Model-based and Statistical Approaches for Sensor Data Monitoring for Smart Bridges

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Abstract*— At present, bridge maintenance management typically consists of regular visual building inspections. Structural damage frequently remains undiscovered until it becomes clearly visible, a situation which makes little economic sense. However, it is often the case that damage and critical reactions to a bridges internal structure occur in inaccessible and concealed places, and are caused by existing but often unknown effects on the construction. Existing as well as newly-constructed bridges should therefore be able to provide information about their condition and it's development at an early stage in addition to the building inspections. To achieve this, flexible and adaptable modular systems are required in and on the bridge structures to provide measurement-technology support, together with differentiated evaluation procedures and a correspondingly enlarged maintenance management program. The instrumentation required must consist of capable and durable sensor technology to register effects on the structures and the reactions of individual structural elements; on the other hand smart measurement data processing must also be in place to ensure the plausibility, fusion, interpolation and reduction of sensor data streams in situ. This article summarizes the approaches and prospects of implementing a high-performance sensor data analysis and monitoring concept which has been examined in the context of current research with a focus on practical aspects of monitoring bridge structures. The discussion in this contribution focuses on model-based and statistical analysis techniques with regard to areas of application and input-to-benefit-ratios. The findings of this research are of general interest and therefore transferable to other areas of infrastructure maintenance management.

I. Introduction

With its central position in Europe, the federal trunk road network in Germany (BFSt) carries the main burden of traffic in the European internal market and furthermore, have to withstand with ever-rising volumes of traffic in the future. The federal trunk road network contains over 39,400 bridges with a total bridge surface area of approx. 30 million m^2 [2]. Maintaining these structures requires an ongoing process of observation and inspection, a task of considerable importance for the road construction authorities. Bridges are awarded a score denoting their condition as the result of regular, manual (visual) structural inspections in accordance with DIN 1076, which include damage assessments with regard to stability, durability and traffic safety [2][3]. The road construction authorities of the federal countries use the results of these structural inspections as the basis for their maintenance planning. The current approach is based in the first instance on identifying damage and is therefore responsive; since damage is only discovered within the scope of the regular inspections at a late stage after it has become obvious, this leads to high costs for maintenance and repair.

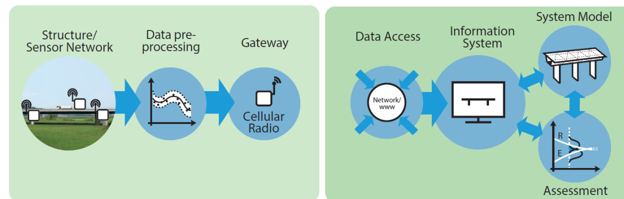

Fig. 1. Conception of Smart Bridges: adaptable modular systems for registration and wholistic evaluation of relevant information on changes in actions and resistance on bridges.

In order to continue providing a reliable road infrastructure in the long term and under strict budget limitations, it is necessary to integrate new and innovative approaches into maintenance management procedures which enable damage to be detected at an early stage. This is particularly important in the context of establishing the condition of building structures, ideally in real time. It is therefore necessary to design and develop a modular system which can be fitted to specific, individual structures and which can deliver relevant information regarding changes in action and resistance on bridge structures. This system should also include an assessment of the current condition which is appropriate to the structure and which comprise the condition parameters comprehensively. It is possible to achieve this by equipping the instrumentation on the building structures with sensors which match the requirements of these individual structures. Sensor data registered in this way can be applied for the remote monitoring of the BFSt in real time. They as well can be employed for predicting changes in the condition of structures by using program-based structural bridge models and deterioration models. In these models damage related issues for individual elements and their relevance for the overall static integrity of the structure are combined and subsequently assessed (Figure 1). Furthermore, process data for structures which are capable of adapting to operational conditions (adaptive structures) can be obtained possibly, e.g. the load-dependent control of the prestressing of tendons. This paper is an extended version of [1] containing substantially novel aspects such as statistical approaches and new simulation results.

II. Sensor Data Monitoring and Analysis System

For the above mentioned scope, the generation of reliable information with the least possible error using a robustly

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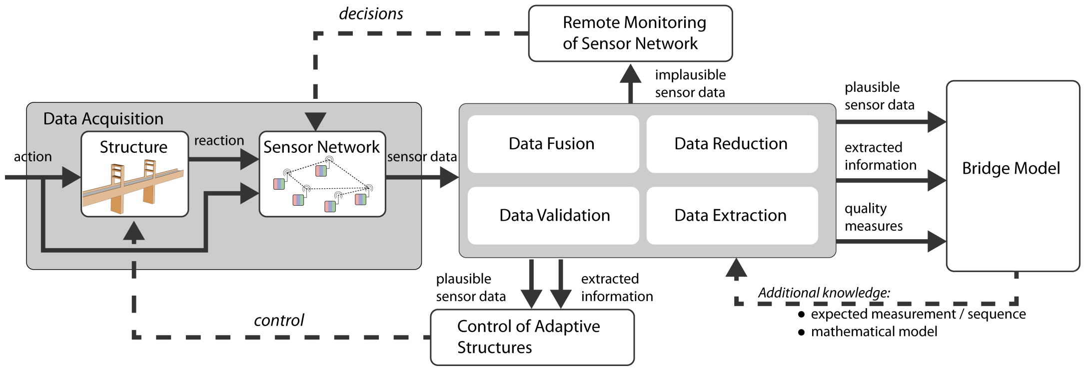

Fig. 2. Concept for a sensor data monitoring and analysis system.

defined concept for measurement-technological condition monitoring is of primary importance. A major contributory factor here is provided by a powerful system of sensory data monitoring and analysis (cf. Block Data Preprocessing Figure 1) which is upstream of further data processing and use.

The essential tasks to be carried out by this system are (Figure 2):

- **Validating the Plausibility of Sensor Data** by detecting errors in sensor signals which are caused by malfunctions, aging, various types of interference in the way the instrumentation is set up such as line crosstalk, electromagnetic interference and drift; quality assessment is applicable.
- **Fusing Sensor Data** (merging and integration of information) of similar or different measurement and registration variables for determining the condition of structures or structural elements.
- **Interpolating Sensor Data** as input variables for program-based damage prediction algorithms, temporal and spatial interpolation for the generation of plausible data streams necessary for suppressing sensor signal errors.
- **Deriving higher-value Information (automatically)** on selected condition parameters with the aim of independently identifying specific technical issues with predefined measurement-technological and/or structure-specific significance.

The last three functions enable to achieve a degree of data reduction in the registered data so that the configuration size of data transfer channels and power supply components can be reduced.

A. Methodological Approach

In assembling a reliable body of data on the current condition of building structures, simple monitoring and analysis technique which are for example based on the value range and trend monitoring of measurement parameters are insufficient for the required technical standard due to their poor detection performance and the lack of correction potential for faulty data. Procedures based on a probabilistic approach which takes account of signal-stochastic and/or signal-theoretical aspects, as well as approaches used in artificial intelligence, can lead to a significant increase in performance in the area of measurement-technological condition monitoring on building structures within the task scope detailed above. This paper seeks to present the results of research which was conducted in the form of a feasibility study which examined real sensor data [4] which shows promising potential approaches for implementing a powerful sensor data monitoring and analysis system which would fulfill possible future operational requirements on bridges.

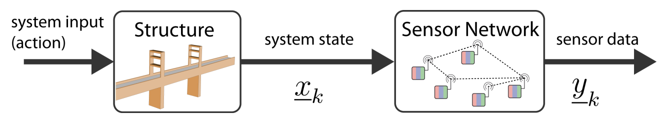

Fig. 3. Representation of structural and element properties and measurement characteristics.

The following representation serves to describe the investigation of data on actions (e.g load resistance, freeze-thaw cycle stresses) and resistance (corrosion resistance, the current moment of resistance), i.e. the process of registering the current properties of a structural element and/or the system condition of the bridge x_k with all its parameters covering action, durability and load-bearing capacity, which in turn form the basis for further analysis and statements on the condition of the structure (Figure 3).

III. Model-Based Approaches

Model-based analysis technique can be used constructively for displaying sensor information and condition information, for increasing plausibility of this information and for data reduction purposes. In general, an explicit mathematical model is adopted which describes the physical and chemical characteristics and relationships in the process being examined: e.g. time-independent material laws, analytical lifetime models and models which illustrate the load and deformation behavior of a building structure. The more precise the modeling of the physical process being described is, the more precise the result of the condition data being calculated. To this end, a number of initially unknown and/or still to be determined physical/chemical parameters must be set. In an inhomogeneous system such as structural elements,

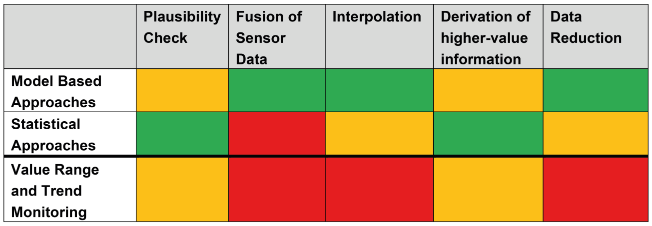

Fig. 4. Areas of application for model-based and statistical analysis technique (green: supports perfectly, yellow: moderately applicable).

these parameters are location-dependent. This can lead to a high degree of complexity and high levels of computation for models of this kind, especially when sensor data need to be evaluated and checked locally, i.e. in a sensor node. It would therefore be worthwhile to identify simplified models as approximations which are sufficient for the plausibility check and the sensor fusion of the registered data [5][6][7]. Figure 4 provides a current assessment of the areas of application suitable for model-based analysis technique in comparison with the other very simple procedures, on the basis of knowledge gained in the course of this study.

A. Modeling System and Measurement Behavior

In general, a mathematical model serves to describe a system or process such as the deformation of a structure under load. This model is made up of a model structure as well as model parameters. It displays the relation between input variables and output variables, e.g. the load as an input variable and the associated deformation (stress) of a structural element as an output variable. The physical parameters, which clearly describe the condition of the physical process, are identified as system status x_k. Depending on the type of system being described, various physical/chemical parameters can be used as condition variables; in the case of mechanical systems these are usually displacements, angles, velocities and accelerations. The approximate modeling is described by a system equation [7].

Sensors which work in the same way on the basis of physical and/or chemical laws can also be displayed descriptively as a physical system. Here, measurement errors and particular sensor characteristics (e.g. nonlinear measurement function, the influence of temperature) can be included in a measurement equation. $y_k$represents the sensor data as they exist directly at the output of a sensor.

Figure 5 illustrates the procedure using a multi-ring electrode with an integrated temperature sensor (*PT 1000*), which represents the parameters temperature T and concrete moisture content f_B in a concrete structural element by changing the electrical resistance (R_T and R_F).

Figure 6 provides a general outline of how a system under observation (physical processes in a structural element) as well as the measurement procedure itself can be modeled together. The system equation describes approximately (deterministically) the behavior of the element in relation to a set of specified physical parameters, whilst the measurement equation describes the non-ideal measurement process. The

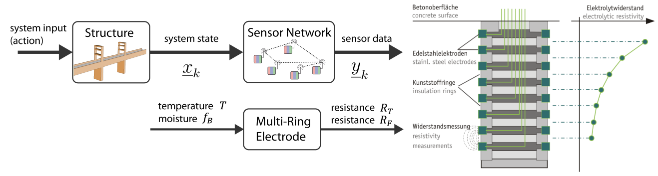

Fig. 5. Definition of system status and sensor data using a multi-ring electrode [12]

data flow in Figure 6 can therefore be seen as a simulation of the actual condition of the element in reality and during the measurement procedure (time-discrete implementation i.e. for interval-based measurements).

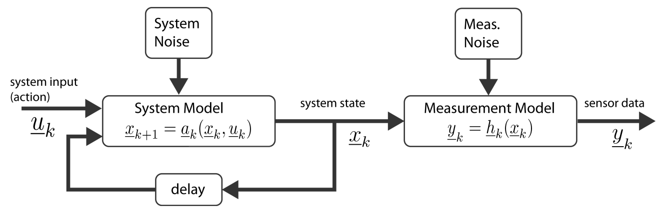

Fig. 6. Modeling of structure element and measurement behavior.

By initiating the inverse function in the measurement equation and the measurements y_k (Figure 7) which have been registered on site and which have now been fed into this modified measurement equation, it is possible to reduce measurement errors – thanks to the physical system model and by accounting for the characteristics of the measurement procedure. In addition, this method enables future measurements to be predicted for any given condition parameter of a structural element (model-based state estimator). Both imprecisions that occur during the modeling process and are naturally present in the measurements are considered by means of a probabilistic approach. By conducting a direct comparison between the registered and the predicted measurements, it is possible to carry out an efficient plausibility check on the measurement data. Furthermore, this also allows for fusion, interpolation and data reduction.

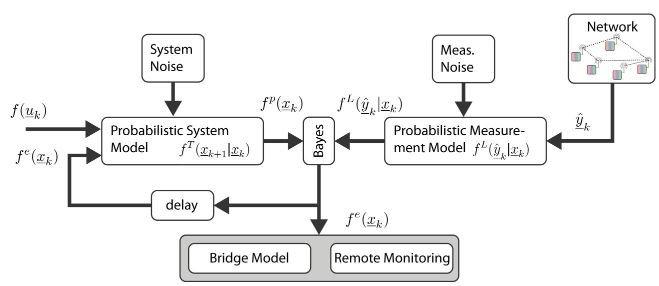

Fig. 7. Realization of a model-based state estimator using the inverse function in the measurement equation.

Using a model-based state estimator [8] [9] [10], it is possible for monitoring purposes, to assess the degree of moisture and its associated variance in a concrete structural element from data registered using two separate sensors (moisture as well as temperature to correct the moisture data)

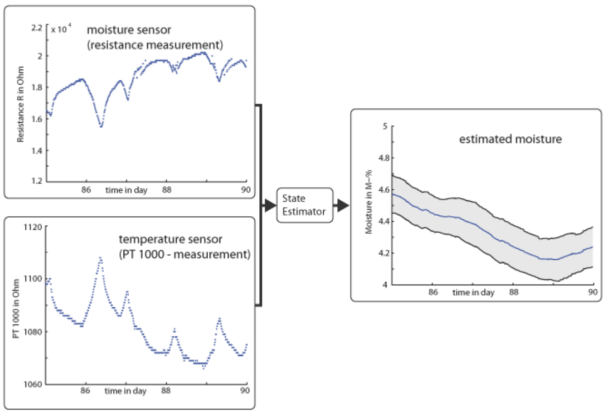

Fig. 8. Data fusion – model-based state estimator – estimating levels of moisture and its variance.

(Figure 8, measurement interval 15 $mins$, input data as in Figure 5). Because of providing the result by combining input data R_T and R_F (two-dimensional measurement dataset), data fusion occur.

The modeling of structural element behavior permits a number of approaches depending on the required capability levels and effort required for implementation. Comparable approaches such as those used in the modeling of structural element behavior can also be used analogously for the modeling of measurement behavior [4]. Figures 11 and 25 show approaches for parameters which are typically registered in situ from the structure itself.

1) Precise Modeling of the Physical Process at Hand: For the purposes of modeling, bridge elements constitute an inhomogeneous system in which the physical/chemical parameters in the elements are location-dependent and which therefore have to be adopted as being parametrically distributed. To achieve precise modeling, it is therefore necessary to arrive at a description of physical parameter using a system of stochastic, partial differential equations (PDE). Precise modeling is therefore highly complex. Often, this complexity is inappropriate in relation to the attainable improvements of accuracy and robustness for the data for sensor fusion and validation of plausibility of the data [11].

2) General Physical Modeling: When carrying out a data plausibility check, it is often most expedient to limit the process to universally valid general laws. Any inaccuracies arising as a result can simply be incorporated into the modeling process (process noise).

In many cases, it can be assumed e.g. that the temperature in an element (and hence in the sensor) cannot simply change suddenly, but requires a certain period of time in order to harmonize the thermal masses involved in the process. This inertia in many physical processes can be described by using a so-called PV model (P stands for physical parameter and V for its time derivation, velocity) or more generally using a PVA model (A stands for the second time derivation, acceleration). For example, simple laws of motion concerning involved masses of the elements and simple meteorological effects concerning the ambient temperature can serve as the basis for addressing acceleration (cf. Figure 11). Adjusting the algorithms to the building structure can only be done generally, and they only become more precise by relearning the parameters automatically while in operation [5][6]. Clearly illustrated the general physical modeling is the tracking of future condition changes in the parameters registered in the structural element based on general laws.

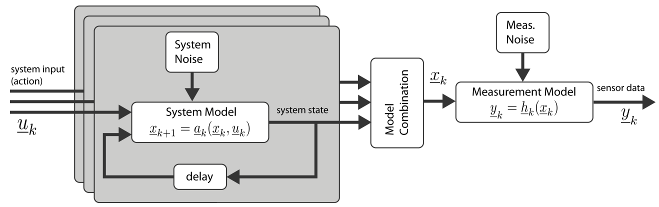

Fig. 9. Multiple models – different system equations running in parallel and subsequent ongoing weighting of the individual system models.

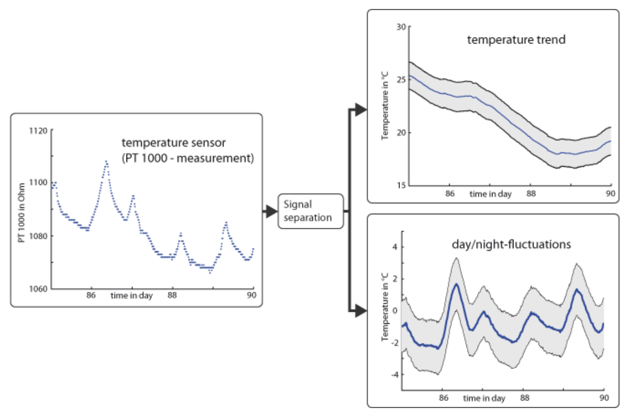

Fig. 10. Separation of signal components - temperature trend and day/night-fluctuations.

3) Approximations using Multiple Model Approaches: In many cases, it is not possible to describe the dynamic behavior of an element satisfactorily by using a single system model. For example, dynamic behavior can be entirely different during sharp rises in temperature (sunshine and shadow constellation) than during sharp falls in temperature (e.g. during a sudden cold front). These behavioral differences can be considered for using a finite number of potential models which describe different aspects of the system behavior (Figure 9). These models can differentiate e.g. between noise levels, the system structure or the dimensionality of the condition parameters. A measurement sequence which switches between slow and fast changes at different points in time can be described using two system models. Depending on the situation, the weighting of the individual models changes and the algorithm therefore adjusts adaptively to the measurement sequence. In addition, higher-value information can be derived from the weighting of the models [13].

4) Separation of Signal Components: By selecting the appropriate probabilistic model, additional information can be extracted from the registered data. It is therefore possible to determine not directly measurable parameters such as tem-

Parameter	gen. Physical Modelling	Multiple Model Approach	Separation of Signals
Temperature	**Physical inertia of heat propagation** simple determination of parameters, e.g. **PV Model**	Various models for various state phases e.g. temperature rises/falls, detecting these, e.g. **Combination of P, PV and PVA models**	Separation of the **temperature signal in a trend signal and day/night fluctuations**
Moisture (Ambient/ Material Moisture Content/ Corrosion)	**Physical inertia of moisture propagation,** temperature dependency e.g. **PV Model**	Various models for various state phases e.g. moisture rises/falls, detecting these, e.g. **Combination of P, PV and PVA models**	Separation of the **moisture signal in a trend signal and day/night fluctuations**
Strain/ Stress	**Smoothness characteristics of strain and stress distribution**, dependency on **temperature** and **traffic loads** e.g. **PV Model**	Various models for **slight changes/ sudden changes.** Detecting steps/ load changes e.g. **combination of various movement models**	Separation **of the long-term trend signal and fluctuations caused by temperature changes**
Acceleration (Vibration)	**physical inertia of moving masses,** dependency on **temperature** e.g. **movement model**	Various models for **slight changes/ sudden changes.** Detecting steps/ load changes e.g. **combination of various movement models**	Separation of **various frequencies** (e.g. eigen frequencies, load changes), **determining frequency spectrum**
Cracking	**physical inertia between individual cases of sudden increases in cracking**, dependency on **temperature** and **traffic loads** e.g. **movement model**	Various models for **slight changes/ sudden changes.** Detecting sudden increases in cracking e.g. **combination of various movement models**	Separation of **various frequencies** (e.g. eigen frequencies, load changes, day/night fluctuations), **determining frequency spectrum**
Traffic Loads	**physical inertia of moving masses** e.g. **movement model**	Various models for **slight changes/ sudden changes,** (e.g. caused by a vehicle crossing the bridge), detecting load changes e.g. **combination of various movement models**	Separation of **various frequencies** (z. B. excitation by load changes), **determining frequency spectrum and load changes**

Fig. 11. Implementation possibilities for typical parameters registered in situ at a building structure.

perature trend rates. The measurement data registered during the measurement process often arises due to various diverse physical effects. Therefore these signals can be separated into different parts, such as their separation into slower and faster changes (e.g. temperature trend and day/night fluctuations). The example Figure 10 (PT 1000 temperature sensor, measurement interval 15 $mins$, input data as in Figure 5) shows temperature profiles for monitoring purposes, together with their associated variations.

IV. Statistical Approaches

Statistical methods of analysis (and in particular machine learning techniques) are in particular suitable for increasing plausibility and extracting higher value information, i.e. the automated recognition of technical situations (see Figure 4). Unlike model-based methods of analysis, the special property of machine learning techniques lies in their independent learning ability, i.e. based on a set of training data, they can learn specific tasks autonomous without being explicitly programmed to do so (no physical model is required). The efficiency and potential to fulfill the set tasks depend on the structure and arrangement of the techniques. The task with techniques of this kind consists of finding an information processing structure for specific tasks and then optimizing it. Once this has been defined for a certain class of problem or type of sensor, the techniques can implement this structure automatically and learn its parameter assignment and therefore its behavior independently [14][15].

A. Machine Learning Algorithms

The following machine learning algorithms in particular come into question when equipping sensor data monitoring and analysis systems:

- **Principal Component Analysis (PCA):** this is a technique from multivariate statistics. Based on the linear combination learned by means of training data, it is possible, for example, to calculate an expected measurement and therefore its variation from the actual measurement [16].
- **Artificial neural networks (ANN)** are mathematical descriptions that attempt to come close to reproducing the structure and information architecture of the nerve system of animals or humans. The special property of artificial neural networks is their independent learning ability, i.e. based on a set of training data, they can learn certain tasks autonomously without being explicitly programmed to do so [14] [19].
- **Self-Organizing Maps (SOM)** are a special type of artificial neural network for the unsupervised learning of features related to differentiated data groups. The features learned may be used to check the plausibility of the measurement and entry data, i.e. to detect anomalies [17].
- **Generative Topographic Mapping (GTM)** can be seen as a probabilistic extension of SOMs; uncertainties in the measurement and entry data and the learned model can be systematically taken into consideration [18].

Without a further presentation of each of these techniques, a brief assessment of their suitability is depicted by way of the results of the study (cf. Figure 14). The Artificial Neural Networks (ANN) represent the most efficient machine learning technique for the range of tasks specified, and will therefore be looked at in greater detail below.

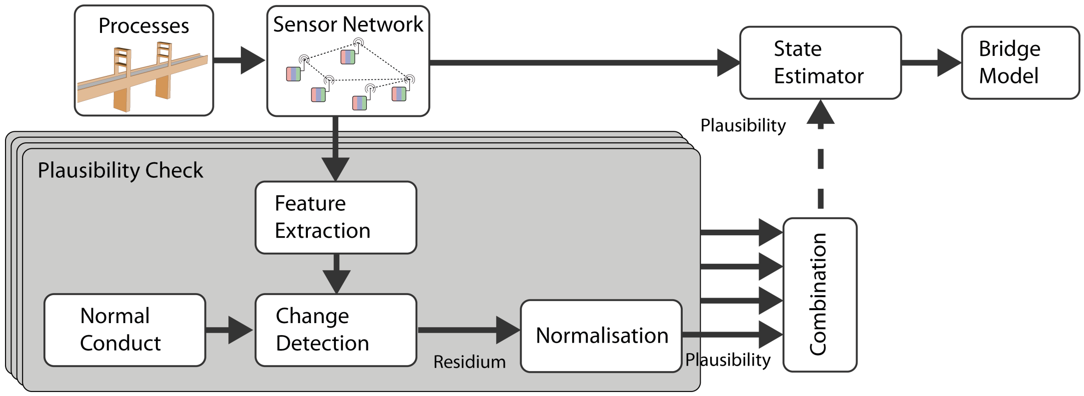

Fig. 12. Unsupervised learning – plausibility check of measurement and test data using machine learning algorithms.

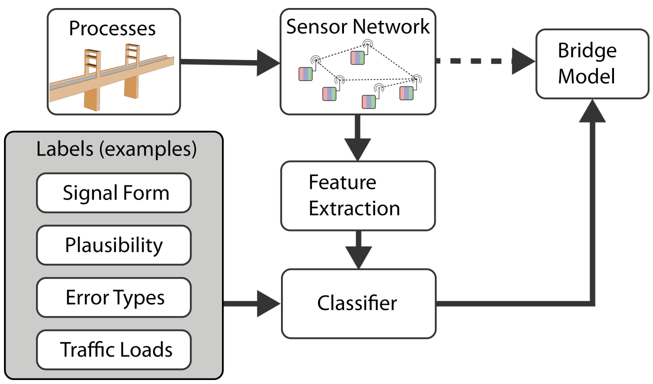

Fig. 13. Supervised learning – extraction of higher value information using machine learning algorithms.

	Plausibility Check	Fusion of Sensor Data	Interpolation	Derivation of higher-value information	Data Reduction
PCA					
KNN					
SOM					
GTM					

Fig. 14. Assessment of the suitability of machine learning algorithms for monitoring bridges (green: supports perfectly, yellow: moderately applicable).

B. Unsupervised Learning Algorithms for Plausibility Checks

Machine learning algorithms in particular from the area of unsupervised learning can be used to check the plausibility of measurement and registration data. These groups of machine learning algorithms work without prior knowledge of target values, i.e. of belonging to certain classes (labels). The class to which the signal events in the training examples belong is therefore not known in advance. The algorithms independently try to detect patterns in the entry data that vary from an unstructured scattering (noise).

During the learning phase a kind of imprint or model description of the normal behavior is generated on the basis of a certain volume of training data. Data which differ from each other due to characteristic patterns are arranged in several classes or categories using feature extraction and clustering techniques. This describes the general structure of the data. In the operation phase the measurement data described as having normal behavior are then checked for any existing deviations and implausibility. If there are discrepancies between the learned normal behavior and the measured signal form, these are detected (see Figure 12). A data prediction is possible.

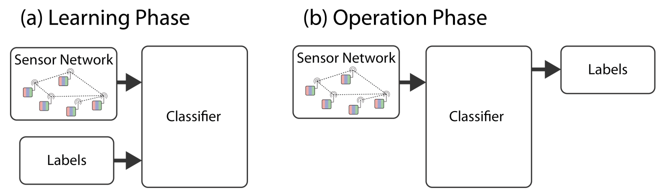

Fig. 15. Supervised learning – learning and operation phase.

C. Supervised Learning Algorithms for Extracting higher Value Information

Supervised learning describes machine learning algorithms that operate with known target values (classes). Inputs and outputs of the algorithm are therefore known, as is the classes that the training examples belong to. For a desired plausibility check of measurement data, it is necessary to specify, for example, whether the training data used are plausible or implausible data (resulting in two classes or target values <Data plausible> and <Data implausible>). Such techniques enable relevant features and information to be filtered from extensive data material without explicit prior knowledge of the model.

In the first step, relevant features are extracted using the unsupervised learning algorithms described above. These features are then linked to target values in a learning phase (Figure 15). The target values depend on which information is to be extracted from the data in the subsequent operation phase (Figure 13).

In the second step of the learning phase, a classifier is used to learn the relationship, i.e. the dependency, between the extracted features and the defined target values. Classification processes are methods and criteria to classify objects, situations or feature spaces into classes. Classifiers are therefore always used to suit the particular application. For example, the signal form (various types of signal forms, e.g. disproportionate rise, sinus oscillation, jumps, transient responses while warming up etc.), plausibility (plausible or implausible measurement and registration data), error types (various types of damage to the structure or sensor system, mains frequency interference, erratic changes to the width of cracks etc.), traffic load (information about the vehicles crossing, e.g. axle number, vehicle models etc.) are detected.

V. Experimental Results

A. Model-based Approach

Model-based state estimators can be used for the extraction and filtering of relevant condition variables from the measurement data. This is illustrated using the multi-ring electrode (cf. Figure 5) as an example. From the respective changes in resistance (R_T and R_F), it is possible to determine the parameters temperature T and concrete moisture f_B in the structural element.

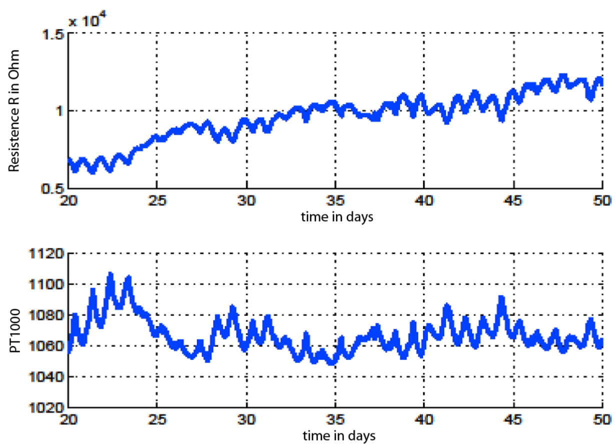

Fig. 16. Raw data from the multi-ring electrode for temperature and moisture.

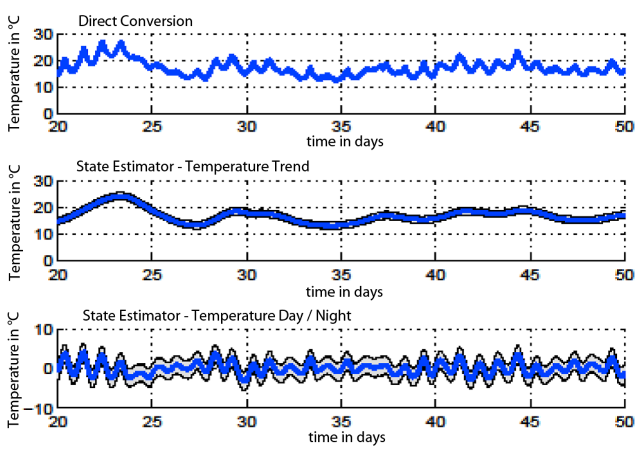

Fig. 17. Data fusion – temperature, temperature trend and day/night-fluctuations.

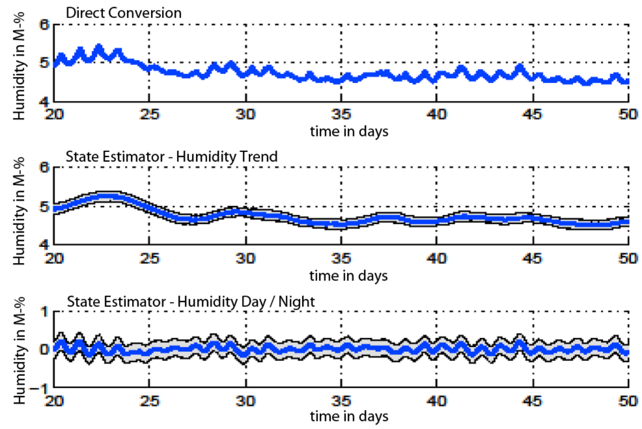

Fig. 18. Data fusion – moisture, moisture trend and day/night-fluctuations.

For the modeling of the temperature and concrete moisture, different linear system models are used (P, PV and PVA), each of which takes into account the different temporal changes in the measurement data. For the temperature and concrete moisture respectively, the condition in this case is divided into the components trend (model approach: approximate constant speed model) and periodic day/night fluctuations (model approach: dynamic sinusoidal model). A two-dimensional measurement transformation is used to model the relationship between the sensor data of the multi-ring electrode and the temperature and concrete moisture, (temperature sensor: assumption of a linear measurement relationship between temperature and measurement; multi-ring electrode: assumption of a non-linear relationship between temperature, concrete moisture and measurement). Figure 16 shows the raw data (changes in resistance R_T and R_F). The uppermost graphs in Figure 17 and Figure 18 show the temperatures or concrete moisture levels determined. The graphs below show the respective results of the model-based state estimators for temperature or moisture trends and their day/night fluctuations.

The depicted procedure clearly shows how by using preassigned model configurations it is possible to selectively extract beforehand supposed signal or information components or types from the data stream as well as to determine parameters which are not directly measurable.

If the data T or f_B extracted from the model-based state estimator were selected for further processing with a lower data rate (e.g. every 30 $mins$) – as against feeding the state estimator with sensor data (measurement interval 15 $mins$) – it would be possible to achieve a data reduction without significant loss of precision.

The method described here serves only as an example. At the time of implementation, it will still be necessary to determine targeted parameter-related specifications for extracted information for the various condition parameters required. In a similar way also the interpolation of measurement data is successful.

B. Statistical Approach – Plausibility checks on sensor data

The basic functionality of the analysis technique based on neural networks using real sensor data with different physical parameters is set out below.

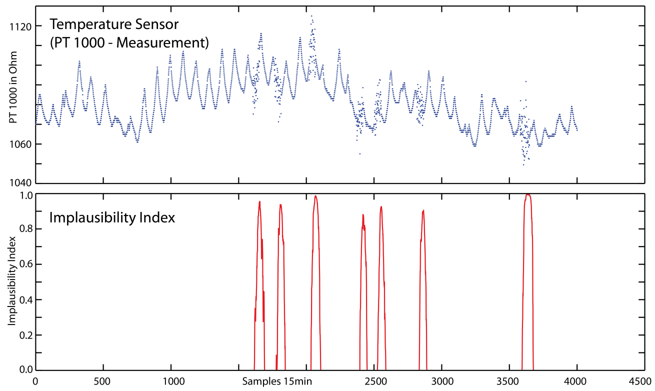

Fig. 19. Plausibility check for a temperature sensor – noise.

Figure 19 shows an example of a plausibility check for a temperature sensor that registers the temperature in a solid construction (raw data, measurement at 15 min intervals). The normal behavior of the sensor signal was thus identified from a large volume of training data by means of artificial neural networks. By comparing the current temperature measurement with the learned model of this normal behavior, an implausibility index can be calculated that presents recognized, event-related anomalies, such as the intermittent superimposed noise in the measurement data here (e.g. due to corroded contact points on the sensor cables, simulated here). Large readings that are close to a value of one indicate low plausibility regarding the corresponding section of measurement data.

A further example (Figure 20) involves recording the carriageway temperature on the old canal bridge in Berkenthin, Schleswig-Holstein (B 208) every 20 minutes (raw data). Outliers in the measurement data in various directions and of an increasing nature (simulated) are accurately characterized with the help of the plausibility index, thereby enabling a quantitative characterisation to be made about this interference.

Figure 21 shows a distance sensor signal sampled at 100 Hz that was superimposed by brief interference with a 50 Hz mains frequency burst signal. In the following example, two different amplitudes were used to produce variously strong interference, which is then presented accordingly in the evaluation of plausibility using the algorithm (bottom images).

Sensor drifts can in particular be identified by the fact that the measurement data for mutually dependent parameters can be considered jointly (e.g. force (a) and distance (b), as in the following example of a fatigue test (Figure 22), envelope curve display – the individual cycles are not displayed in long-term representation). A defective sensor can, for example, generate disproportionate readings with reference to the second parameter to be registered or as shown

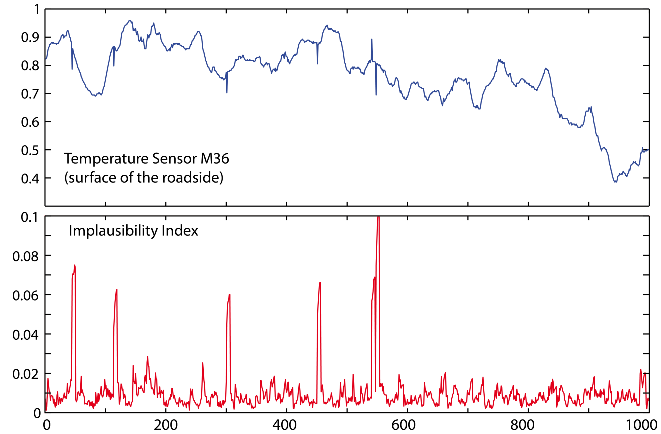

Fig. 20. Plausibility check for a temperature sensor – outliers.

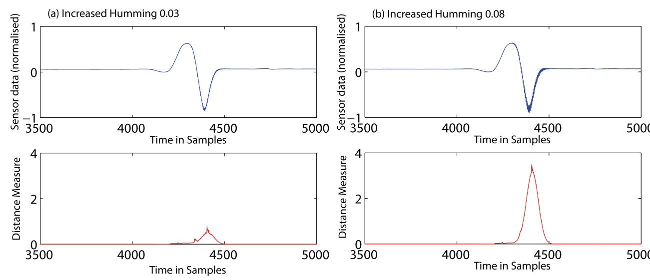

Fig. 21. Plausibility check of a traffic sensor – interference 50 Hz mains frequency.

here readings that are shifted around the zero point. The implausibility therefore increases analogous to the zero offset (Graph (c) below).

C. Statistical Approach – Deriving higher value information from sensor data

With the help of machine learning algorithms, it is possible to obtain more extensive, higher value information about technical situations in a automated form based on sensor data or fused data. This may refer to previously differentiated measurement-technological statements (disproportionate increase in measurement data series, conspicuous overshoots in the signal of accelerometers etc.) or to structure-related statements (the moisture or crack width determined in the component increases unusually quickly). These statements can help to safeguard the function of the acquisition equipment (evidence of quality, i.e. regarding the functionality of the measurement chain, i.e. sensors, measuring amplifiers, transducers, analogue/digital conversion, data transmission, power supply etc.), as well as providing additional information through the automatic detection of potential situational changes to the structure or its components.

Figure 23 shows a preliminary study on event detection (carriageway temperature on the Berkenthin canal bridge, measurement at 20 min. intervals). Significant signal forms of the sensor data which may have a physical/chemical relation on the structure during the fault-free operation of the registration equipment can, among other things, be detected

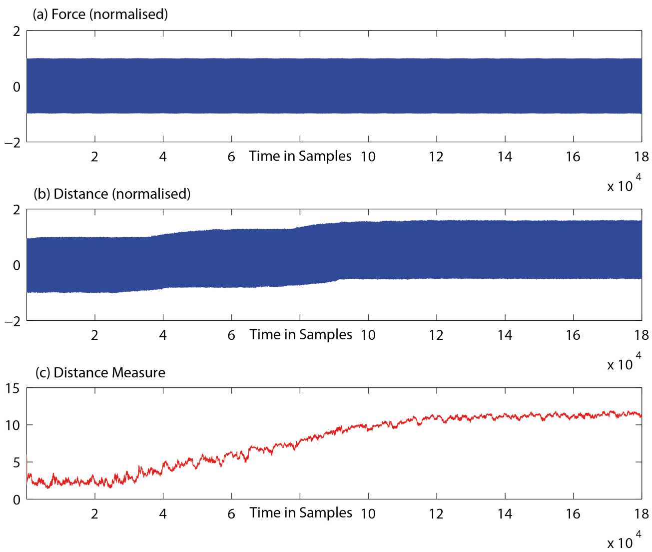

Fig. 22. Plausibility check of force and distance sensors – sensor drift.

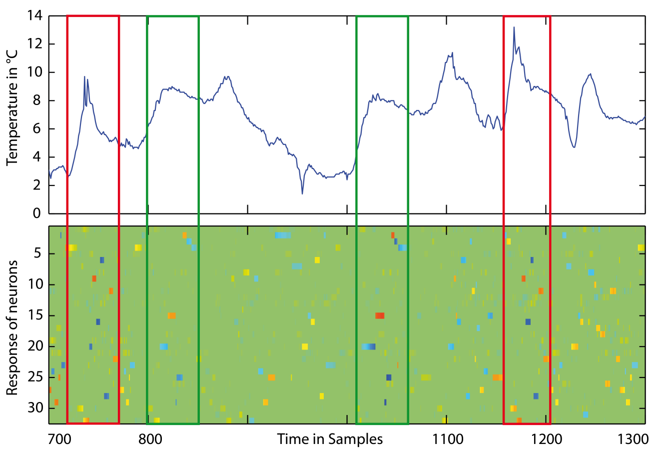

Fig. 23. Event detection of temperature sensor (significant signal forms).

by means of artificial neural networks (event detection, here using a system with 32 output neurons). Despite the study no longer providing a classifier to arrange the neuron responses, the visualized responses of the neurons for the corresponding signal forms (see red or green boxes) visually demonstrate a very great correspondence of neuron responses (bottom part of image). On the basis of current knowledge, it is possible to assume that with further refinement of the process steps, it will be possible to achieve a sharp and proper operational detection of events in the future.

Traffic load data, captured by indirect load identification on the bridge, (strain gauges, sampling rate 600 Hz) are a further example of event recognition. The pulse forms can be clearly assigned here to the neuron responses (64 output neurons) (Figure 24).

VI. Conclusion and Future Work

During future application, the implementation of sensor data monitoring and preliminary analysis structures directly at the sensor level (smart sensor) should not be ruled out in

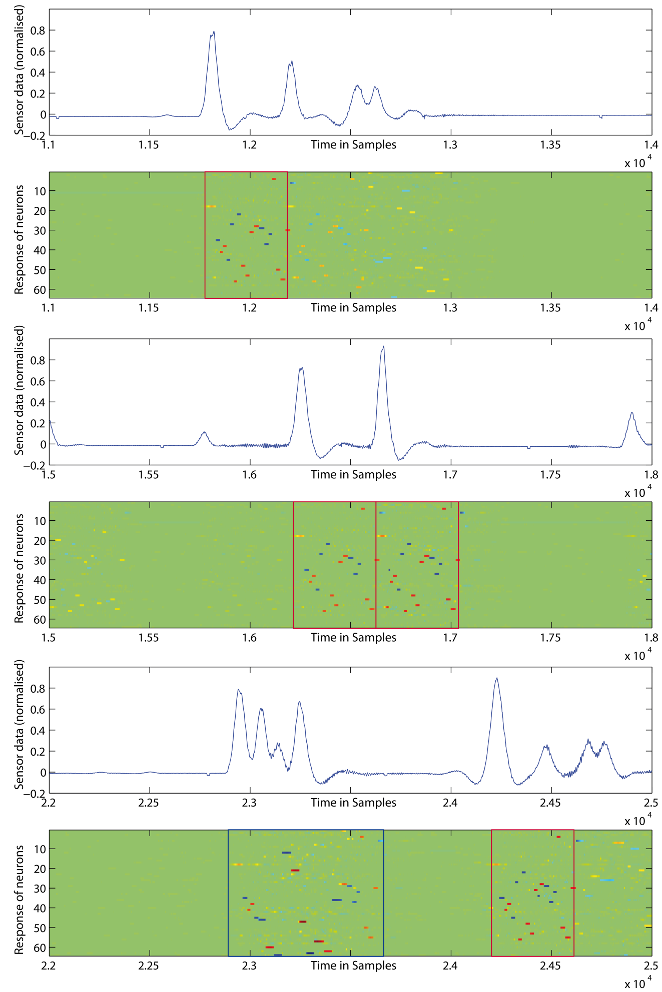

Fig. 24. Event detection of traffic load data.

the system concept. In this way, information on plausibility, functional reliability and thus a quality assurance of data, together with data fusion, reduction and possibly interpolation, can be conducted at the measurement data acquisition site. Against the background of the possible use of energy harvesting concepts (also see [20]), estimates of energy consumption must be made beforehand for the potentially usable model-based and statistical analysis techniques. The result of the study is that the average CPU load (especially that of the multiplication operations on a micro controller) and thus the energy requirements of artificial neural networks are around 10 times high for the tasks discussed (operation phase) than in the model-based processes (and even 100 times higher during the learning phase). Figure 25 therefore shows proposed examples for possible algorithmic features of model-based techniques for different parameters when using energy harvesting. The second half of the table presents energy-saving solutions with a loss of performance of analysis algorithms (see [4]).

This feasibility study shows that the selected algorithms from the field of model-based and statistical analysis technique highly support the implementation of a concept for

	Recommended Solution			Energy-Saving Solution (Energy Autarky)		
	System Model	**Measurement Model**	**State Estimator**	**System Model**	**Measurement Model**	**State Estimator**
Cracking / Temperature	PV Model	Precise Modeling	LRKF	PV Model	Direct Measurement	Kalman Filter
Moisture	PV Model	Precise Modelling	LRKF	PV Model	Direct Measurement	Kalman Filter
Corrosion	PV Model	Direct Measurement	Kalman Filter	P Model	Direct Measurement	Kalman Filter
Incline	PV Model	Precise Modelling	LRKF	PV Model	Direct Measurement	Kalman Filter
Shift (Subsidence)	PV Model	Precise Modeling	LRKF	PV Model	Direct Measurement	Kalman Filter

*) LRKF = Linear-Regression-Kalman-Filter

Fig. 25. Model-based procedures – suggestions for algorithmic configuration of various parameters.

a high-performance sensor data monitoring and analysis within the framework of registration and assessing relevant information on changes in action and resistance on bridges. This applies for the purposes of plausibility checking, fusion, interpolation and furthermore the derivation of higher-value information. Assessments were undertaken to identify potential areas of application for algorithms. It was possible to demonstrate their fundamental performance capability based on testing conducted with real sensor data encompassing various physical parameters.

Follow-up research will seek to prototypical investigate the operational safety and practicability of this kind of system on a real, existing concrete bridge structure which has been equipped with the requisite instrumentation. In this context, and in addition to any potential adjustments and refinements to the monitoring and analysis techniques, the identification of any additional possible measures as well as operational resources for the functional implementation of the system on a building structure will be a central point of focus. In addition, the research will seek to determine the possible intervals between the functional testing of the measurement apparatus while it is being set up on the structure, and whilst it is in operation.

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