A support vector regression-based approach towards decentralized fault diagnosis in wireless structural health monitoring systems

M. STEINER, D. LEGATIUK and K. SMARSLY

ABSTRACT

The reliability of sensors in structural health monitoring (SHM) systems is affected by sensor faults that compromise the quality of monitoring, causing erroneous judgment of structural conditions. To ensure reliable operation of SHM systems, techniques for diagnosing sensor faults have been proposed. In wireless SHM systems, embedding techniques for fault diagnosis (FD) into sensor nodes is of increasing importance as sensor nodes process data on board and communicate analysis results instead of large sets of raw data. As a consequence of on-board processing, raw data is frequently unavailable and sensor faults remain undetected. In this paper, a decentralized fault diagnosis approach based on support vector regression (FD-SVR) is proposed. Due to the high accuracy of the support vector regression (SVR), which can be achieved even with relatively small data sets, the FD-SVR approach enables wireless sensor nodes autonomously self-diagnose sensor faults, enhancing the reliability of wireless SHM systems without a need for large data sets to be used for fault diagnosis. The ability of the embedded FD-SVR approach to detect and isolate sensor faults, increasing the reliability of sensors in wireless SHM systems, is validated in laboratory experiments.

INTRODUCTION

The threats posed to public safety by aging civil infrastructure have paved the way for non-invasive methods to perform structural condition assessment in civil engineering [1]. Advancing cost-efficient condition assessment and timely detection of structural damage, structural health monitoring (SHM) aims at collecting and processing structural response data on a continuous basis. By analyzing structural response data in real time, alerts may be issued in the presence of abnormal structural conditions [2]. Furthermore, using wireless SHM systems facilitates easier installation and higher scalability as well as decentralized data processing through the processing capabilities of wireless sensor nodes [3]. However, the reliability of sensors is affected by sensor faults that compromise the quality of monitoring, causing erroneous judgment of structural conditions.

Maria Steiner, Dmitrii Legatiuk, Kay Smarsly, Computing in Civil Engineering, Bauhaus University Weimar, Coudraystraße 7, 99423 Weimar, Germany. Email: maria.steiner@uni-weimar.de; Internet: www.uni-weimar.de/cce.

Sensor faults are usually visible in the data collected by the sensors [4]. The five most common sensor fault types are bias, drift, gain, precision degradation, and complete failure [5].

To ensure reliable operation of wireless SHM systems, in the field of fault diagnosis (FD), strategies for detecting, isolating, identifying, and accommodating sensor faults are investigated since many years [6–8]. FD approaches in SHM are usually based on comparisons between virtual sensor outputs calculated from non-faulty, correlated senors and actual sensor outputs [9]. To reduce cost of material, installation, and maintenance, the information inherent to SHM systems is exploited to produce virtual sensor outputs ("analytical redundancy") instead of installing multiple redundant sensors ("physical redundancy") [10]. The analytically redundant information in structural response data is computed either via physics-based models or using data-driven models. While physics-based models require further knowledge related to underlying physical behavior, data-driven models build upon input-output data without a priori knowledge. For example, artificial neural networks have been used in several studies, representing data-driven models for fault diagnosis [11–13].

Most FD approaches, due to the limited resources of wireless sensor nodes, have in common to require centralized data storage and centralized data processing, which contradicts the decentralized nature of wireless SHM systems. Therefore, accurate and computationally efficient decentralized approaches to perform fault diagnosis on-board of the sensor nodes are essential. Most data-driven analysis methods employed for FD, such as artificial neural networks, are classified as "big data methods", requiring large data sets to ensure satisfying quality. In this paper, a fault diagnosis approach based on support vector regression (FD-SVR) is presented, which generally performs better compared to the big data methods when only small data sets available. By implementing the FD-SVR approach presented in this study, wireless sensor nodes are enabled to autonomously self-diagnose sensor faults in a decentralized manner, enhancing the reliability of SHM systems. The reliability is validated through laboratory tests using a prototype wireless SHM system installed on a laboratory bridge structure. Within the critical steps of fault diagnosis (fault detection, fault isolation, fault identification, and fault accommodation), this study focuses on fault detection and fault isolation.

DECENTRALIZED FAULT DIAGNOSIS BASED ON SUPPORT VECTOR REGRESSION

Concept of support vector regression

Numerical models or physical experiments can generally be characterized as an unknown (i.e. black-box) mapping f from input model/experiment parameters to the model output. The support vector regression (SVR) is used to construct an approximation function $\hat{f}$ of the black-box mapping f [14]. In the field of FD, the approximation function is used for creating virtual data for comparison with measured data. The function $\hat{f}$ is constructed from *training data* consisting of input points $\mathbf{x}_1, ..., \mathbf{x}_n \in \mathbb{R}^k$ and the responses $y_1 = f(\mathbf{x}_1), ..., y_n = f(\mathbf{x}_n)$. In this paper, the so-called ε-SVR is applied [15]. The approximation function is formulated as

$$\hat{f}(\mathbf{x}) = \mu + \sum_{i=1}^{n} w_i \psi(\mathbf{x}, \mathbf{x}_i), \tag{1}$$

where $[w_1, ..., w_n]^{\mathrm{T}} := \mathbf{w}$ and μ are unknown model parameters, whose values are determined through optimization. The function ψ is a Gaussian kernel function, i.e. $\psi(\mathbf{x}_i, \mathbf{x}_j) := \exp(-|\mathbf{x}_i - \mathbf{x}_j|^2/\sigma^2)$, with σ^2 denoting the variance, defining the correlation between a new point $\mathbf{x}$ and the training data. The SVR training process results in the following constrained optimization problem:

$$\begin{aligned} &\min_{\mathbf{w},\mu,\boldsymbol{\xi}} \frac{\|\mathbf{w}\|^2}{2} + C \sum_{i=1}^{n} (\xi_i^+ + \xi_i^-), \\ \text{subject to} \quad &\varepsilon - \xi_i^- \leq y_i - \hat{f}(\mathbf{x}_i; \mathbf{w}, \mu) \leq \varepsilon + \xi_i^+, \quad \xi_i^+, \xi_i^- \geq 0, \end{aligned} \tag{2}$$

where $\|\cdot\|$ is the Euclidean norm, ε is a tolerance parameter, ξ_i^+ and ξ_i^- are slack variables allowing error larger than ε, the parameter C controls the trade-off between the flatness of $\hat{f}$ and the influence of slack variables on the tolerance [16]. The solution of the convex optimization problem (2) can be constructed directly after reformulating it into a dual quadratic optimization problem by the Lagrangian function and the Karush-Kuhn-Tucker conditions [17]. In this paper, the coefficient of determination R^2 is used as an approximation quality measure [18]. The R^2 coefficient describes the part of the variation of f that can be mapped by $\hat{f}$ and is given by:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} \left(y_i - \hat{f}\left(\mathbf{x}_i\right) \right)^2}{\sum_{i=1}^{n} \left(y_i - \overline{y}\right)^2}, \tag{3}$$

where $\overline{y}$ denotes the mean value of $y_1, ..., y_n$. A high approximation quality is indicated by an R^2 value close to 1.

A support vector regression approach for decentralized fault diagnosis (FD-SVR approach)

For the FD-SVR approach, it is assumed that the structural response data, such as acceleration, at a sensor node j can be described by a function of the response data recorded from $(k-1)$ neighbored sensor nodes, as given below:

$$x^{(j)}(t_i) = f_j(x^{(1)}(t_i), ..., x^{(j-1)}(t_i), x^{(j+1)}(t_i), ..., x^{(k)}(t_i)), \quad \forall t_i \in [0, T], \tag{4}$$

with $[0, T]$ denoting the observed time interval. Based on non-faulty sensor data, which is used as training data for the SVR, the behavior of f_j is approximated with $\hat{f}_j$. Continuity of f_j is required for the convergence of $\hat{f}_j$ to f_j, leading to the condition that response data from different sensor nodes must be correlated. The FD-SVR approach consists of the following phases:

(i) Training phase, where the data is first pre-processed and then used to construct the approximation functions $\hat{f}_j$ for $j = 1, ..., k$. The results of the training phase are validated through the coefficient of determination by using additional validation data. Based on the R^2 values, the bounds for the fault detection are defined.

(ii) Initialization phase, where the approximation functions and the bounds are embedded into the corresponding sensor nodes, enabling decentralized fault diagnosis.

(iii) Observation phase, where each sensor node, in a decentralized manner, measures continuously structural response data and compares the data with virtual outputs approximating the measured data. In the event of discrepancies between the virtual and the actual sensor outputs higher than the bounds, sensor alerts are issued.

(iv) Decision phase, where the sensor alerts are interpreted by distinguishing between sensor faults and structural changes. Because of the decentralized nature of the FD-SVR approach, the fault isolation (i.e. localization) is automatically done.

Implementation of the FD-SVR approach into wireless SHM systems

The FD-SVR approach described in the previous subsections is designed to be implemented in wireless SHM systems for diagnosing sensor faults. Each sensor node measures structural response data from sensors to analyze data on board and to transmit or receive data within the SHM system. Based on the specific capabilities of the wireless sensor nodes, pre-processing of the data and data analyses are performed using embedded algorithms. The results of the analyses are transmitted via a base station to a server or to cloud-based devices for data storage and further data analysis.

Since the main monitoring tasks of wireless SHM systems are performed on the sensor nodes, decentralized computing on several hardware components is required. The FD-SVR applications, materializing the decentralized FD-SVR approach, to be implemented in wireless SHM systems are categorized into two groups, (i) the implementation running centralized on the server ("host application") and (ii) the implementation embedded in the sensor nodes ("on-board application"). The on-board application includes programs managing the sensor nodes operation (e.g. calibration, synchronization, and data collection) as well as programs for calculating virtual data and comparing actual and virtual data during the observation phase described earlier. The host application is assigned with calculating the approximation function $\hat{f}_j$ for each sensor node upon receiving sets of structural response data (training data) from all sensor nodes, as part of the training phase. The approximation functions are implemented into the corresponding sensor nodes during the initialization phase. The distinction between sensor faults and structural changes is performed on-board or on the server in the decision phase. A flowchart of the FD-SVR algorithm is shown in Figure 1.

VALIDATION OF THE FD-SVR APPROACH

The FD-SVR approach is implemented into a prototype wireless SHM system that is installed on a laboratory bridge structure to validate the reliable, i.e. non-faulty, operation of the sensors in the wireless SHM system.

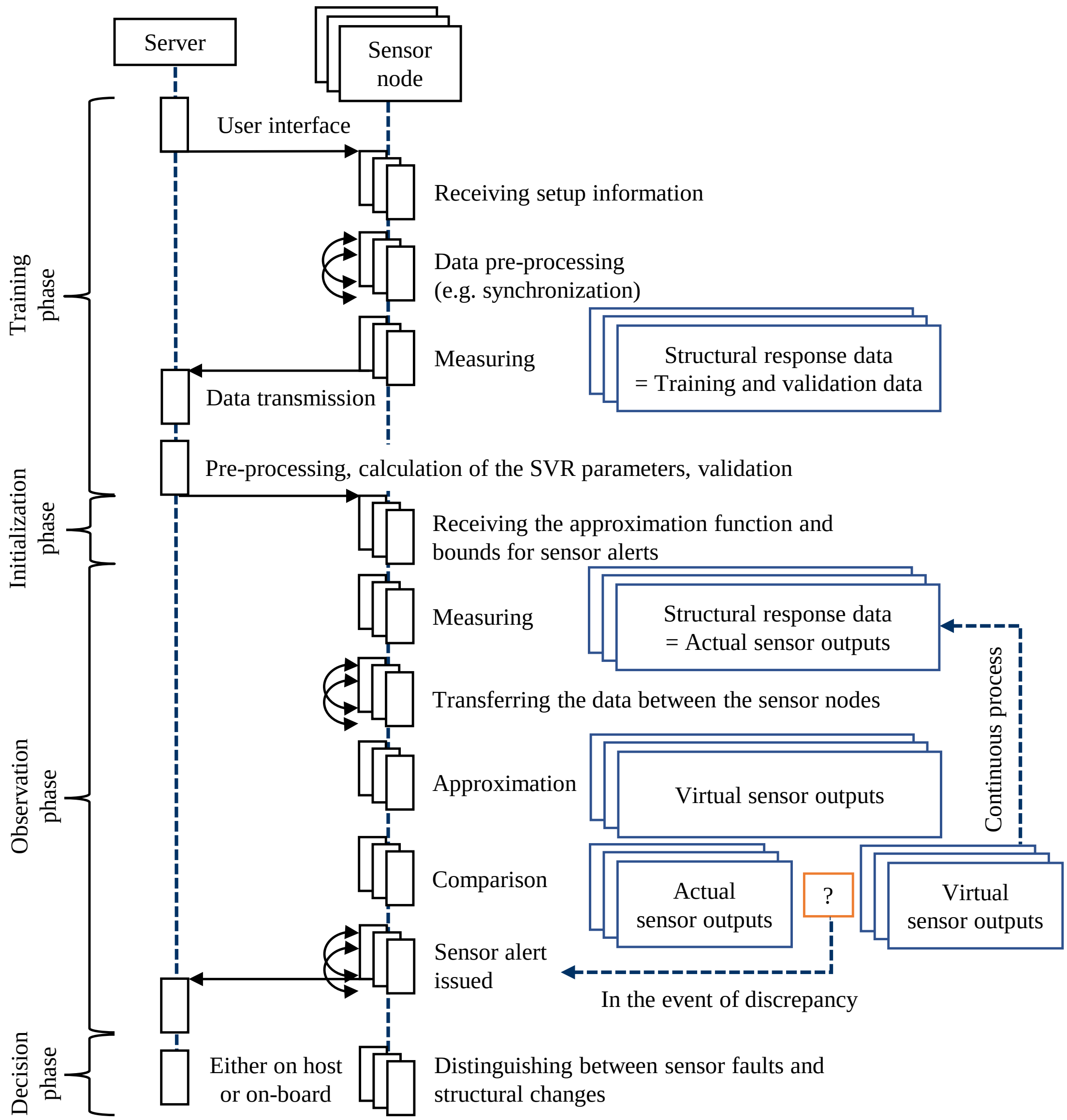

Figure 1. Flowchart of the FD-SVR algorithm.

Experimental setup

The wireless SHM system is installed on a laboratory test structure, shown in Figure 2, which is a single-span bridge of $1{,}600\,\mathrm{mm}$ length. The main bridge girders are made of aluminum plates of $2 \times 20\,\mathrm{mm}$ cross sections, resting on two blocks and supported by a superstructure made of aluminum plates of $L10 \times 10 \times 1\,\mathrm{mm}$. Along the length of the bridge, beams of $2 \times 20\,\mathrm{mm}$, perpendicular to the main girders, are distributed every $25\,\mathrm{mm}$. The wireless SHM system consists of sensor nodes, type Raspberry Pi 3 Model B+. Each Raspberry Pi features a quad core $1.4\,\mathrm{GHz}$ Broadcom BCM2837B0 64-bit CPU with $1\,\mathrm{GB}\,\mathrm{RAM}$, $2.4\,\mathrm{GHz}$, and $5\,\mathrm{GHz}$ wireless LAN compliant to IEEE $802.11.\mathrm{b/g/n/ac}$. To measure acceleration, an 3-axis accelerometer, type ADXL345, is connected to each Raspberry Pi, measuring at a resolution of 13 bits and up to $\pm 16\,\mathrm{g}$.

The placement of the sensors is determined according to the first eigenmode of the

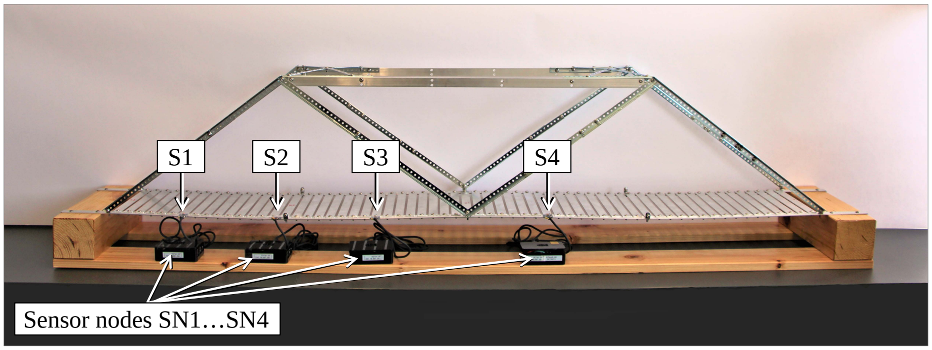

Figure 2. Sensor placement on the test structure.

simply-supported bridge structure. The first eigenmode corresponds to a double sinusoidal wave for a simply-supported bridge, with maximum amplitude at about one-quarter and three-quarters of the bridge length. Consequently, three sensors are located in one half of the bridge for capturing the sinusoidal shape (S1, S2, and S3), and the fourth sensor (S4) is located in the other half of the bridge for determining the direction of the next sinusoidal shape. The validation tests are performed by manually exciting different points along the bridge length, allowing free vibration of the bridge. Since the test structure is a one-span bridge, it is expected that the structural response in free vibration is predominantly governed by the fundamental mode of vibration, in which all sensor outputs are in phase with each other. As opposed for engineering practice where a combined contribution of several modes may compromise the accuracy of the FD-SVR approach, a correlation of the sensor outputs is expected at the laboratory structure.

Validation tests

In the following, the focus lies on sensor node SN2, because SN2 shows the highest correlation with the other senor nodes. To determine the optimum number of training points in the training phase, the number of training points is incrementally increased until a stable behavior of R^2 is reached. Increasing the number of training data normally improves the accuracy of the approximation, but large data sets may induce overfitting problems and increase the computational costs, influencing the effectiveness of the observation phase. Discussions on the size of training data and adaptive sampling strategies can be found, e.g., in [14, 19]. The decentralized implementation of the FD-SVR approach on sensor node SN2 is done with $n = 600$ data points used as training data. Through validation data of size $N = 4{,}096$, the quality of the approximation is calculated with $R^2 = 0.87$, which is used as the reference value for further investigations.

In the observation phase, observation data is continuously measured and compared to virtual data. To show the influence of each fault on the comparison, the different fault types (bias, drift, gain, precision degradation, and complete failure) are simulated, i.e. injected into sensor node SN2, by changing the observation data (size $N = 4{,}096$). The values for the faults and the results of the comparisons are presented in Table I. Therein, the faulty data is characterized by a function f^* defined by the faults compromising f. With a small deviation from the references value ($0.84 < R^2 < 0.87$), a fault is suspected; with higher deviations ($R^2 \leq 0.84$), a fault is considered ”detected”. The results indicate that the FD-SVR approach is capable of detecting even small sensor faults of all fault types considered in this study, and, as expected, larger faults are easier detectable.

SUMMARY AND CONCLUSIONS

In wireless SHM systems, embedded fault diagnosis is becoming increasingly important due to the decentralized nature of the systems. Therefore, in this paper a decentralized approach for embedded fault diagnosis based on FD-SVR has been presented. The decentralized FD-SVR approach enables wireless sensor nodes autonomously self-detecting sensor faults using the inherently redundant information in wireless SHM systems. The ability of the approach to detect different fault types has been shown by performing a validation test on a laboratory bridge structure. The test results have demonstrated that the FD-SVR approach enables accurate fault detection and isolation, ensuring reliable operation of sensors in wireless SHM systems even in case of relatively small sets of sensor data. Future research may focus on the extension of the approach to the other stages of fault diagnosis, i.e. fault identification and fault accommodation.

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TABLE I. FAULT DETECTION RESULTS.

Fault type	Fault parameter	Comparison result	Fault detection
Non-faulty $f(t)$	-	$R^2 = 0.87$	Reference value
Bias	$b = 0.02\,\mathrm{g}$	$R^2 = 0.85$	Fault suspected
$f^*(t) = f(t) + b$	$b = 0.05\,\mathrm{g}$	$R^2 = 0.81$	Fault detected
	$b = 0.1\,\mathrm{g}$	$R^2 = 0.68$	Fault detected
Drift	$b = 0.2 \cdot 10^{-4}\,\mathrm{g/s}$	$R^2 = 0.82$	Fault detected
$f^*(t) = f(t) + b \cdot t$	$b = 0.5 \cdot 10^{-4}\,\mathrm{g/s}$	$R^2 = 0.64$	Fault detected
	$b = 1 \cdot 10^{-4}\,\mathrm{g/s}$	$R^2 = 0.14$	Fault detected
Gain	$b = 1.02$	$R^2 = 0.86$	Fault suspected
$f^*(t) = b \cdot f(t)$	$b = 1.05$	$R^2 = 0.82$	Fault detected
	$b = 1.1$	$R^2 = 0.72$	Fault detected
Precision degradation	$\sigma^2 = 0.02\,\mathrm{g}$	$R^2 = 0.86$	Fault suspected
$f^*(t) = f(t) + w(t)$,	$\sigma^2 = 0.05\,\mathrm{g}$	$R^2 = 0.84$	Fault detected
$w(t) \sim \mathcal{N}(0, \sigma^2)$	$\sigma^2 = 0.1\,\mathrm{g}$	$R^2 = 0.75$	Fault detected
Complete failure			
$f^*(t) = b$,	$b = 0\,\mathrm{g}$	$R^2 = -\inf$	Fault detected
$f^*(t) = w(t) \sim \mathcal{N}(0, \sigma^2)$	$\sigma^2 = 0.1\,\mathrm{g}$	$R^2 = -0.61$	Fault detected

Sampling frequency $128\,\mathrm{Hz}$; range of the parameters: $t \in [0, 32\,\mathrm{s}]$, $x^{(2)} \in [-1.3, 1.3]\,\mathrm{g}$

REFERENCES

1. Hellier, C. 2013. *Handbook of Nondestructive Evaluation*, McGraw-Hill, New York, NY, USA, 2nd edn.
2. Bilek, J., I. Mittrup, K. Smarsly, and D. Hartmann. 2003. "Agent-based Concepts for the Holistic Modeling of Concurrent Processes in Structural Engineering," in J. Cha, R. Jardim-Goncalves, and A. Steiger-Garcao, eds., *Proceedings of the 10th ISPE International Conference on Concurrent Engineering: Research and Applications*, vol. 2, pp. 47–53.
3. Smarsly, K., D. Hartmann, and K. H. Law. 2013. "An Integrated Monitoring System for Life-Cycle Management of Wind Turbines," *International Journal of Smart Structures and Systems*, 12(2):209–233.
4. Ni, K., N. Ramanathan, M. Chehade, L. Balzano, S. Nair, S. Zahedi, E. Kohler, G. Pottie, M. Hansen, and M. Srivastava. 2009. "Sensor network data fault types," *ACM Transactions on Sensor Networks (TOSN)*, 5(3).
5. Qin, S. J. and W. Li. 1999. "Detection, identification, and reconstruction of faulty sensors with maximized sensitivity," *Journal of American Institute of Chemical Engineers*, 45(9):1963–1976.
6. Moore, E. F. and C. E. Shannon. 1956. "Reliable circuits using less reliable relays," *Journal of the Franklin Institute*, 262(3):191–208.
7. Moore, E. F. and C. E. Shannon. 1956. "Probabilistic logics and the synthesis of reliable organisms from unreliable components," *Automata Studies*:43–98.
8. Willsky, A. S. 1976. "A survey of design methods for failure detection systems," *Automatica*, 12:601–611.
9. Smarsly, K. and Y. Petryna. 2014. "A decentralized approach towards autonomous fault detection in wireless structural health monitoring systems," in *Proceedings of the 7th European Workshop on Structural Health Monitoring 2014*.
10. Kramer, P. and C. P. Fritzen. 2007. "Sensor fault identification using autoregressive models and the mutual information concept," *Key Engineering Materials*, 347:387–392.
11. Basirat, A. H. and A. I. Khan. 2009. "Graph neuron and hierarchical graph neuron, novel approaches toward real time pattern recognition in wireless sensor networks," in *Proceedings of the 2009 International Conference on Wireless Communications and Mobile Computing*, Leipzig, Germany.
12. Smarsly, K. and K. H. Law. 2014. "Decentralized fault detection and isolation in wireless structural health monitoring systems using analytical redundancy," *Advances in Engineering Software*, 73(2014):1–10.
13. Dragos, K. and K. Smarsly. 2016. "Distributed adaptive diagnosis of sensor faults using structural response data," *Smart Materials and Structures*, 25(10):105019.
14. Forrester, A. I. J., A. Sobester, and A. J. Keane. 2008. *Engineering design via surrogate modelling: a practical guide*, John Wiley & Sons Ltd, Hoboken, NJ, USA.
15. Schölkopf, B. and A. J. Smola. 2002. *Learning with Kernels*, MIT Press.
16. Vapnik, V. 1995. *The nature of statistical learning theory*, Springer-Verlag.
17. Kuhn, H. W. and A. W. Tucker. 1951. "Nonlinear programming," in *Proceedings of the 2nd Berkeley Symposium on Mathematical Statistics and Probability*, University of California Press, Berkeley, pp. 481–492.
18. Neter, J., M. H. Kutner, C. J. Nachtsheim, and W. Wasserman. 1996. *Applied linear statistical models*, Irwin Professional Publishing, Burr Ridge, IL, USA.
19. Steiner, M., J.-M. Bourinet, and T. Lahmer. 2019. "An adaptive sampling method for global sensitivity analysis based on least-squares support vector regression," *Reliability Engineering and System Safety*, 183(C):323–340.