applications. For the previously specified tolerance T , the capability factors obtained from the MSA are presented in Table 4. Using the local evaluation method for the probe positions, only 15% of the laser tracker measurements and approximately 23% of the photogrammetry measurements meet the requirements for the short-term capability index C_g . In both cases, around 35% of the probes satisfy the C_g criterion. These results indicate that a local evaluation approach is only feasible for larger tolerances in accordance with the relevant standards. Slightly higher C_g indices were observed for the global evaluation. In fact, more than 55% of the measurement points exhibited no significant bias with respect to the tolerance T . After correction, this proportion increased to over 70% of the indices. In particular, the bias-related index C_{gk} exceeded

Tab. 4: Capability indices from the MSA of the sensor network in the global and local evaluation method.

		Laser tracker		Photogrammetry	
		Local			
		SN	Poly SN	SN	Poly SN
C_g	1.00 – 1.33	9.1%	–	18.2%	–
	1.33 <	4.5%	–	4.5%	–
C_{gk}	1.00 – 1.33	13.6%	–	9.1%	–
	1.33 <	22.7%	–	27.3%	–
C_{MP}	1.00 – 1.33	3.4%	–	3.4%	–
	1.33 <	13.8%	–	13.8%	–
		Global			
		SN	Poly SN	SN	Poly SN
C_g	1.00 – 1.33	9.1%	18.2%	13.6%	36.4%
	1.33 <	13.6%	50.0%	22.7%	40.9%
C_{gk}	1.00 – 1.33	13.6%	18.2%	13.6%	0%
	1.33 <	50.0%	77.3%	40.9%	100%
C_{MP}	1.00 – 1.33	22.7%	9.1%	0.0%	18.2%
	1.33 <	22.7%	68.2%	36.4%	77.3%

95% compliance in both systems. Also, the measurement process index is met with 80-90% for the corrected data. By applying corrected measurement data to a regular surface, the results can be significantly improved for industrial applications.

Conclusion

In this work, the sensor network is compared with conventionally used industrial measurement systems, namely the laser tracker and photogrammetry, based on a dedicated experimental setup. The study is further designed to evaluate the performance of the network in accordance with relevant standards for a specified tolerance. In this context, multiple evaluation methods are applied to compare the reference systems with the sensor network. The correction of the sensor network data using a surface fit leads to a significant improvement, with more than 70% of the indices meeting the required capability criteria. These results demonstrate the feasibility of the system for deployment in an industrial environment, particularly for regularly shaped components.

Acknowledgements

The authors would like to acknowledge Mr. Michael Geist and Mr. Dominik Hack for their highly appreciable support.

This research is funded by dtec.bw – Digitalization and Technology Research Center of the Bundeswehr. dtec.bw is funded by the European Union – NextGenerationEU (project “Digital Sensor-2-Cloud Campus Platform” (DS2CCP), <https://dtecbw.de/home/forschung/hsu/projektds2ccp>).

References

- [1] DIN ISO 22514-7: Statistische Verfahren im Prozessmanagement – Fähigkeit und Leistung – Teil 7: Fähigkeit von Messprozessen, Berlin., Mar. 2025.
- [2] S. Bracke, Technische Zuverlässigkeit: Datenanalytik, Modellierung, Risikoprognose, 1. Aufl. 2022. Berlin, Heidelberg: Springer Berlin Heidelberg, 2022. doi: 10.1007/978-3-662-65015-8.
- [3] BIPM, “Evaluation of measurement data — Guide to the expression of uncertainty in measurement,” Sep. 2008, doi: 10.59161/JCGM100-2008E.
- [4] L.-M. Bretthauer, R. Heynicke, and G. Scholl, “Uncertainty Modeling of a Cyber-Physical Finite Element Sensor Network for Surface Measurements,” vol. 22. GMA/ITG-Fachtagung Sensoren und Messsysteme 2024, pp. 380–387, Jun. 2024, doi: 10.5162/sensoren2024/D5.1.
- [5] L.-M. Bretthauer, R. Heynicke, and G. Scholl, “Design methodology and uncertainty estimation of a wireless sensor network for surface strain and shape measurements,” *tm - Technisches Messen*, Apr. 2025, doi: 10.1515/teme-2025-0008.
- [6] C. P. Keferstein and M. Marxer, *Fertigungsmesstechnik: Praxisorientierte Grundlagen, moderne Messverfahren*. Wiesbaden: Springer Fachmedien, 2015. doi: 10.1007/978-3-8348-2583-4.
- [7] L.-M. Bretthauer, R. Heynicke, and G. Scholl, “Proposal of a Cyber Physical Finite Element Sensor Network for Surface Measurements,” in 2024 IEEE International Instrumentation and Measurement Technology Conference (I2MTC), May 2024, pp. 1–6. doi: 10.1109/I2MTC60896.2024.10560668.
- [8] A. Segal, D. Haehnel, and S. Thrun, “Generalized-ICP,” in *Robotics: Science and Systems V, Robotics: Science and Systems Foundation*, Jun. 2009. doi: 10.15607/RSS.2009.V.021.
- [9] BIPM et al., “Evaluation of measurement data — Supplement 2 to the ‘Guide to the expression of uncertainty in measurement’ — Extension to any number of output quantities,” Oct. 2011, doi: doi.org/10.59161/JCGM102-2011.