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Design methodology for optimal sensor placement for cure monitoring and load detection of sensor-integrated, gentelligent composite parts

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Abstract

Selecting right positions for composite-integrated sensors for monitoring cure during manufacturing and loads during product use presents challenges for engineering design. Since an optimal sensor placement (OSP) methodology for both phases is not emphasised enough in literature, a new methodology is proposed. This methodology is based on a Genetic Algorithm and strain gauges, temperature sensors and interdigitated electrode sensors for cure monitoring and physics-informed neural network-based load detection. Additionally, it includes sensor node positions optimization in a sensor network.

Keywords: design methods, data-driven design, optimal sensor placement, wireless sensor networks, artificial intelligence (AI)

1. Introduction

Integrating sensors into structural components can enhance the digitalisation to load carrying structures, resulting in smarter products. From a product development point of view, these integrated sensors enable a robust data acquisition for the product generation development (Welzbacher *et al.*, 2023). Those sensor-integrated structural components for product generation development could be described as "gentelligent" components in context of technical inheritance, where new product generations are optimized for the loads during the use phase of data from previous product generations (Lachmayer *et al.*, 2014; Lachmayer *et al.*, 2016). Especially composite materials, which are often used in the aircraft industry, and their layup are well suited for the integration of sensors into the material itself like it is shown in Klein and Middendorf (2016) and Damm *et al.* (2020). On the other side, the use of composite structural components brings different challenges with it. For example, the manufacturing of those composite parts requires a high amount of energy and time. Furthermore, it directly defines the mechanical characteristics (Mirzaei *et al.*, 2021; Hasselbruch *et al.*, 2015). The assembly of composite parts can also be difficult due to available joining technologies and requirements regarding a stress-free assembly. This leads to the need for a holistic view on the manufacturing, assembly, and use of composite components. For example, during the manufacturing process, structure integrated sensors have the potential to monitor the curing process in an autoclave by sensor measurements. This cure monitoring allows to reduce residual stresses in the part (Prussak *et al.*, 2019; Wiedemann *et al.*, 2022). In assembly, the sensor measurements could be used to adjust the process in order to achieve minimal stresses in the assembled product. Besides, the sensors are applicable for the detection of damages (application in structural health monitoring, SHM) besides of the data acquisition for the product generation development (Teimouri *et al.*, 2016; Bergmayr *et al.*, 2023) during the product use-phase.

Furthermore, the sensors are useable to monitor external loads on the corresponding part (Altun *et al.*, 2020; Esposito *et al.*, 2021). Besides, instead of monitoring external loads, the deformation of a part could be reconstructed with different shape sensing techniques (Gherlone *et al.*, 2018). However, choosing the right sensors for the measurement task and placing them in the right position is a challenging task, since the choice cannot be changed after the integration. Therefore, the optimal sensor placement (OSP) has to be considered methodically to ensure a reliable data acquisition process (Meyer zu Westerhausen *et al.*, 2023).

In literature, different OSP methodologies are presented, but few publications address more than one product lifecycle phase, e. g., the product creation with manufacturing and assembly, or product use in a holistic approach. Therefore, in this paper a methodology is proposed with focus on the OSP for cure monitoring in manufacturing as well as the monitoring of external loads during assembly and product use on the example of an aircraft wing box. The validation of the methodology is another work and will be the aim of a future paper. For the load monitoring, a physics-informed neural network (PINN)-based approach is used for a near real-time load detection, which could not be reached with numerical methods, e. g. simulations using the finite elements method (FEM) (Hoffer *et al.*, 2021). To fulfil this, the paper is structured as follows. In Section 2, an overview on related works in the field of OSP for load detection, Wireless Sensor Network (WSN) configuration and cure monitoring is given. In Section 3, a comparison of the works presented in Section 2 is shown, underlining the research gap for this paper. Next, the methodology of this paper is proposed and described in Section 4. Finally, Section 5 concludes this paper and gives an outlook on future research.

2. Related works to OSP for shape sensing and manufacturing monitoring of composite parts

In literature, different methodologies for OSP are found. For example in Ostachowicz *et al.* (2019), the optimization of sensor placement for SHM is reviewed. The authors classified OSP literature in this area into "SHM techniques", "optimization algorithms" and "application demands". Regarding the optimization algorithms, especially biology-based algorithms appear very often in literature (Ostachowicz *et al.*, 2019). Furthermore, the authors derived from their analysis a general framework for OSP problems based on the following eight steps: (1) Define application demands, (2) choice of sensor types, (3) define operational parameters, (4) determine cost function, (5) choice of optimization algorithm, (6) define inputs, (7) optimal Sensor placement and (8) deployment. This framework is not specific for SHM and could be applied on various kinds of OSP problems. For example, in the first step, application demands specific for WSNs could be defined (e. g. a specific maximal energy consumption) as well as for the sensors itself. These demands on the other hand influence the choice of sensors in the next step. For the focus of this paper, especially the steps 4 to 7 ("determine cost function" to "optimal sensor placement") are of interest, since the design methodology begins after the sensors and operational parameters are chosen regarding manufacturing and loads. Furthermore, step 8 "deployment" requires practical activities, so the proposed methodology ends after the optimal sensor placement. Therefore, the following presented works are mainly focussed on these steps in the OSP framework.

In the field of shape sensing using the inverse FEM (iFEM) method of Tessler and Spangler (2005), a genetic algorithm (GA) as biology-based optimization algorithm for the problem of OSP is used by Esposito and Gherlone (2020) and Ghasemzadeh and Kefal (2022). The cost function in these works is the error between the reconstructed displacements from discrete, simulated strain measurements and the FEM reference solution at different points of their models. So, the goal of the optimization algorithm is to minimize this error and choose the configuration as optimal, which has the least deviation to the reference solution. Special about the work of Esposito *et al.* (2021) is the application of the iFEM method to identify loads applied on the structure. In comparison to other shape sensing techniques, such as Ko's displacement theory (Ko *et al.*, 2007), the iFEM method necessitates a greater number of sensors. For example, in the study by Esposito and Gherlone (2020), the OSP for shape sensing on a composite wing box required 324 for the application of iFEM. In contrast, in this study a number of 28 strain gauges is required for the application of Ko's displacement theory (Esposito and Gherlone, 2020). Besides, PINNs, which were introduced by Raissi *et al.* (2019), have piqued interest

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as they may provide another solution to this challenge. This is because a relatively small number of sensors is required and the PINN's applicability for shape sensing is less dependent on the training data then for conventional artificial neural networks (Qiu *et al.*, 2023). Finding optimal sensor positions for shape or load reconstruction tasks with a PINN is addressed by Zhu *et al.* (2023) on the example of pressure sensors for reconstruction of the pressure profile on a wind energy application. The OSP problem for pressure identification with a PINN is also focussed by Ye *et al.* (2022) on the example of a pipeline system. However, all these also do not consider the optimization with respect to the manufacturing process or the in the use-phase configuration of a whole WSN.

Taking a wider look at the topic of SHM itself, further OSP methodologies could be observed. For example, (Bhuiyan *et al.*, 2014) proposed a three-phase sensor placement methodology for damage detection in SHM. In the first two steps, a whole WSN is created and divided into subnetworks with high-end and low-end sensor nodes. The classification is performed on the basis of availability of resources (e. g. battery lifetime and communication abilities). In the third phase, redundant nodes are placed to enhance the networks' reliability. The optimization is constrained regarding connectivity, transmission load and data delivery in the network and the placement quality is measured by use of Fishers Information Matrix. The approach of Thiene *et al.* (2016) has a similar look on the optimization problem and is also more focussed on connectivity and coverage issues of sensor networks for damage detection. Both methodologies have in common that they are mainly network reliability and data transmission focussed as well as damage detection focussed.

Besides the applications of OSP in the field of shape sensing and load and damage detection, there were no publications found addressing the OSP topic directly related to the curing of fibre reinforced plastics in an autoclave during the manufacturing process. It could be observed that in each publication with suitable content, the OSP was performed with focus on the use of the sensors for SHM purposes. For example in Ruzek *et al.* (2017), Fiber Bragg Gratings (FBGs) were integrated into the structure for monitoring the compressive behaviour of a composite component with respect to the cure of the component, but without measuring it and without addressing the sensor placement for this purpose. Hudson *et al.* (2019) on the other side focus on the use of piezoelectric sensors and FBGs for cure monitoring, but also didn't focus on OSP for this task. In Kyriazis *et al.* (2022), different cure monitoring techniques (a kinetic curing model supplied with thermal data, an integrated interdigitated electrodes sensor, a structure-borne acoustic measurement system, a refractive index measurement technique, and a strain gauge) are analysed regarding their limits and compatibilities. The results show, that a combination of strain gauges and interdigitated electrode sensors could yield good information of the curing reaction. However, even this specific publication on the topic of cure monitoring does not consider, where sensors should be placed optimally.

3. Comparison of related works

In Table 1, the different presented works are compared to one another regarding their applications for OSP and WSN optimization for the product creation and the product use phase for cure monitoring in manufacturing as well as load detection and identification. For comparison, the Harvey-balls analysis is used. There are many different approaches and methodologies in literature, which are more focussed on the monitoring and reconstruction of loads, shapes and damages. Just a few publications are focussed on the cure monitoring process. Furthermore, these publications are mainly addressed on how to monitor and are not taking a look on the optimization of sensor positions for this task. This shows that most of OSP methodologies are mainly focussed on the use-phase of composite parts. Besides, the optimization of the positions of many sensors is considered in different publications, but the configuration of a whole WSN is not. On the other hand, publications that focus on optimizing the network configuration do not always cater to the use of WSNs themselves, such as for cure monitoring or shape sensing. Notably, the optimization of WSN configurations often involves heuristics rather than optimization algorithms. When optimization algorithms are employed, the use of biology-based algorithms is commonplace, as observed in Bhondekar *et al.* (2009). A comparison of related works highlights the need for a methodological approach that takes into account the OSP and its linkage to a complete WSN.

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Table 1. Comparison of the presented works regarding their focusses and use

Comparison criterion \ Publications	Esposito et al. 2021	Ghasemzadeh and Kefal, 2022)	Zhu et al., 2023)	Ye et al., 2022	Bhuiyan et al., 2014	Thiene et al., 2016	Ruzek et al., 2017	Hudson et al., 2019	Kyriazis et al., 2022
Technique for OSP used	●	●	○	○	●	●	○	○	○
Focus on product creation phase	○	○	○	○	○	○	◑	◑	●
Focus on product use phase	●	●	●	●	●	●	●	●	○
Use for load identification or shape sensing	●	●	●	●	○	○	○	○	○
Use for damage detection	○	○	○	○	●	●	●	●	○
Use for cure monitoring	○	○	○	○	○	○	○	○	●
Configuration of a WSN is considered	○	○	○	○	●	●	○	○	○

○: Not fulfilled; ◑: Partly fulfilled; ●: Completely fulfilled

4. Proposal for a methodological approach for OSP

Picking up the need to define a methodology for OSP for product creation and product use, a first approach will be presented in the following. For presenting this approach, we follow the steps of the framework defined by Ostachowicz *et al.* (2019).

Regarding the application demands of the sensors, the product creation and product use are focussed. Furthermore, the sensors should be applied for cure monitoring and load detection and identification. Therefore, the integration of the sensors into the composite layup should be achieved. Concerning cure monitoring, the results of Kyriazis *et al.* (2022) show that integrated interdigitated electrodes sensors (IDS) and strain gauges (SG) are well suited for the use in cure monitoring. Besides, the use of thermo elements as temperature sensors (TS) is a good enhancement to yield a whole picture of the curing process. For the purpose of load detection and identification, the results presented in Section 2 have shown that most publications rely on strain gauges for the application in shape sensing. It is worth mentioning, that FBGs could be used as well instead of SG. However, since SG will already be integrated into the part, there is no need to integrate another kind of sensor which would result in a higher weight of the part. To allow a robust data acquisition, the SG are selected as full bridges to have a better temperature compensation during measurement. Regarding the third step in the OSP framework, the operational parameters have to be defined. Therefore, the component considered has to be chosen first. In case of this paper, a part of a scaled airplane wing box is considered. It should be manufactured from a prepreg material of carbon fibre reinforced plastics (CFRP) with dimensions of 120 x 50 x 2,000 mm. In our case, the sensors should operate from the inside of the CFRP layup during manufacturing, assembly and use. Furthermore, they should operate during the curing process in the autoclave for temperatures up to 180 °C. During assembly and use, the sensors have to operate in a wide temperature range (e. g. from 60 °C in direct sunlight on the ground and -60 °C at travel altitude) and have to work for high deformations of the composite parts. Last, the sensors should be connected to a WSN after manufacturing of the component which should enable the online load detection and identification with use of a PINN. The choice of a PINN is made due to the recent advantages in this research area and the little computational effort for shape sensing applications in comparison to numerical methods (Qiu *et al.*, 2023; Xu *et al.*, 2023; Hoffer *et al.*, 2021).

After these steps are considered, the OSP framework requires the definition of a cost function, the choice of an optimization algorithm, the definition of inputs, the optimal sensor placement and last the deployment. Since the following proposal of an OSP methodology is only for cure monitoring and PINN-based load detection and identification, it will be presented only for these purposes. Furthermore, the deployment-step is not considered yet.

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The methodology in this paper could be divided into a procedure of three main steps, following each other linearly: (1) Calculate the maximum number of sensors, (2) find optimal sensor positions and (3) conceive a sensor network architecture. These steps will be explained in the following in more detail.

4.1. Calculation of the maximum number of sensors

The process of finding the maximum number of sensors is shown in Figure 1. It begins by loading the FE-models of the part, like in this example the CFRP wing box. For this task, three FE-models are needed. The first model results from the analysis of the manufacturing process with the change of temperature, degree of cure, and the strains due to residual stresses. Besides, a conventional, structural analysis is performed to get the second model with the resulting strains during assembly. Last, the third model is a structural analysis of a load case during the use-phase. The second and the third FE-model are based on the results of the first model, since the residual stresses and strains are exported and mapped to them before starting the simulations.

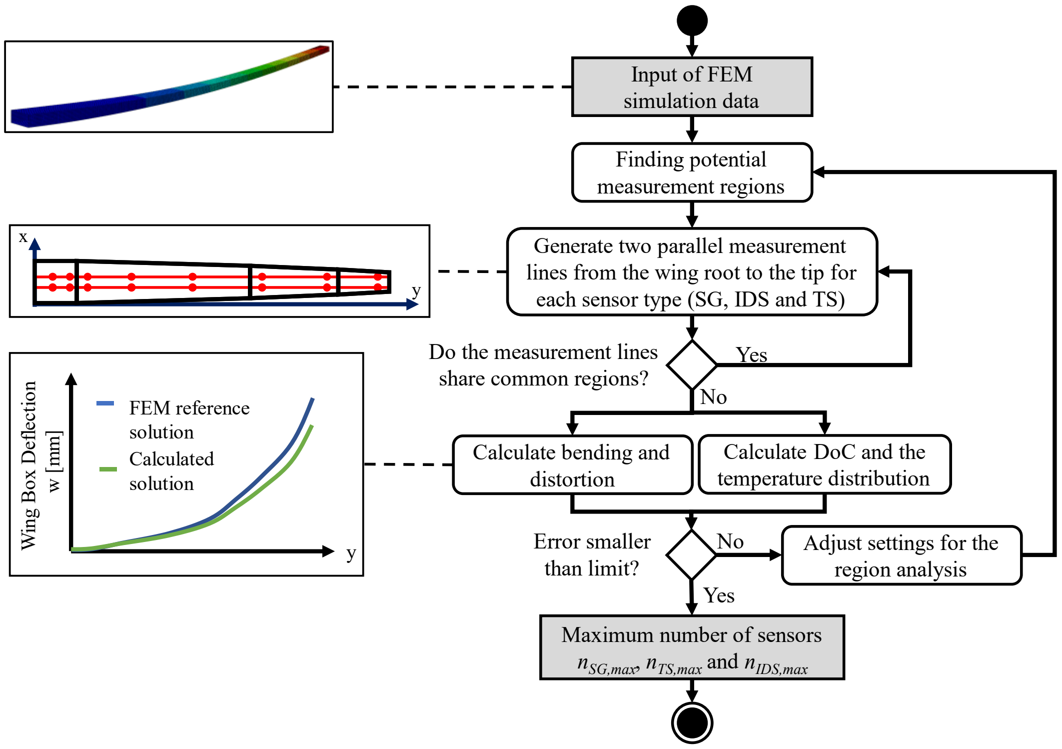

Figure 1. Process of finding the maximum number of sensors required for the measurement task of cure and load monitoring

For each of the FE-models, a region analysis is performed. In this analysis, the models are used to identify potential measurement regions. For example, areas with elements close to one another with similar strains will form a measurement region, where a sensor could be placed. This procedure allows to identify areas, where sensors would measure very similar values and where therefore only one sensor will be needed with a measurement without redundancy. For the distinction of values from each element, a tolerance has to be defined, which is equal to the measurement tolerance of the chosen sensor. The region analysis makes it possible to find out how many sensors would be needed at maximum. Therefore, it will be performed on the first FE-model to identify measurement regions for TS and IDS to monitor the temperature and degree of cure. The second and third FE-model are used to identify potential measurement regions for SG regarding the strains during assembly and use.

After the regions are built, two parallel sensor lines are generated. This idea is based on the shape sensing performed based on Ko's displacement theory by Valoriani *et al.* (2022), where two parallel lines of SGs are used to reconstruct the displacement of a wing according to beam bending. The use of two lines is chosen because it allows to calculate the distortion between the two lines as well as the displacement of each. These calculations are then used to estimate the shear force, bending moment, and torque for

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detecting and identifying applied loads and their application areas, like in Richards and Ko (2010). Besides the load detection and identification, the measurement lines should yield the distribution of cure and temperature relevant measurements along the wing box.
For the first sensor line, two requirements have to be fulfilled: The line has to reach from root to tip of the wing box and has to include a maximum number of measurement regions along its path. These requirements are chosen to generate a measurement line with a maximum number of sensors due to the high number of regions and to acquire data along the whole part. This allows to choose the optimal positions along the line from a high number of possibilities. After the first line, a second line is generated, which has to be parallel to the first one and has to reach from the root to the tip of the wing box and should share no common region with the first line. If this is not the case, the process of line generation is repeated. In case the two lines are generated correctly, results are calculated by assuming a sensor in the middle of each region section along the corresponding line. In Figure 1, for example, the bending deflection is calculated on the basis of strains as well as the corresponding bending force by the use of a PINN. The PINN is used in this optimization since it should be applied in the real-world load detection and identification as well. Therefore, the sensor positions should be optimized by considering how well it works for the simulation results. The calculated results are then compared to the FEM reference solution. For this comparison, the user has to define a limit for the error between the solutions, which can vary from one application to another. If the error limit is not exceeded, the found sensor positions in the regions along the two lines are used as maximum number of sensors needed for the measuring task for the minimization of sensor numbers and their OSP in the second step of the methodology. In case the error limit is exceeded, the settings for the region analysis have to be adjusted to find more regions for a higher number of sensors and therefore a higher accuracy between the reference and calculated results.

4.2. Optimization of the sensor placement

The second step of the OSP methodology is directly focussed on the optimization of the arrangement and quantity of the sensors and is shown in Figure 2. In the beginning, the solution with a maximum of sensors is used as reference solution, since none of the solutions should exceed this number of sensors.

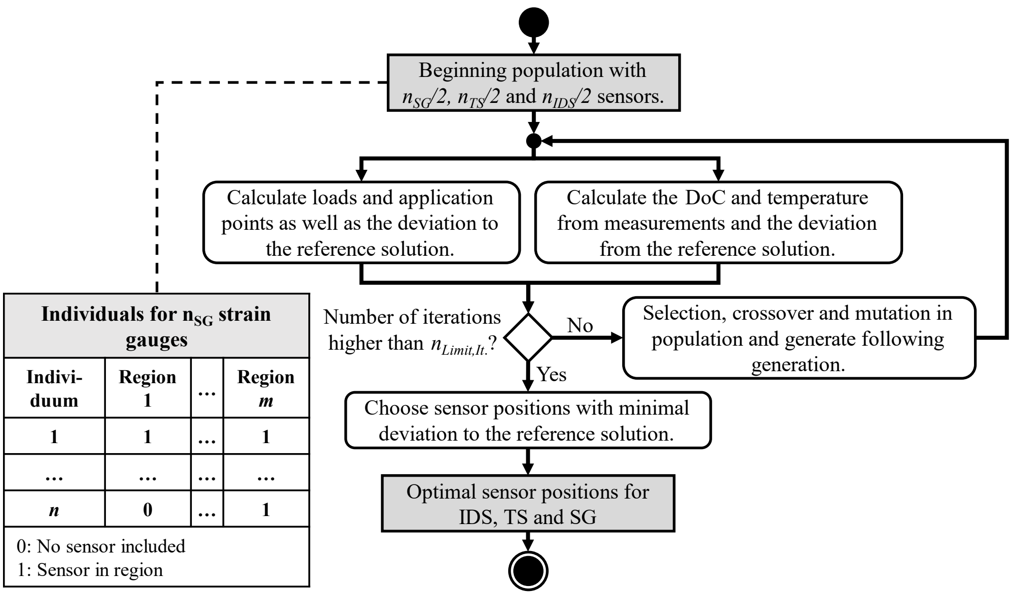

Figure 2. Process of finding the optimal number and position of sensors for the measuring task of cure and load monitoring

After the maximal number of sensors is defined as a first constrain for the optimization, the sensor positions in the middle of each region on the measurement line are used for the sensor placement in the optimization. This is results in a geometrical constraint for the OSP. For the optimization process,

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a GA is used for a multi-objective optimization with the goal to minimize the number of sensors $n_{Sensors}$ used and to minimize the error to the reference solutions, in our case the root mean square percentage error (*%ERMS*) from the FE simulation reference solution (see Equation 1). For this purpose, the NSGA-II optimization algorithm is suitable due to its performance in terms of finding a diverse set of Pareto-optimal solutions and converging near the true Pareto-optimal set (Deb *et al.*, 2002).

$$f_1 = \min(\%ERMS) \quad \text{and} \quad f_2 = \min(n_{Sensors}) \tag{1}$$

From the values of the maximum number of sensors from the first step, a population of individuals is generated for the GA, like it is shown in Figure 2. Therefore, $n_{Sensors}$ for each measurement (temperature, cure and strain) is reduced to half and the sensors are placed along the lines randomly. If a sensor is included or not is shown with a zero or one exemplarily by the table in Figure 2 on the example of the number of strain gauges.
Each of the sensor configurations depicts an individuum of the population in the GA. Therefore, for each individuum, the temperature and degree of cure distribution is calculated as well as the loads and their application points by use of the PINN. Afterwards, the results are checked for each individuum at discrete points i of the model. If the maximum number of iterations $n_{\text{Limit,It.}}$ of the GA is not exceeded, the *%ERMS* is calculated according to Equation 2. In this equation, k is the number of points, for which the reconstructed or identified quantity g ($g = F$ for load detection, $g = DoC$ for identifying the degree of cure and $g = T$ for identifying the temperature) is calculated. Therefore, g is calculated at each reconstruction point i and is compared to the reference solution at this point g_i^{ref} and the global maximum of the corresponding quantity g_{max}^{ref}.

$$\%ERMS = 100 \cdot \sqrt{\frac{1}{k} \cdot \sum_{i=1}^{k} \left(\frac{g_i - g_i^{ref}}{g_{max}^{ref}} \right)^2} \tag{2}$$

If *%ERMS* is less than the defined limit, a new population is generated from the individuals with the best results. From this crossover of the parents' genes, which are the positions of the sensors, a new offspring generation is created. Furthermore, mutation occurs during this process by adding and dismissing sensors randomly inside the offsprings (Ghasemzadeh and Kefal, 2022). Besides, in the new generation, the number of sensors is reduced to half of the number of the parent-generation. This is performed only for the types of sensors whose *%ERMS* in the calculation was smaller than the limit. Otherwise, if *%ERMS* exceeds the defined limit, a new generation is created from the individuals with best results and the number of sensors is increased by half of the number of the old generation. Therefore, the number of sensors is minimized with respect to the accuracy of the calculated solution. This process is repeated until the limit of iterations $n_{\text{Limit,It.}}$ is reached. This number could be defined by the user and be for example around 50 iterations, since (Ghasemzadeh and Kefal, 2022) showed a convergence of the cost function in the optimization to a minimum around this value. Then, the optimization algorithm stops and the configuration with the minimal deviation to the reference solution is chosen as the optimal solution for the positions.

4.3. Conception of a WSN architecture

After finding the optimal number and position of sensors for the monitoring of the autoclave process and the loads in assembly and use, the position of the sensor nodes has to be defined for building a sensor network. The process for finding optimal node positions is shown in Figure 3 and requires a definition of a permitted number of sensors nodes by the engineer. The optimization of the node positions is based on the Iterative Relocation heuristic for optimizing the position of warehouses regarding customer demands in the field of production management (Thonemann, 2015). This heuristic is chosen since the computational effort is very low in comparison to an optimization algorithm and is well suited to minimize distances between a clustering node as "warehouse" and the sensors as "customers".

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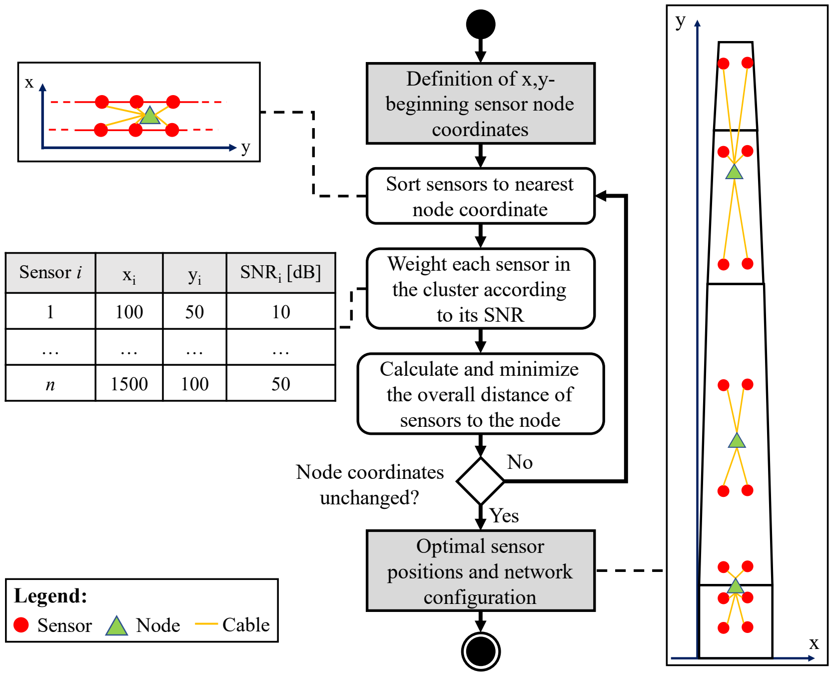

Figure 3. Optimal configuration process for a sensor network on the basis of optimizing sensor node positions by SNR-weight for each sensor

At first, a random solution is created for the x- and y-coordinates of the nodes. Afterwards, the sensors are clustered to the node by finding the node with the minimal Euclidian distance to the corresponding sensor. Since the goal of the optimization of node positions is to minimize the overall distance to the sensors to reduce cable lengths and negative influences on the signal quality, the distance between sensors and corresponding nodes has to be minimized. Therefore, the requirement in Equation 3 is used for each sensor. In this equation, the distance $Z(x, y)$ of a sensor node to all the sensors should be minimized. Therefore, the distance between each sensors coordinate x_i and y_i to the corresponding nodes coordinate $x_{Node,i}$ and $x_{Node,i}$ is calculated and weighted with each sensors weight w_i.

$$\min_{x,y}[Z(x,y)] = \min_{x,y}\left[\sum_i w_i\left(\left|x_i - x_{Node,i}\right| + \left|y_i - y_{Node,i}\right|\right)\right] \tag{3}$$

In the presented approach, the SNR of each sensor is used for weighting. Therefore, sensors with better SNR are weighted less than such with bad SNR. This reduces the distance to sensors with an already poor signal quality, so that further influences on them are minimized. From this approach, new node coordinates are derived. This process is repeated as long as the node coordinates change. If the resulting coordinates remain unchanged, the node positions are considered as optimal for the found sensor positions.

5. Conclusion and future work

Structure integrated sensors in composite parts can fulfil different functions during the product life, like the monitoring of an autoclave-based manufacturing process (cure monitoring) or load detection and identification during assembly and product use. To ensure reliable data acquisition in these tasks, it is crucial to have optimal sensor placement (OSP) during product development. Since in literature there is a gap in addressing OSP for both, the cure monitoring and the load detection and identification with the same sensors, a new methodology for this purpose is proposed in this paper. This methodology consists of three steps, involving the minimization of sensor quantity, finding optimal sensor positions and determining optimal positions of sensor nodes to minimize cable length and optimize the overall signal-to-noise-ratio (SNR). As an use case for the methodology development, a CFRP wing box is used.

In future work, the proposed methodology has to validated on the basis of FEM simulations and tests with a real CFRP wing box. To do so, a first characterization of the resins cure properties to derive a FE-cure-model, yielding the degree of cure, the temperature distribution and residual stresses is needed. Afterwards, an assembly process should be simulated with parameter variations as well as an exemplary

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load-case in the use-phase. On this data, a PINN could be trained for load detection and identification based on strain measurements. To take measurement uncertainties due to changing measurement properties after the manufacturing process into account, a variation of the SNR should be performed. In the end, the methodology has to be validated on a real demonstrator, based on data gathered before from tests on simple specimens, like for example CFRP plates with thickness variations.

References

Altun, O., Zhang, D., Siqueira, R., Wolniak, P., Mozgova, I. and Lachmayer, R. (2020), "Identification of dynamic loads on structural component with artificial neural networks", *Procedia Manufacturing*, Vol. 52, pp. 181–186. https://doi.org/10.1016/j.promfg.2020.11.032.

Bergmayr, T., Höll, S., Kralovec, C. and Schagerl, M. (2023), "Local residual random forest classifier for strain-based damage detection and localization in aerospace sandwich structures", *Composite Structures*, Vol. 304, p. 116331. https://doi.org/10.1016/j.compstruct.2022.116331.

Bhondekar, A.P., Vig, R., Lal Singla, M., Ghanshyam, C. and Kapur, P. (2009), "Genetic Algorithm Based Node Placement Methodology For Wireless Sensor Networks", *Proceedings of the International MultiConference of Engineers and Computer Scientists 2009, IMECS 2009.*

Bhuiyan, M.Z.A., Wang, G., Cao, J. and Wu, J. (2014), "Sensor Placement with Multiple Objectives for Structural Health Monitoring", *ACM Transactions on Sensor Networks*, Vol. 10 No. 4, pp. 1–45. https://doi.org/10.1145/2533669.

Damm, A.M., Spitzmüller, C., Raichle, A.T.S., Bühler, A., Weißgraeber, P. and Middendorf, P. (2020), "Deep learning for impact detection in composite plates with sparsely integrated sensors", *Smart Materials and Structures*, Vol. 29 No. 12, p. 125014. https://doi.org/10.1088/1361-665X/abb644.

Deb, K., Pratap, A., Agarwal, S. and Meyarivan, T. (2002), "A fast and elitist multiobjective genetic algorithm: NSGA-II", *IEEE Transactions on Evolutionary Computation*, Vol. 6 No. 2, pp. 182–197. https://doi.org/10.1109/4235.996017.

Esposito, M. and Gherlone, M. (2020), "Composite wing box deformed-shape reconstruction based on measured strains: Optimization and comparison of existing approaches", *Aerospace Science and Technology*, Vol. 99, p. 105758. https://doi.org/10.1016/j.ast.2020.105758.

Esposito, M., Gherlone, M. and Marzocca, P. (2021), "External loads identification and shape sensing on an aluminum wing box: An integrated approach", *Aerospace Science and Technology*, Vol. 114, p. 106743. https://doi.org/10.1016/j.ast.2021.106743.

Ghasemzadeh, M. and Kefal, A. (2022), "Sensor Placement Optimization for Shape Sensing of Plates and Shells Using Genetic Algorithm and Inverse Finite Element Method", *Sensors (Basel, Switzerland)*, Vol. 22 No. 23. https://doi.org/10.3390/s22239252.

Gherlone, M., Cerracchio, P. and Mattone, M. (2018), "Shape sensing methods: Review and experimental comparison on a wing-shaped plate", *Progress in Aerospace Sciences*, Vol. 99, pp. 14–26. https://doi.org/10.1016/j.paerosci.2018.04.001.

Hasselbruch, H., Hehl, A. von and Zoch, H.-W. (2015), "Properties and failure behavior of hybrid wire mesh/carbon fiber reinforced thermoplastic composites under quasi-static tensile load", *Materials & Design*, Vol. 66, pp. 429–436. https://doi.org/10.1016/j.matdes.2014.07.032.

Hoffer, J.G., Geiger, B.C., Ofner, P. and Kern, R. (2021), "Mesh-Free Surrogate Models for Structural Mechanic FEM Simulation: A Comparative Study of Approaches", *Applied Sciences*, Vol. 11 No. 20, p. 9411. https://doi.org/10.3390/app11209411.

Hudson, T.B., Auwaijan, N. and Yuan, F.-G. (2019), "Guided Wave-based System for Real-time Cure Monitoring of Composites using Piezoelectric Discs and Phase-shifted Fiber Bragg Gratings", *Journal of composite materials*, Vol. 53 No. 7, pp. 969–979. https://doi.org/10.1177/0021998318793512.

Klein, L. and Middendorf, P. (2016), "Functionalized lightweight parts: Application of LCM for the integration of automotive sensors in CFRP structures", in *21–25 September 2015, Graz, Austria*, Author(s), p. 90001.

Ko, W.L., Richards, W.L. and van Tran, T. (2007), "Displacement Theories for In-Flight Displacement Theories for In-Flight Deformed Shape Predictions of Aerospace Structures", *NASA/TP-2007-214612*, October 2007.

Kyriazis, A., Pommer, C., Lohuis, D., Rager, K., Dietzel, A. and Sinapius, M. (2022), "Comparison of Different Cure Monitoring Techniques", *Sensors (Basel, Switzerland)*, Vol. 22 No. 19. https://doi.org/10.3390/s22197301.

Lachmayer, R., Mozgova, I., Reimche, W., Colditz, F., Mroz, G. and Gottwald, P. (2014), "Technical Inheritance: A Concept to Adapt the Evolution of Nature to Product Engineering", *Procedia Technology*, Vol. 15, pp. 178–187. https://doi.org/10.1016/j.protcy.2014.09.070.

Lachmayer, R., Mozgova, I. and Scheidel, W. (2016), "An Approach to Describe Gentelligent Components in their Life Cycle", *Procedia Technology*, Vol. 26, pp. 199–206. https://doi.org/10.1016/j.protcy.2016.08.027.

Meyer zu Westerhausen, S., Schneider, J. and Lachmayer, R. (2023), “RELIABILITY ANALYSIS FOR SENSOR NETWORKS AND THEIR DATA ACQUISITION: A SYSTEMATIC LITERATURE REVIEW”, *Proceedings of the Design Society*, Vol. 3, pp. 3065–3074. https://doi.org/10.1017/pds.2023.307.

Mirzaei, S., Krishnan, K., Al Kobtawy, C., Roberts, J. and Palmer, E. (2021), “Heat transfer simulation and improvement of autoclave loading in composites manufacturing”, *The International Journal of Advanced Manufacturing Technology*, Vol. 112 No. 11-12, pp. 2989–3000. https://doi.org/10.1007/s00170-020-06573-3.

Ostachowicz, W., Soman, R. and Malinowski, P. (2019), “Optimization of sensor placement for structural health monitoring: a review”, *Structural Health Monitoring*, Vol. 18 No. 3, pp. 963–988. https://doi.org/10.1177/1475921719825601.

Prussak, R., Stefaniak, D., Kappel, E., Hühne, C. and Sinapius, M. (2019), “Smart cure cycles for fiber metal laminates using embedded fiber Bragg grating sensors”, *Composite Structures*, Volume 213, pp. 252–260. https://doi.org/10.1016/j.compstruct.2019.01.079.

Qiu, Y., Arunachala, P.K. and Linder, C. (2023), “SenseNet: A Physics-Informed Deep Learning Model for Shape Sensing”, *Journal of Engineering Mechanics*, Vol. 149 No. 3. https://doi.org/10.1061/JENMDT.EMENG-6901.

Raissi, M., Perdikaris, P. and Karniadakis, G.E. (2019), “Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations”, *Journal of Computational Physics*, Volume 378, pp. 686–707. https://doi.org/10.1016/j.jcp.2018.10.045.

Richards, W.L. and Ko, W.L. (2010), *PROCESS FOR USING SURFACE STRAIN MEASUREMENTS TO OBTAIN OPERATIONAL LOADS FOR COMPLEX STRUCTURES* No. US 7,715,994 B1.

Ruzek, R., Kadlec, M., Tserpes, K. and Karachalios, E. (2017), “Monitoring of compressive behaviour of stiffened composite panels using embedded fibre optic and strain gauge sensors”, *International Journal of Structural Integrity*, Vol. 8 No. 1, pp. 134–150. https://doi.org/10.1108/IJSI-11-2015-0052.

Teimouri, H., Milani, A.S., Seethaler, R. and Heidarzadeh, A. (2016), “On the Impact of Manufacturing Uncertainty in Structural Health Monitoring of Composite Structures: A Signal to Noise Weighted Neural Network Process”, *Open Journal of Composite Materials*, Vol. 06 No. 01, pp. 28–39. https://doi.org/10.4236/ojcm.2016.61004.

Tessler, A. and Spangler, J.L. (2005), “A least-squares variational method for full-field reconstruction of elastic deformations in shear-deformable plates and shells”, *Computer Methods in Applied Mechanics and Engineering*, Vol. 194 No. 2-5, pp. 327–339. https://doi.org/10.1016/j.cma.2004.03.015.

Thiene, M., Khodaei, Z.S. and Aliabadi, M.H. (2016), “Optimal sensor placement for maximum area coverage (MAC) for damage localization in composite structures”, *Smart Materials and Structures*, Vol. 25 No. 9, p. 95037. https://doi.org/10.1088/0964-1726/25/9/095037.

Thonemann, U. (2015), *Operations Management: Konzepte, Methoden und Anwendungen, Pearson Studium - Economic BWL*, 3rd ed., Pearson Studium.

Valoriani, F., Esposito, M. and Gherlone, M. (2022), “Shape Sensing for an UAV Composite Half-Wing: Numerical Comparison between Modal Method and Ko’s Displacement Theory”, *Aerospace*, No. 9, pp. 1–18. https://doi.org/10.3390/aerospace9090509.

Welzbacher, P., Geipl, A., Kraus, B., Puchtler, S. and Kirchner, E. (2023), “A FOLLOW-UP ON THE METHODICAL FRAMEWORK FOR THE IDENTIFICATION, ANALYSIS AND CONSIDERATION OF UNCERTAINTY IN THE CONTEXT OF THE INTEGRATION OF SENSORY FUNCTIONS BY MEANS OF SENSING MACHINE ELEMENTS”, *Proceedings of the Design Society*, Vol. 3, pp. 141–150. https://doi.org/10.1017/pds.2023.15.

Wiedemann, J., Prussak, R., Kappel, E. and Hühne, C. (2022), “In-situ quantification of manufacturing-induced strains in fiber metal laminates with strain gages”, *Composite Structures*, Volume 297. https://doi.org/10.1016/j.compstruct.2022.115967.

Xu, C., Cao, B.T. and Meschke, G. (2023), “Transfer learning based physics-informed neural networks for solving inverse problems in engineering structures under different loading scenarios”, *Computer Methods in Applied Mechanics and Engineering*, Volume 405 No. 115852. https://doi.org/10.1016/j.cma.2022.115852.

Ye, J., Do, N.C. and Lambert, M. (2022), “Physics-informed neural networks for hydraulic transient analysis in pipeline systems”, *Water Research*, Volume 221 No. 118828. https://doi.org/10.1016/j.watres.2022.118828.

Zhu, Q., Zhao, Z. and Yan, J. (2023), “Physics-informed machine learning for surrogate modeling of wind pressure and optimization of pressure sensor placement”, *Computational Mechanics*, Vol. 71 No. 3, pp. 481–491. https://doi.org/10.1007/s00466-022-02251-1.