

# Machine learning techniques for structural health monitoring

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## Abstract

*Data-driven approaches are particularly useful for computer-supported assessment of civil engineering structures (i) if large quantities of sensor data are available, (ii) if the physical characteristics of the structure are complex to model (or even unknown), or (iii) if the computational efforts are to be reduced. This paper, upon a classificational review of machine learning techniques in structural health monitoring, reports on an embedded machine learning approach for decentralized, autonomous sensor fault detection in wireless sensor networks, facilitating reliable and accurate structural health monitoring. Based on decentralized artificial neural networks, the embedded machine learning approach is applied to perform autonomous detection of sensor faults injected in the acceleration response data collected by a prototype structural health monitoring system. As demonstrated through laboratory tests, the results highlight the ability of the embedded machine learning approach to autonomously detect sensor faults in a decentralized manner, thus enhancing the reliability and accuracy of structural health monitoring systems.*

## 1 INTRODUCTION

Advancements in sensor technologies have enabled economically affordable sensor installations for long-term monitoring of civil engineering structures. Structural health monitoring involves installations of hundreds to thousands of sensors to collect valuable data about the structure. With increasing complexity and heterogeneity of sensor data, data integration and data analysis have become important issues for decision making with respect to diagnosis of the structural condition and the prognosis of structural damage [1, 2].

Data analysis in structural health monitoring, from a computer science perspective, aims at transforming sensor data into useful information and probably into knowledge about the structure. The information and knowledge gained from the sensor data is then used for structural assessment and for decision making in several respects, such as life-cycle management [3] or lifetime prediction [4]. Two general approaches exist for assessing the structural condition of civil engineering structures, physics-based approaches and data-driven approaches [5]. Physics-based approaches establish first-principle models, mapping the physical characteristics of the structure (e.g. using finite element analysis), and then compare the outputs of the physical models with sensor data obtained from the monitored structure in order to assess the structural condition [6]. Although significant efforts have been undertaken to render physics-based models more efficient in terms of computational performance, for example for embedment into resource-constraint wireless sensor nodes [7, 8], physics-based

approaches are generally more computationally intensive than data-driven approaches.

Data-driven approaches also establish models for comparison with sensor data, but data-driven models exploit information from previously collected sensor data, referred to as “training data” [9]. While physics-based approaches are valid in a large operating range without the need for extensive quantities of sensor data, data-driven approaches allow learning patterns in the sensor data without any knowledge on the physical characteristics of the structure [10]. Data-driven approaches are particularly useful, if (i) large quantities of sensor data are available, (ii) the physical characteristics of the structure are complex to model (or even unknown), or (iii) the computational efforts are to be reduced.

A variety of data-driven approaches, particularly machine learning techniques, has been proposed in structural health monitoring (SHM) for assessing civil engineering structures. Machine learning in the context of SHM can be described as the task of generating knowledge from past experiences (or, more precisely, from collected sensor data), focusing on the prediction of new sensor data. While in artificial intelligence research machine learning techniques have been studied since many decades (e.g. for robot control, human-computer interaction, or speech recognition), its importance in SHM applications substantially continues to grow since about 20 years [11, 12]. For example, Worden and Manson [13] have illuminated the utility of machine learning to damage identification, concluding that neural networks are still popular, and systems like support vector machines are beginning to appear more regularly. Figueiredo et al. [14] have investigated auto-associative neural networks, factor analysis, Mahalanobis distance, and singular value decomposition to study operational and environmental variability and its influence on damage detection of civil engineering structures. Dervilis [15], centered on SHM of wind turbine blades, also explores auto-associative neural networks and formulates pattern recognition algorithms. In addition, robust multivariate statistical methods are introduced to account for the influence of operational and environmental variation on damage-sensitive features; the algorithms described are the Minimum Covariance Determinant Estimator and the Minimum Volume Enclosing Ellipsoid. Park et al. [16], also focusing on wind energy research, couple Gaussian Discriminative Analysis and Gaussian Mixture Models to analyze and to predict wind turbine loads in various atmospheric conditions. Nick et al. [17], reporting significant trade-offs between accuracy and runtime of the machine learning techniques proposed, have used unsupervised learning for identifying the existence and location of damage (k-means and self-organizing maps) and supervised learning for identifying the type and severity of damage (support vector machines, naive Bayes classifiers, and feed-forward neural networks).

This paper presents an embedded machine learning approach for decentralized, autonomous fault detection in wireless SHM systems. Sensor faults and miscalibrations substantially affect sensor data and may compromise the reliability and accuracy of SHM systems. Specifically in data-driven approaches, the integrity of the sensor data needs to be preserved to enhance the reliability and accuracy of SHM system outputs as well as the robustness of algorithms implemented for structural health monitoring. In the study reported in this paper, the efficient detection of sensor faults and miscalibrations is based on the correlations among the response data of different sensor nodes, referred to as “analytical redundancy”, which is implemented through an embedded machine learning approach based on artificial neural networks. This paper is organized as follows: First, an overview of machine learning techniques commonly used in structural health monitoring is provided. Then, the embedded machine learning approach for decentralized, autonomous sensor fault detection, based on artificial neural networks, is implemented into a wireless SHM system.

Serving as a testbed for the proposed approach, a laboratory test structure is used in this paper for validation, followed by a concise summary of the study presented herein.

## **2 AN EMBEDDED MACHINE LEARNING APPROACH FOR DECENTRALIZED, AUTONOMOUS SENSOR FAULT DETECTION**

In computer science and in computational engineering, the process of detecting patterns and structures within data sets is commonly known as data mining. The detection of patterns enables future predictions and decision making, while representing the patterns in terms of structures facilitates the extraction of conclusions on the patterns. In data mining, the techniques employed to detect patterns within data sets fall into the category of machine learning.

As mentioned previously, due to the computational burden of physics-based approaches in structural health monitoring, data-driven approaches, such as machine learning, have been gaining increasing attention. In SHM, machine learning is understood as the task of generating knowledge about the structural behavior from previously collected sensor data. While structural responses are theoretically well explained and documented, the detection of such responses in full-scale structures is non-trivial due to the complex nature of actions and the actually unknown properties of the structure. Furthermore, SHM outputs may be affected by sensor faults and miscalibrations, which may be hardly visible in the collected data. In this context, machine learning is applied to detect such hidden, non-evident, or inadequately described phenomena. In this section, the machine learning techniques typically applied in SHM are briefly discussed. Then, an embedded machine learning approach for decentralized, autonomous detection of sensor faults and miscalibrations is presented.

### **2.1 Classification of machine learning techniques for structural health monitoring**

Machine learning techniques can be classified into three broad categories according to the nature of learning: 1) supervised learning, 2) unsupervised learning, and 3) semi-supervised learning [18]. Supervised learning provides a learning scheme with “labeled data”, i.e. examples that include specified outputs (pairs of input data and output data). Using labeled data, rules are developed in an attempt to classify new data sets. Unsupervised learning encompasses the detection of patterns within the data sets consisting of “unlabeled data”, i.e. data sets with unspecified outputs, which fit to a general rule and can, therefore, be grouped together. From an SHM viewpoint, unsupervised learning can be used, e.g., for detecting the existence of damage through clustering of structural response data, while supervised learning can advantageously be employed to detect the type and severity of damage [19]. Semi-supervised learning, representing a combination of the two aforementioned learning schemes, typically aims at obtaining a classification of data using both labeled and unlabeled data. Semi-supervised learning schemes have been applied combined with other monitoring techniques to extract information on modal characteristics of bridges [20].

Since most SHM problems require inferring a function from labeled training data (e.g. to assess the data or to predict new data), supervised learning is an appropriate means to solve these problems. In supervised learning, the algorithms, according to [21], can be categorized as logic-based algorithms (e.g., decision trees and rule-based classifiers), perceptron-based algorithms or neural networks (e.g., single-layered perceptron, multi-layered perceptron and radial basis function networks), statistical learning (e.g., naive Bayes classifiers and Bayesian networks), instance-based learning (e.g., k-nearest neighbor algorithm), and support vector machines.

## 2.2 Prototype implementation of the machine learning approach

In this study, decentralized autonomous sensor fault detection is based on the principle of analytical redundancy [22]: Instead of physically installing multiple sensors for measuring one single parameter, analytical redundancy takes advantage of the redundant information inherent in the SHM system and utilizes the coherences and relationships between the sensors installed in the structure. It has been proven that the peak amplitudes of the frequency spectrum, obtained by the Fourier transformation of acceleration response data, corresponding to resonant response (i.e. modal peak amplitudes) from different sensors of the same structure are correlated [23]. This correlation can be exploited to predict the modal peak amplitudes of selected sensors, using the modal peak amplitudes of correlated sensors as input data. Deviations between expected amplitudes and actual amplitudes (i.e. from the measured data) are indicative of sensor faults and miscalibrations. Importantly, no a priori knowledge about the structure or about the sensor instrumentation is required because, as a purely data-driven approach, previously collected sensor data is taken as the sole basis for fault detection.

A wireless SHM system is designed that comprises wireless sensor nodes, each of which including an integrated 3-axis accelerometer, a base station, and a host computer. The monitoring tasks executed by the SHM system are illustrated in Figure 1. During operation, acceleration response data is sampled by each sensor node and locally transformed into the frequency domain via an embedded Cooley-Tukey FFT algorithm. A peak detection algorithm selects the highest peak of the frequency spectrum corresponding to the fundamental eigenfrequency (modal peak amplitude), and the modal amplitudes are communicated among the sensor nodes. Each sensor node predicts the modal amplitude of its own acceleration response data (expected amplitude) using the modal peak amplitudes of correlated sensor nodes and decides upon the existence of sensor faults based on deviations between the expected and the actual modal peak amplitude. The outcomes of the fault detection procedure of the sensor nodes are transmitted to the host computer via the base station for storage and decision making.

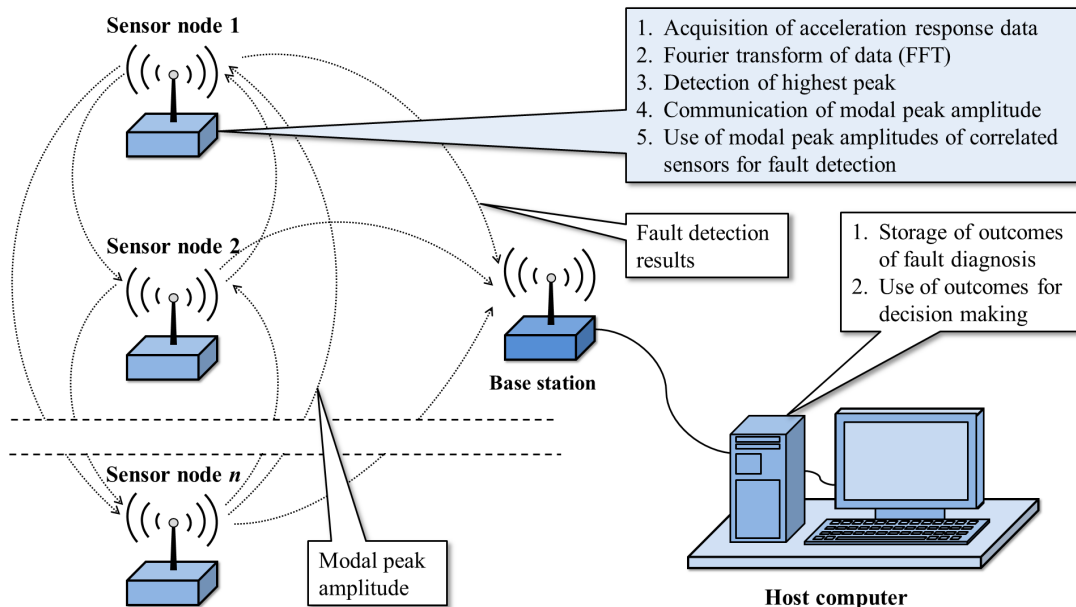


Figure 1. Decentralized, autonomous fault detection procedure executed by the wireless SHM system

The decentralized autonomous fault detection procedure proposed in this study relies on the relationships among the modal peak amplitudes from different sensors. To map these relationships an embedded machine learning approach with a supervised learning scheme is introduced. To this end, artificial neural networks (ANNs) are designed and distributedly embedded into each sensor node. As shown in Figure 2, the ANNs consist of three layers of neurons: 1) an input layer of  $k$  neurons, 2) a hidden layer of  $m$  neurons to account for the non-linear relationship among the modal peak amplitudes of different sensors [24], and 3) an output layer of one neuron, which represents the predicted modal peak amplitude of the sensor under consideration. The data is propagated through the ANN via the “synapses” (i.e. connections between neurons), based on the weight of each connection. During the ANN training, the weights of the synapses are adjusted until a selected set of input data results in the desired output data. The ANN properties (i.e. ANN topology and neuron behavior) are determined based on computational steering and trial-and-error tests. For further details, the interested reader is referred to [9, 22, 24, 25].

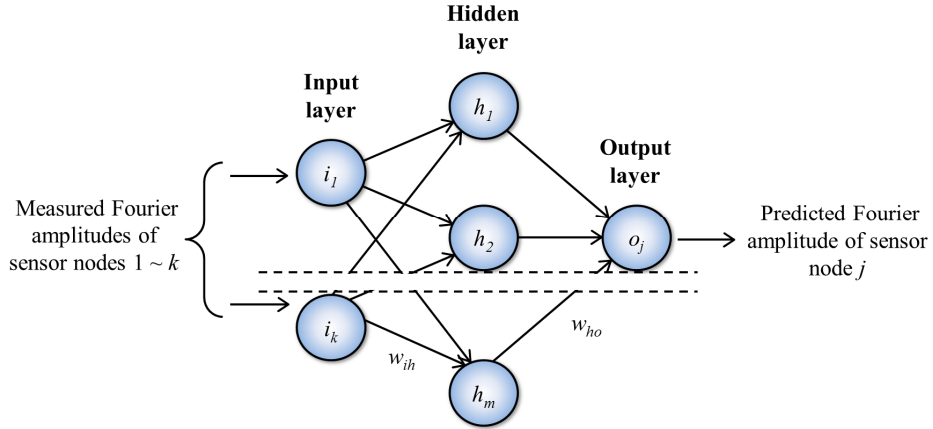


Figure 2. Schematic of the artificial neural network embedded into the wireless sensor nodes

### 3 VALIDATION OF THE MACHINE LEARNING APPROACH

Validation tests to showcase the ability of the embedded machine learning approach are performed on a laboratory test structure. In the first part of this section, the laboratory test setup is described. In the remainder of this section, the training of the ANN and the determination of the ANN properties are presented. Finally, the application of the embedded machine learning approach is illuminated.

#### 3.1 Laboratory test setup

To validate the embedded machine learning approach, the wireless sensor nodes are installed on the test structure, as shown in Figure 3. The test structure is a 4-story frame structure consisting of steel plates of 250 mm x 500 mm x 0.75 mm. The plates are mounted on threaded rods with a vertical clearance of 23 cm. At the bottom of the structure, the rods are fixed into a solid block of 400 mm x 600 mm x 300 mm. A total of four wireless sensor nodes, labeled “A”, “B”, “C” and “D”, are placed on the structure at the center of each story. In addition to the wireless sensor nodes, a base station, connected to a local computer, is placed next to the test structure.

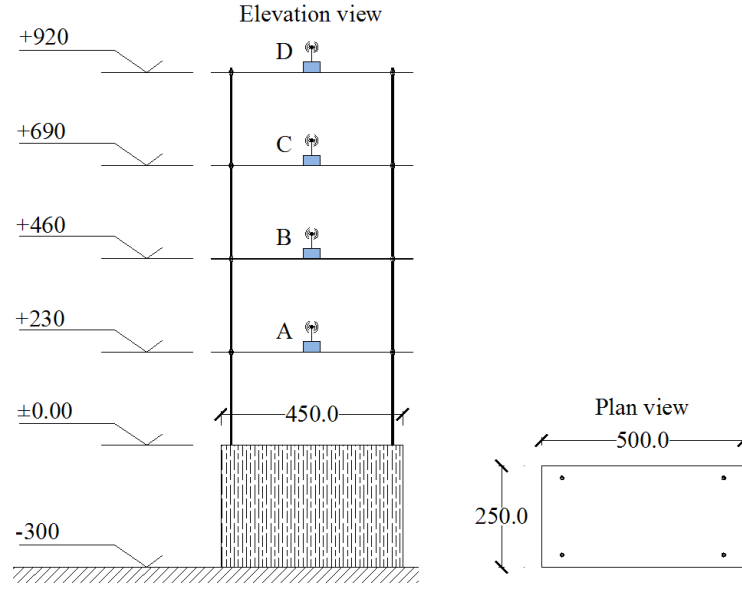


Figure 3. Schematic of the laboratory test structure

### 3.2 Training and determination of the artificial neural network properties

Preliminary tests are conducted to determine the ANN properties [24]. Several combinations of topologies and neuron behaviors are tested. The determination of the properties is based on the performance of the ANN in terms of time required for training and on the output accuracy. The output accuracy (or the predictive power) is expressed through the root mean squared error between the expected and the actual amplitudes, as shown in Eq. 1. For training, 100 sets of 4 modal peak amplitudes (from all sensor nodes) are created. Following the standard practice in ANN training, the data set is divided to 80% training sets to establish the relationship between inputs and outputs, 10% validation sets to decide when to stop training, and 10% test sets to check the predictive power of the trained ANN.

$$\varepsilon_{RMS} = \frac{1}{N} \sum_{i=1}^N \sqrt{F_{expected_i}(\omega_1)^2 - F_{actual_i}(\omega_1)^2} \quad (1)$$

In Eq. 1,  $\varepsilon_{RMS}$  is the root mean squared error,  $N$  is the number of testing sets,  $F_{expected}$  is the expected modal peak amplitude,  $F_{actual}$  is the actual amplitude, and  $\omega_1$  is the fundamental eigenfrequency. The sets of modal peak amplitudes are split into three inputs and one output; the modal peak amplitudes of sensor nodes A, C, and D are used as input to predict the modal peak amplitude of sensor node B. Therefore, each of the tested ANNs has three neurons in the input layer and one neuron in the output layer. Between the input layer and the output layer, several hidden layers with varying number of neurons per hidden layer are tested. In terms of neuron connections, both interlayer connections (between adjacent neurons) and supralayer connections (i.e. between distant neurons) are tested. Finally, for neuron behavior, both backpropagation and resilient backpropagation algorithms are applied. The results of the preliminary tests are presented in Table 1.

Neuron behavior	Topology	Neurons per sensor node	Computing time (s)	$\varepsilon_{RMS}$ (-)
Interlayer, backpropagation	3-1	4	6.6	0.149
	<b>3-2-1</b>	<b>6</b>	<b>13.0</b>	<b>0.102</b>
	3-3-1	7	17.2	0.144
	3-5-1	9	25.0	0.081
	3-7-1	11	32.2	0.063
	3-2-2-1	8	21.0	0.092
Interlayer and supralayer, backpropagation	3-3-1	7	15.2	0.147
	3-5-1	9	22.6	0.132
	3-2-2-1	8	19.4	0.137
Interlayer, resilient backpropagation	3-3-1	7	113.0	0.153
	3-5-1	9	172.4	0.143
	3-2-2-1	8	120.6	0.208

Table 1. Results of preliminary tests to determine the ANN properties (source: [24])

The results of the preliminary tests show that all combinations of ANN properties demonstrate satisfactory output accuracy. However, in terms of performance the time required for training varies significantly. As a trade-off between the time and the output accuracy an ANN with 3-2-1 topology, interlayer connections, and backpropagation neuron behavior is selected. In the next subsection, the application of the selected ANN to detect sensor faults injected into the acceleration response data is presented.

### 3.3 Application of the machine learning approach for autonomous fault detection

Two of the most common fault types, bias and precision degradation, are simulated and injected into the acceleration response data. A bias (Figure 4a) is a deviation between the actual response and the expected response by a constant value; precision degradation (Figure 4b) is a contamination of the response data with excessive-variance white noise. Both faults have a noticeable impact on the modal peak amplitudes of the acceleration response data.

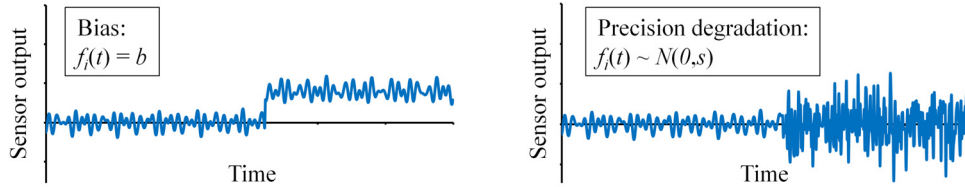


Figure 4. Manifestations of bias (a) and precision degradation faults (b)

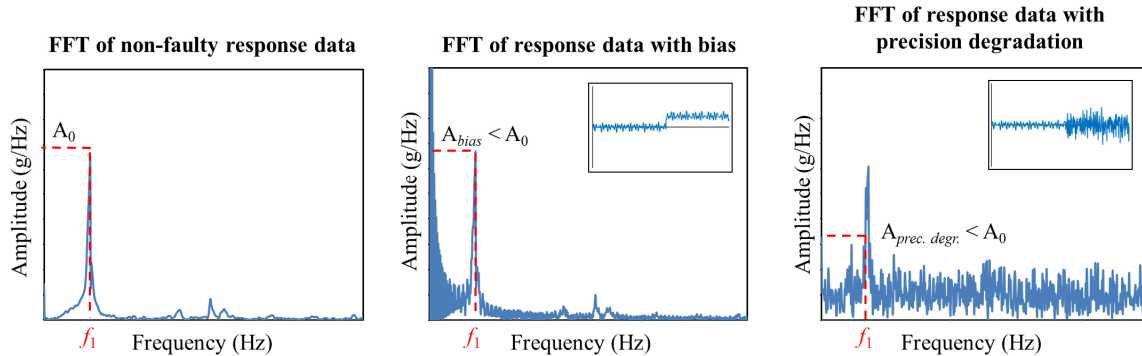


Figure 5. Impact of the simulated and injected sensor faults on the modal peak amplitudes

Bias is injected by rotating one sensor node by  $45^\circ$ , while precision degradation is injected by contaminating the acceleration response data of the sensor nodes with a random Gaussian time series. Similar to the preliminary tests, the modal peak amplitudes from sensor nodes A, C, and D, (as depicted in Figure 3) are used to predict the modal peak amplitude of sensor node B. A threshold for the  $\varepsilon_{RMS}$  at  $\tau = 0.15$  is established from trial-and-error tests. The results of the ANN application are summarized in Table 2.

Root mean square error	No fault	Simulated fault	
		Bias	Precision degradation
$\varepsilon_{RMS}$	0.102	0.603	0.807

Table 2. Fault detection of simulated sensor faults, indicated by root mean square error.

As shown in Table 2, the root mean squared error for both simulated sensor faults significantly exceeds the predefined threshold. It can be concluded that fault detection using the proposed embedded machine learning approach is a promising tool to enhance the reliability and accuracy of monitoring.

#### 4 SUMMARY AND CONCLUSIONS

A broad wealth of data-driven approaches, particularly machine learning approaches, has been proposed in structural health monitoring for assessing the condition of civil engineering structures. In machine learning approaches for structural health monitoring, the learning scheme can be categorized into supervised, unsupervised, and semi-supervised learning. Based on supervised learning, an embedded machine learning approach for decentralized autonomous fault detection has been presented in this paper. The proposed approach makes use of the analytical redundancy, i.e. the redundant information obtained by the sensors. More specifically, the inherent correlations among the amplitudes at peaks of the frequency spectra of acceleration response data obtained from different sensors are utilized. The modal peak amplitude of each sensor is predicted using the modal peak amplitudes of correlated sensors as input data. Deviations between the expected amplitude (i.e. the amplitude obtained from the prediction) and the actual amplitude are indicative of sensor faults. To map the relationship among the modal peak amplitudes of correlated sensor nodes, artificial neural networks have been distributedly embedded into the wireless sensor nodes.

Validation tests have been conducted on a 4-story laboratory test structure. A total of four wireless sensor nodes have been used, each of which placed at the center of one story. Preliminary tests have been performed to determine the properties of the ANN, based on time and output accuracy criteria, in which the modal peak amplitudes of the sensor nodes of three stories have been used to predict the modal peak amplitude of the sensor node of the remaining story. Then, two common sensor faults have been injected into the acceleration response data of one sensor node. Finally, the ANN has been applied, and, using the modal peak amplitudes of the other three sensor nodes the faults have been successfully detected. In conclusion, the results of the validation tests showcase the ability of the proposed machine learning approach to detect sensor faults. Future work could include establishing a solid threshold to distinguish non-faulty from faulty operation as well as implementing the automated adaptation of the fault detection procedure to account for structural changes.

## 5 ACKNOWLEDGMENTS

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