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Design of a Pilot Setup to sort Damaged Returned Empty Beverage Crates in an Automatic Filling Line

The inspection of returned beverage crates as well as bottles in industrial automatic filling lines is mainly performed by imaging systems. These systems are not able to detect invisible damages or embrittlement. A powerful novel system based on the principle of mechanical vibration analysis for the detection of small and concealed damages is presented. The selection of individual crates is performed automatically by a pre-trained artificial neural network (ANN). Numerical finite element simulations form a basic insight into the vibration behaviour of the crates and help to plan a pilot setup. This leads to a final recognition rate of more than 99 % over all checked crates in a prototype for industrial use.

Descriptors: damage recognition, artificial neural network, vibration analysis, finite element simulation

1 Introduction

Statistical data collected by "Genossenschaft Deutscher Brunnenbetriebe" (GDB) from the year 2006 shows that there are around 1.7 trillion reusable bottles (plastic and glass) on the market for mineral water. Therefore, around 165 million plastic crates serve as transport packages which are used up to one hundred cycles on average [1]. This means that a returned crate, just as a bottle, will be refilled and reused after it comes back from the customer. Previously, they had to be cleaned and checked for damages. The inspection of returned beverage crates and bottles in industrial automatic filling lines is mainly performed by imaging systems. The handicap of these systems is that they mainly only detect visible damages. As a consequence, there are a lot of crates in circulation with concealed, undetected damages like broken handles. A study of the GDB from 2003 documents, that the quote of damaged crates in the GDB-pool is about 6.27 % [2].

In terms of feasibility studies, Zacharias et. al. developed a new vibration analysis technique for the detection of damages on beverage crates [3–5]. The crate is put into vibration by temporary mechanical excitation and acceleration spectra are recorded. The spectra of damaged beverage crates clearly differ from those of intact ones and represent reliable criteria for the fault detection [6, 7]. Handicap of this approach is the long term of 10 seconds for one cycle and the complex engineering design. Therefore this method is not practicable for industrial use. The global target of the present contribution is to provide a suitable base for a practicable realization of an automatic selection device for damaged beverage crates. The system provides a rapid and reliable evaluation of oscillation signals by means of a hybrid neuronumerical approach. The main advantage is the ability to abstract and extract information from both experimental and numerical data. Industrial application additionally requires times for analyzing single crates less than one second to avoid a negative influence upon subsequent processes.

The reliable, fast damage recognition leads to an improvement of sorting defective reusable goods from the multi-use cycle. Consequently, few damaged bundles arrive at the final consumer. This leads to an increased product quality and acceptance at the customer. In particular, the safety of the consumer increases. The risk of product liability and of profit setback due to the loss of image is reduced. Also, the safety during the production-process and the transport to the retailer is secured. At one side damaged packaging units can disturb the flow of a filling line and therefore they will cause a decrease of the plant-efficiency. On the other hand these crates are not as stable as undamaged ones. Therefore, they can not cover the bundled bottles perfectly and lead to a destruction of the product.

In Germany beverage and food enterprises are predominantly small and medium enterprises (SME). The presented research project intends to improve product quality and even to lower the manufacturing costs, which is especially important for this target group.

The new system is characterized by the possibility of a fast update of the pattern recognition, which requires only a short machine downtime in the case of conversion to new bundle types. In particular the possibility for the upgrade of existing systems extends the demand for the developed system. This leads to an extended

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Tables and figures see Appendix

sales market for SME as manufacturers of bottling plants or measuring systems.

2 Materials and Methods

The analysis of vibration due to a defined mechanical excitation represents the core of this investigation. The characteristics of vibration of a body due to a mechanical excitation mainly depend on the geometry on the one hand and material parameters on the other. If all boundary-conditions like fixation, excitation or temperature are well defined the characteristics for one specimen should be constant, provided that the experiment will not disturb the crate and the material behaviour is linear elastic. On this account it is possible to identify changes on the geometry or the material like little breaks or the aging of the specimen. Also, it is possible to identify different types of crates because of their geometry. The used methodology is explained more in detail in the following chapter; see also [8].

For this investigation one model of a crate was used, which has been on the market since 1969. This polyethylene-crate can cover 12 bottles of carbonated soft drinks and is patented for the "Genossenschaft Deutscher Brunnen" (GDB). The advantage of this established model is that there are many exemplars in the multi-use-cycle and therefore it is highly available in every super-market or beverage-discount. Furthermore there exists a big amount of different damages in this pool of crates due to the long terms of use. There are still some crates which were the first in use, which are now about 37 years old. So it is also possible to investigate the aging of the material which can be observed mainly because of changed material parameters.

2.1 Numerical Analysis with Finite Element Method (FEM)

To get insight into the basic vibration behaviour of the crate, numerical simulation is carried out by the use of the finite-element method. This provides a general overview of different experimental possibilities without cost-intensive and time-consuming experiments. The specimen was virtualized as real as possible by the use of the original CAD-files and material-data delivered by the manufacturer. The resulting FEM-model consists of more than 121.000 tetraedrical elements (TET10) with a medial edge length of 10 mm and about 244.000 nodes on the edges of the elements (cp. Fig. 1).

Simulating the situation given in practice requires implementing initial and boundary conditions like temperature as well as strength and localization of the applied shock-signal or the clamping force of the fixation.

This simulation facilitates investigating, on the one hand, the mode-shapes (respectively the eigen-frequencies) and, on the other hand, the vibration-behaviour to variable conditions, e.g. different excitation-methods and locations. The crucial factor was the industrial practicability.

In present investigations the stimulation of the crates is carried out by a single shock signal.

In FEM-simulations therefore a simple time-varying pressure was induced at different locations on the outer surface of the crate.

To avoid rigid body movements of the whole crate it is essential to fix it for the time of oscillation. Therefore the interacting forces of a virtual clamping device were induced in varying intensity and at different regions on the crate.

After the excitation the crate is in motion for about 0.2 s. The FEM-simulation delivers the displacements of every single point of the mesh of the whole crate for the time of movement. To detect this behaviour experimental, a non-invasive laser-vibrometer is used. The acquisition of the vibrations must take place in one point on the outer surface of the crate which is accessible by the laser beam.

The evaluation of these results allows the improvement of the experimental procedure as they can be used to determine appropriate locations for data acquisition and excitation in pre-test planning stages (cp. Fig. 2).

Overall 26 different damages, e.g. broken handle, broken base, etc. were simulated to investigate targeting boundary conditions.

The consequent implementation of the results provided by simulation leads to the experimental constructions shown in Figures 3 and 4. First the laboratory setup was built for preliminary tests. Results of these experiments and the adaptation to industrial boundary conditions lead to the final pilot-setup.

2.2 Laboratory Setup

In order to record the frequency response spectra experimental the crate must be fixed for the time of measurement. Two quick release clamp jaws fix the crate in a centred position. The clamping force can be adjusted over the pressure in the air-cylinder and assure reproducible conditions. An electrodynamic vibration device with a shock-ram is arranged below the fixation base and serves for the excitation. As excitation-signal short shocks are used. The maximum acceleration is about 50 m/s^2 and the time needed for the excitation is 15 ms. Due to the short shock excitation in the bottom a propagation of the vibration through the whole body can be observed. This effect depends on the condition of the complete system and therefore every little variation in material or geometry leads to a different acceleration-spectrum. The system response can be recorded at different locations on the crate by a laser-vibrometer. Here one of the short handles is most suitable as simulations and experiments show. The laser-vibrometer provides a voltage which is proportional to the displacement, respectively velocity or acceleration. The acceleration-signal was digitalized with a sample-rate of 10 kHz. The record of 2048 samples leads to a signal-time of 0.2048 s. This measurement contains adequate information to draw conclusions about the constitution of the specimen. Also one acceleration sensor in the shock-ram and two reference sensors on the clamping-equipment are used to monitor the system. Figure 3 illustrates the described experimental setup for laboratory tests.

2.3 Pilot Setup

The presented damage-detection-method was adopted for an industrial application. Hence, changed boundary conditions were considered. The filling of reusable bottles takes place in an industrial filling line. Different procedures like packaging, cleaning, inspection or filling will be carried out in a logical order. Filling lines work with a varying flow of bottles and crates. The transport between the stations is mostly carried out with conveyers. They act as buffers to ensure a constant throughput of the central filling-station. The required maximum duration for testing of a single crate within 1 s is derived from the capacity of 60.000 bottles per hour and an amount of 20 bottles per crate in a typical bottling plant. For a reliable measurement with the laser-vibrometer it is also necessary to bring the crate in a defined position. To avoid stop and go of the crate-conveyor every second for a single measurement, every specimen will be undocked from the conveyor with a pneumatic lift. Thus, influences of the vibration from the conveyors are also excluded as far as possible. Before the excitation with the pneumatic-shaker takes place, the crate must be fixed to prevent undesired movements. Therefore pneumatic clamps are mounted. After the shock-excitation and the data-acquisition the crate will be pushed down in the crate-flow and the data-analysis takes place. The condition of the crate finally leads to a separation of the damaged ones in the following separation-unit. Figure 4 shows the designed prototype for use in an industrial filling plant.

2.4 Data Analysis

The analysis of the measured acceleration spectra allows differentiating damaged and intact crates. Extracting this information, for example, with an artificial neural network requires a pre-processing of the raw data material.

In a first step, the temporal series is transferred in the frequency-domain with the help of a Fast-Fourier-Transform. Hereby, the acceleration-spectrum is transformed in 1,024 equidistant frequency classes with a width of 4.88 Hz. Depending on the sample rate of 10 kHz, the highest detectable frequency with this method is 5 kHz. However, from the finite element simulations and additional experiments it can be deduced that the maximum frequency of interest is below this limit. After this procedure differences between spectra become evident (cp. Fig. 8, Fig. 9).

To extract information about the condition of the crates artificial neural networks (ANN) are used; see, for example [3, 4]. As a part of neuro-informatics the fundamental idea of ANN is to mimic in a strongly simplified manner learning processes in the human brain by using artificial neurons. Every neuron normally consists of multiple inputs and one output to interact with other neurons. In every neuron simple mathematical functions are used to compute an output value depending on the multiple inputs. The combination of multiple neurons leads to an artificial neural network. In the network the nodes are combined to functional layers (cp. Fig. 5). The input layer consists of input neurons and transmits the data patterns into the ANN. The output layer consists of output neurons and presents the result to the user. Neurons in layers between the in- and output layer are hidden units and serve for data processing. The neurons are interconnected by weighted links to propagate the input over the net. To compute an expected output for a given set of input data the net must be trained during the training-phase. Therefore, a special learning-algorithm (in this case resilient-propagation-algorithm) adjusts the link-weights of the neuron-connections to minimize the difference between the expected and the actual output for all trainings-patterns. This creates the general abilities of ANN for classification and approximation. They can handle manufacturing tolerances as well as little signal variations.

The remaining parameters of the ANN are fixed and must be defined before the training-phase. The basic configuration is based on preliminary tests and references in the literature [9–13]. Table 1 shows the configuration of the used ANN and the parameterization of the training-algorithm “Resilient Propagation (RPROP)” [9, 11].

To use the frequency-spectrum from the Fast-Fourier-Transformation as input-data for the neural net, an input-layer must be defined. It contains as many neurons as classes are in the spectrum. In this context an effective data reduction procedure is of essential importance with respect to the performance of the calculations in the industrial use. The reduction of neurons in the input layer leads to a shrunken ANN with fewer connections. This affects directly the computational effort and reduces the training time required. The method suggested in the present contribution has proven to be fast and reliable. It is based on the partition in equidistant frequency bands and their numerical integration. The resulting discrete frequency distribution contains as much information as required to classify the tested objects (see also Fig. 6).

Before training takes place, the data pool consisting of all measured spectra was separated into three categories:

- trainings data for ANN-training
- validation-data for validation during the training phase
- independent test data to test the completed ANN after the training

It is necessary that all three categories of data-sets consist of the expected output to learn the correlation between an input-dataset and the condition of the specimen. For this reason the crates were checked manually to find out if they are still reusable. The respective datasets get the classification “1”. Datasets of damaged specimen were assigned the number “0.” This is important for the training of an ANN both to find the best topology and weight set and to evaluate the results.

After the training the ANN approximates autonomous the output-value “1” for intact crates and “0” if the specimen is damaged. Values between the two classes like “0.5” imply a non-definite allocation and must be interpreted. By implementing a flowing transition between the classes the quality of sorting can be affected specifically (cp. Fig. 7). This allows the operator of industrial filling lines to adapt the sorting on his quality-standards.

3 Results and Discussion

Depending on the intensity of the occurring damage and the resulting difference to the intact state, the acceleration signals and the extracted frequency patterns differ. The frequency pattern of two different crates, measured with the laboratory setup, is pictured in Figure 8. The variation of the amplitudes of the signals is plainly obvious. The damaged crate (black line) has two overhanging peaks at 200 and 900 Hz. Above a frequency of 2 kHz there are just low amplitudes with an acceleration of less than 1 m/s^2. The undamaged crate (red line) shows, like the damaged, the highest peak at 200 Hz. Overall it has more peaks but the maximum amplitudes are lower. In the range from 2 kHz to 3.5 kHz there are still frequencies with considerable amplitude.

The frequency patterns from experiments with the same crates measured with the pilot-setup are pictured in Figure 9. A comparison with signals from Figure 8 indicates a modification. This must be founded in the changed boundary conditions because the condition of the specimen is still the same. Most notably the number of low frequency peaks of the undamaged crate changed. This induces movement of the whole setup. A lightweight construction (a lot of moving parts due to industrial requirements) is responsible. The difference between the two signals is still observable.

This difference of these spectra is also trained and evaluated by the ANN to result in a classification.

3.1 Data-Processing with Data from Experimental Setup

Artificial neural nets were used to extract the information about the condition of each specimen. A neuronal net composed of three layers (64x32x1) was trained with 2393 data-sets of damaged and intact crates measured with the experimental laboratory setup. It can be observed that the network is able to predict damages correctly in more than 99 % of all presented cases.

3.2 Data-Processing with Data from Pilot Setup

With the pilot-setup and about 150 crates a data-pool of response-spectra was built to investigate a good method for industrial analysis. This stock of crates contains exemplars with all imaginable damages like broken handles, broken compartments or a broken base, as well as new ones and used specimen without obvious defects to cover a wide range of possible conditions. The results from these experiments are 1473 single datasets for data analysis. 70 % of the datasets are from the category "undamaged" with an expected ANN-output of 1; the other 30 % are from the category "damaged" and have the expected ANN-output of 0. The training of a neuronal net with 64 input nodes, 32 hidden nodes and one output node leads to a rate of recognition of 99 % over all used datasets.

Figure 10 shows the result of the neural net to the described 1473 data records. On the abscissa are the samples from 1 to 1473 and on the ordinate there are the deviations of the ANN-forecast-value to the expected teaching output in percent. Sample number 220 for example has an ANN-forecast-value of 0.8198 and according to the detected condition "undamaged" a teaching output value of 1. The deviation is 0.1802 or 18.02 %.

The separation of the two categories ("damaged" and "undamaged") as described before is fluent and must be defined depending on the quality standards. In these investigations the separation border is the value 0.5. Accordingly deviations over 50 % cause a classification failure. Figure 10 illustrates that sample 1046 and sample 1185 are wrong classified because of deviations in a range above 90 %. It is noticeable that only 7 datasets of 1473 have a deviation of the ANN-forecast-value and the ANN-teaching-input higher 5 %.

One Reason for this phenomenon could be a lack of these specific spectra in the training-data-sets. The general ability of the ANN is to generalize and interpolate. So it is possible to classify similar patterns. If one pattern is out of all trained ranges the similarity to other patterns is not given. This leads to a classification error because the net has not learned to classify this or similar pattern exactly.

Second reason for the phenomenon of high deviations could be the teacher of the ANN. To provide the ANN with datasets for training it is necessary to check every single crate manually to set the expected ANN-teaching-output. If the trainer overlooks little damages in this phase these trainings-data-sets are classified wrong and lead to a deficient ANN-training. In the prediction phase the net classifies this specimen right (damaged) but the wrong teaching-output (undamaged) causes the failure.

Subsequent the crates causing the highest 7 deviations are described more precisely in Table 2.

The locations of the described damages are marked in Figure 11 with different geometric marks. The front side, were the laser-vibrometer captures the movement, is marked with a cross.

Sample number 563 was classified wrong by the trainer but the net has calculated the right classification. All other samples are classified right by the trainer but the ANN has problems to identify them.

Manufacturer of traditional crate inspection systems claim that their systems are able to detect over 99 % of all damages [14]. But the crux is the definition of "all damages". It is very difficult to detect "invisible" damages with imaging systems based on one or more CCD-Cameras. They can detect visible failures like lacking parts of the specimen or deviant dimensions which indicates damages or foreign exemplars. But "invisible" damages are not included. At the moment the only way to sort this kind of defect crates out of the multiuse cycle is by hand. Otherwise these crates stay in the crate pool. The statistic of GDB impressively documents this [2].

4 Conclusions – Summary

The outstanding aspect of the current research activities lies in the basic development of an innovative method for the damage detection on reusable crates of beverages and bottles taking into account the requirements of an industrial filling line.

A prognosis system based on vibration-behaviour analysis by artificial neural networks overcomes drawbacks of present systems and represents the principal innovative contribution. For the first time vibration-analysis is applied in the food and beverage industry to improve the quality and reliability of industrial sorting processes.

In particular, small and hidden damages can be detected, which definitely cause a major problem for conventional detection systems. Additionally, the system provides a precise selection of samples of other manufacturers as well as modifications of the material, e.g. aging (embrittlement) and recyclates. An accuracy of more than 99 % proves the extreme reliability of the system. At present principal component analysis will be carried out to extract selective information out of the response spectra for the training of an artificial neural network. A reduction of the computational effort could be the effect because of shrunken ANNs.

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Appendix

Table 1 Parameterization of the used ANN

Parameter of the net	**Adjustment respectively initial value**	
Method of learning	Supervised learning	
Dynamic of the net	Static	
Format of input neurons	No scale	
Format of output neurons	No scale	
Artificial noise of input data	0 – 1 %	
Initial weights	Random range: –1,0 to 1,0	
RPROP – coefficients	Learning rate η increasing:	1,2
	Learning rate η decreasing:	0,5
	Weight Decay Term:	2,0
	High Limit:	50,0
	Low Limit:	1,0 e^{-6}
	Step size - Delta Weight:	0,1
Activation function	Sigmoid: $akt_j = \frac{1}{1+\exp(-net_j)}$	
Adoption of weights	online	
Quality factor	Half of mean square error $E_{ges} = \frac{1}{2}\sum E_w^2$	
Considered failures at the minimization of error in the net *t_{pj} = desired output* *o_{pj} = actual output* *pattern: p* *outputneuron: j* *total number ot outputneurons: n*	MSE (mean square error): $E_{RAE} = \frac{\sum (t_{pj}-o_{pj})^2}{n}$ RAE (relative absolute error): $E_{RAE} = \frac{\sum \left\lvert \frac{(t_{pj}-o_{pj})}{t_{pj}} \right\rvert}{n}$	
Data material (m = number of datasets)	$\frac{m_{validation}}{m_{Training}} = 0{,}1;\quad \frac{m_{Test}}{m_{Training}} = 0{,}35;$	

Table 2 **Description of hard-detectable crates**

Sample number	**220**
ANN-forecast-value	0.8198
ANN-teaching-output	1
Deviation to ANN-forecast-value	18.02 %
Condition	Undamaged
Year of manufacture	08/1994
Damages	Normal traces of usage
Sample number	**563**
ANN-forecast-value	0.7596
ANN-teaching-output	1
Deviation to ANN-forecast-value	24.04 %
Condition	Damaged
Year of manufacture	08/1976
Damages	a) Some compartments are twisted b) Part of base is broken (hard visible)
Sample number	**714**
ANN-forecast-value	0.7283
ANN-teaching-output	1
Deviation to ANN-forecast-value	27.17 %
Condition	Undamaged
Year of manufacture	Unknown
Damages	Normal traces of usage
Sample number	**1046**
ANN-forecast-value	0.9264
ANN-teaching-output	0
Deviation to ANN-forecast-value	92.64 %
Condition	Damaged
Year of manufacture	Unknown
Damages	a) Handle with a little hole is broken b) Angle is broken
Sample number	**1131**
ANN-forecast-value	0.1044
ANN-teaching-output	0
Deviation to ANN-forecast-value	10.44 %
Condition	Damaged
Year of manufacture	10/1972
Damages	a) Part of base is broken off b) Some compartments are broken c) Side wall ripped
Sample number	**1185**
ANN-forecast-value	0.9993
ANN-teaching-output	0
Deviation to ANN-forecast-value	99.93 %
Condition	Damaged
Year of manufacture	06/1974
Damages	a) Center bar of side wall is broken
Sample number	**1204**
ANN-forecast-value	0.1482
ANN-teaching-output	0
Deviation to ANN-forecast-value	14.82 %
Condition	Damaged
Year of manufacture	08/1978
Damages	a) Handle of small sidewall is broken

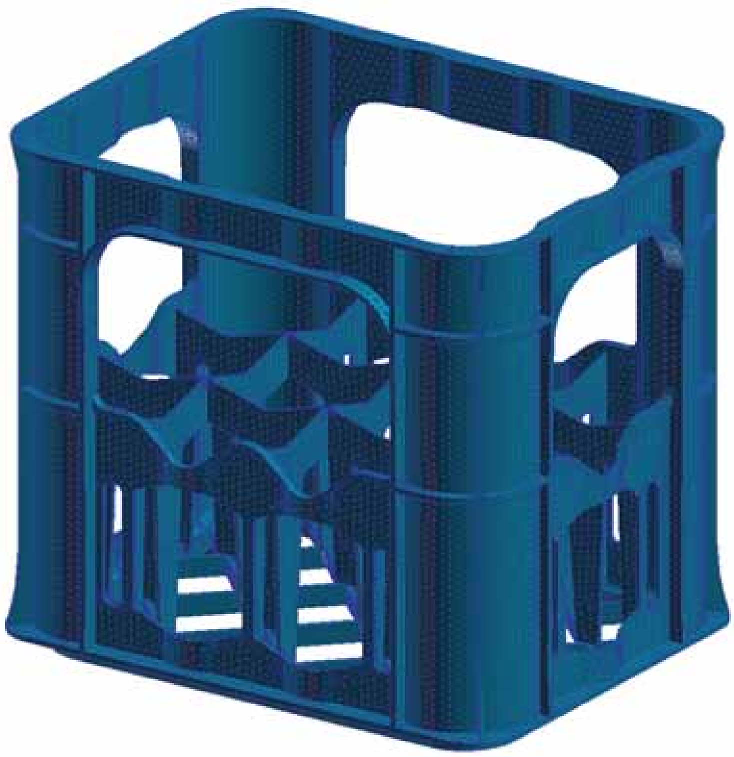

Fig. 1 **FEM-model for simulations (Meshed with TET10-Elements)**

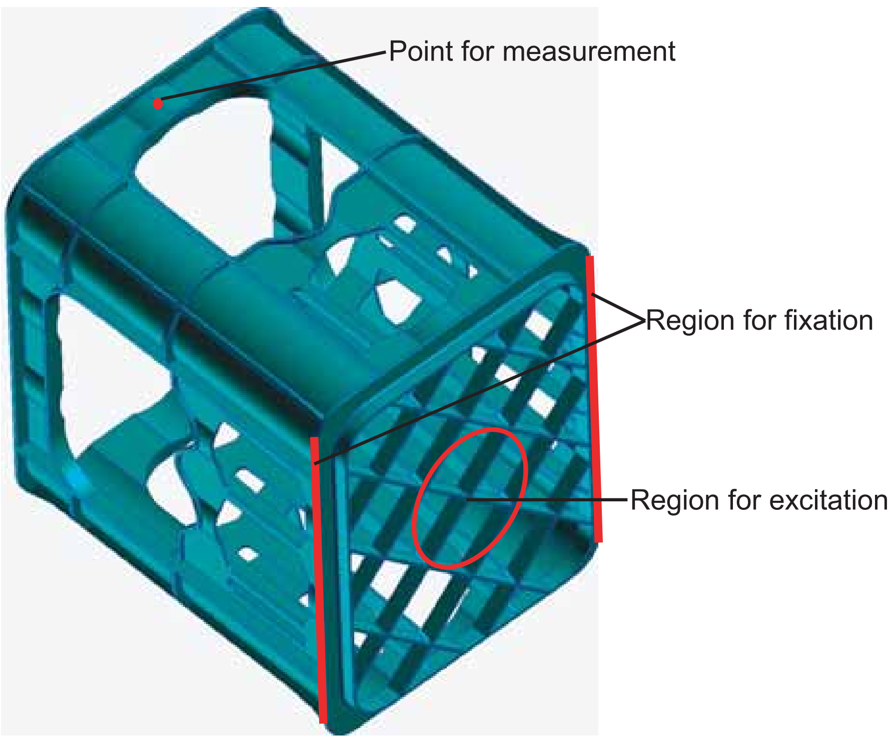

Fig. 2 **Results of investigations for good applicable experimental conditions**

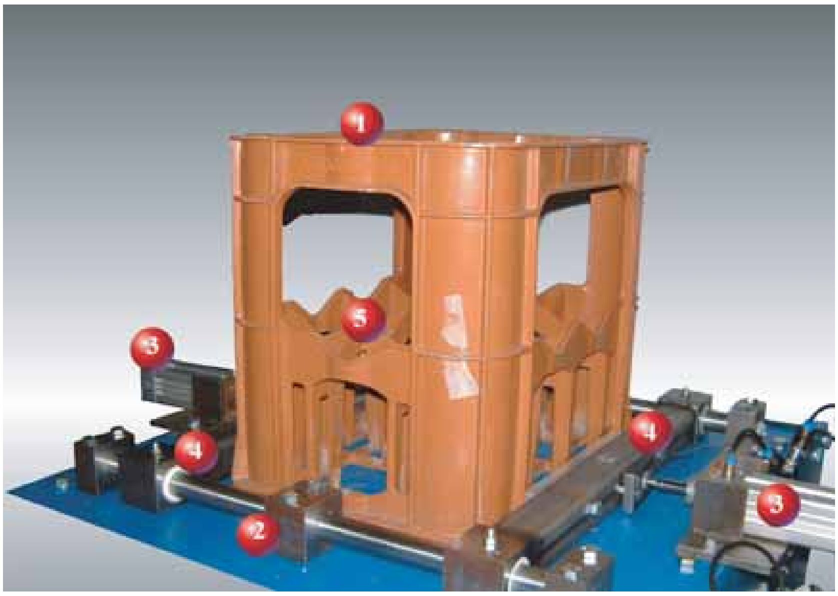

Fig. 3 Laboratory setup
1) Laser point for measurement
2) Tracking for clamp jaws
3) Air cylinder for clamping
4) Clamp jaws
5) Crate of beverage

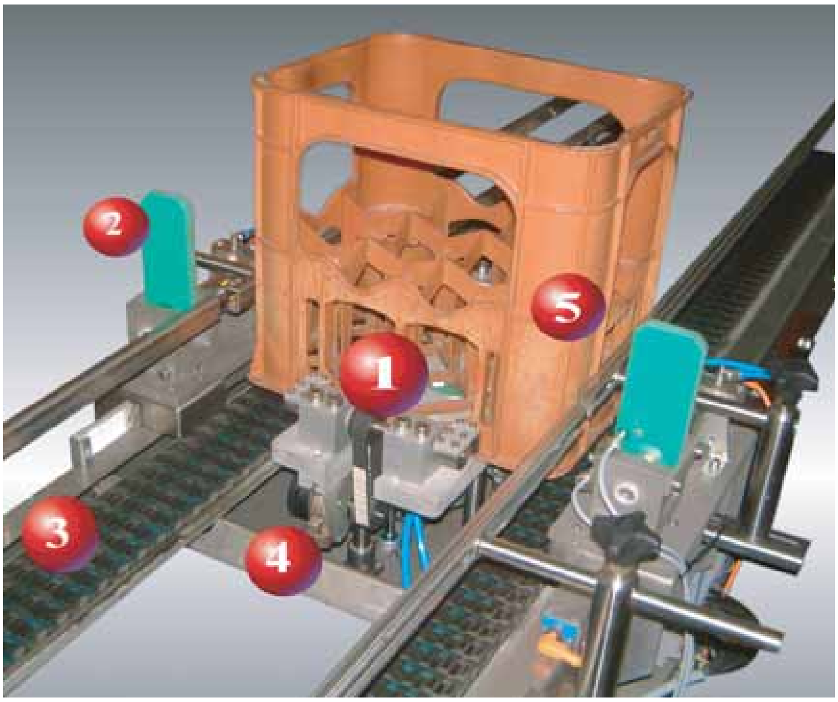

Fig. 4 Pilot setup
1) Pneumatic quick release fastener
2) Pneumatic positioning
3) Belt conveyor
4) Pneumatic lift
5) Crate of beverage

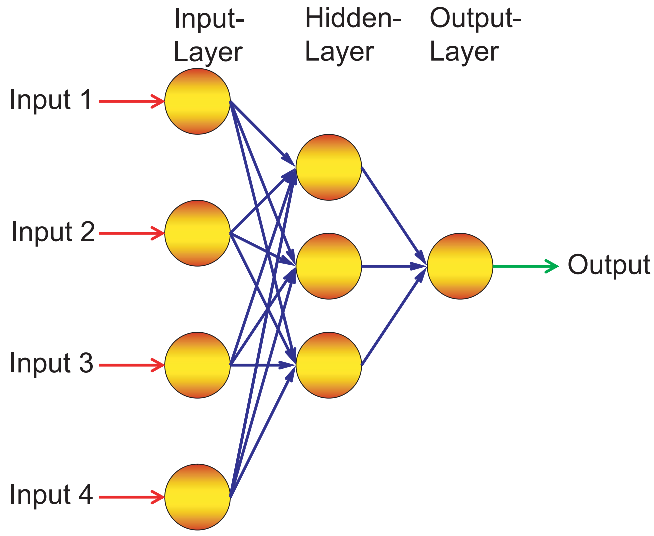

Fig. 5 **Scheme of an artificial neural network (ANN)**

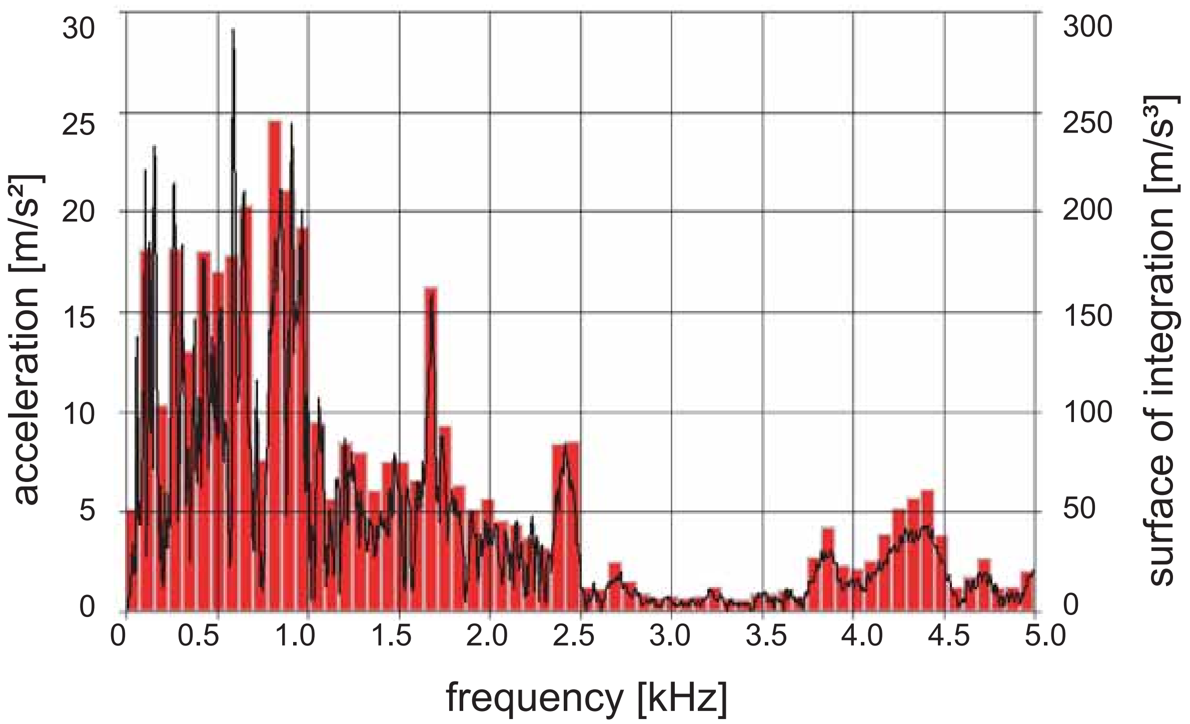

Fig. 6 **Data-compression with integration**

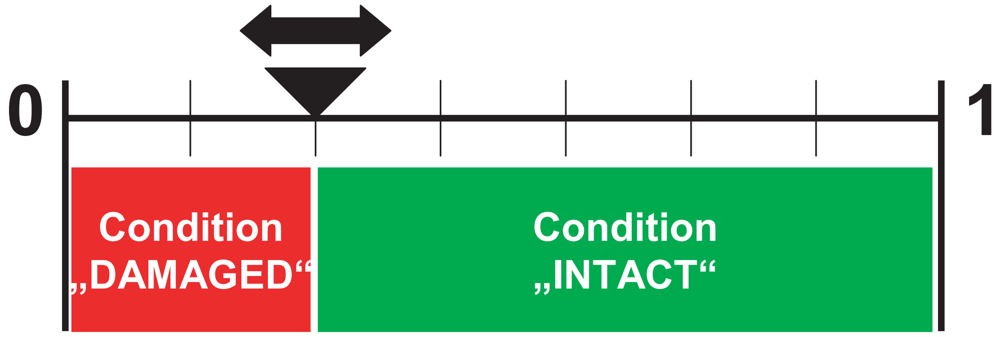

Fig. 7 Smooth transition of the condition

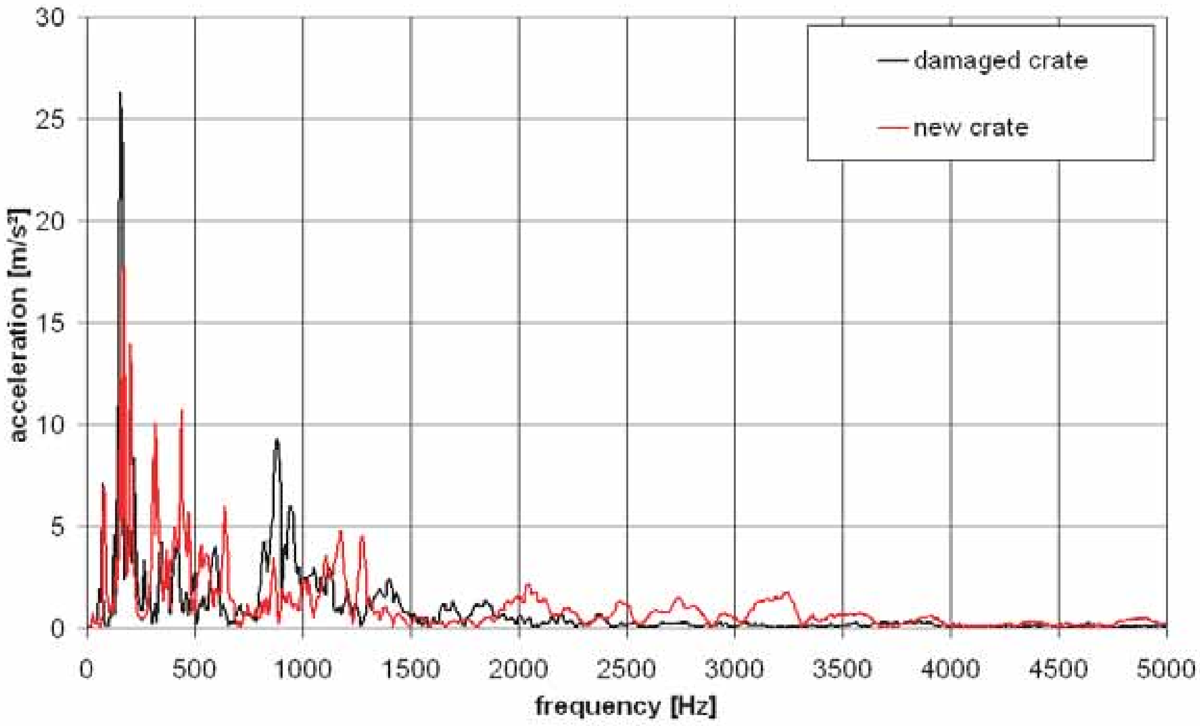

Fig. 8 Comparison of experimental spectra (laboratory setup)

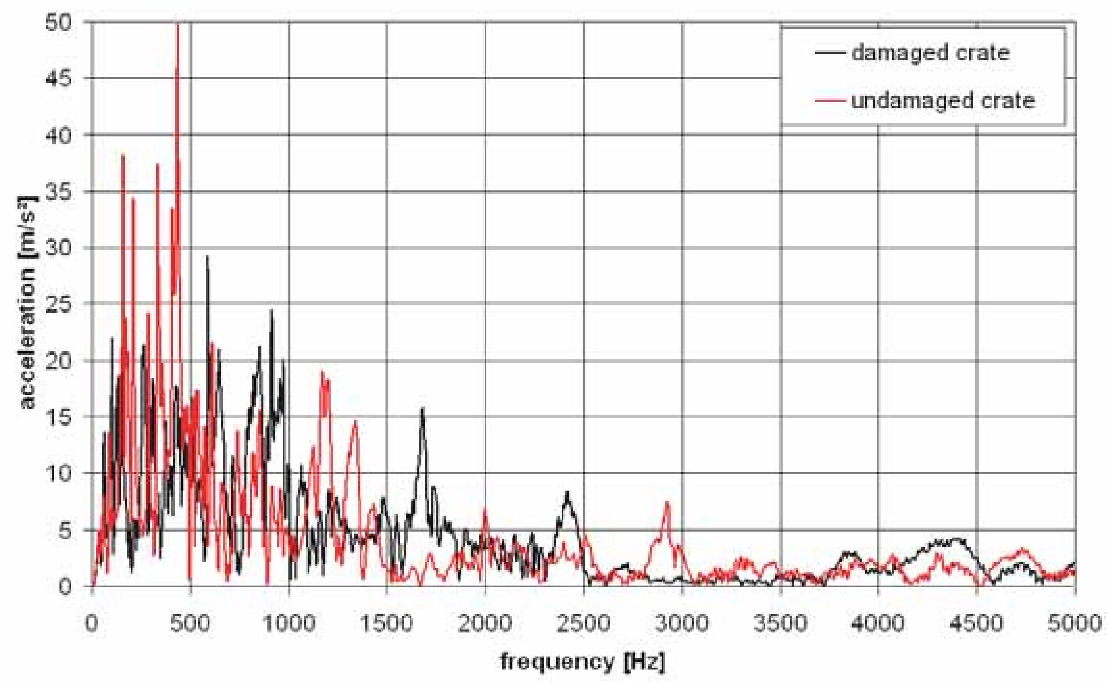

Fig. 9 **Comparison of experimental spectra (pilot setup)**

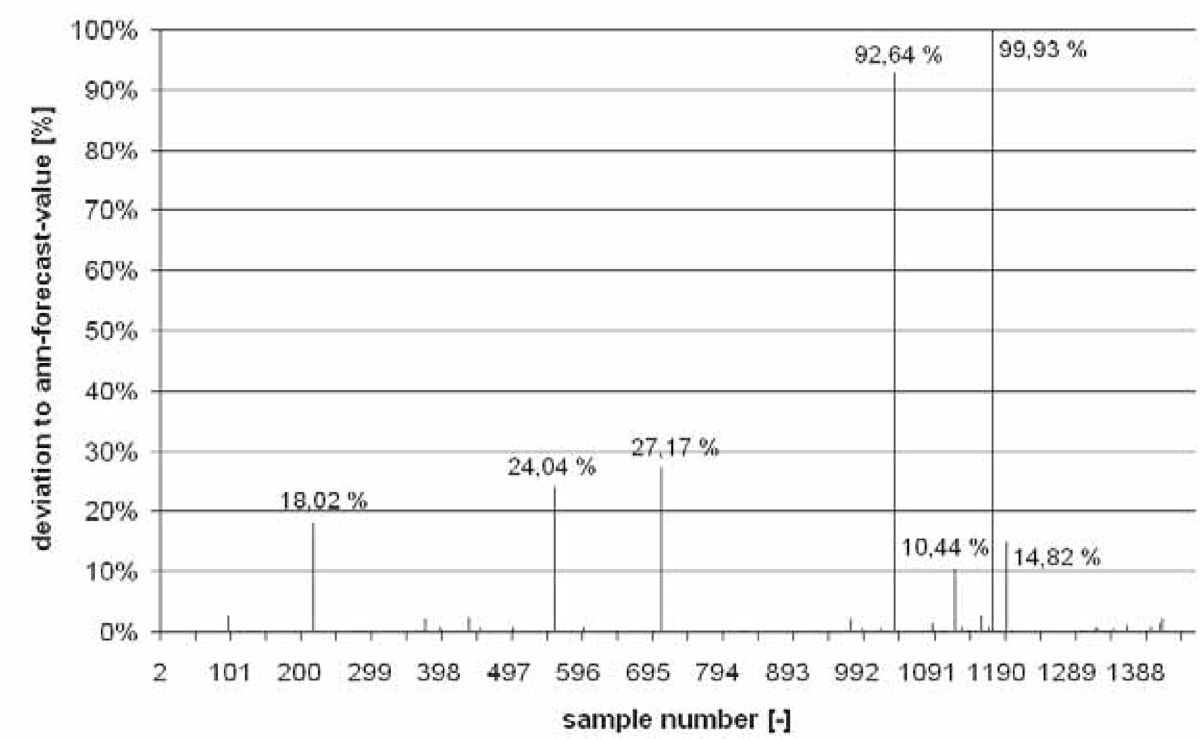

Fig. 10 **Deviations of the ANN-forecast-value to the expected teaching output in percent**

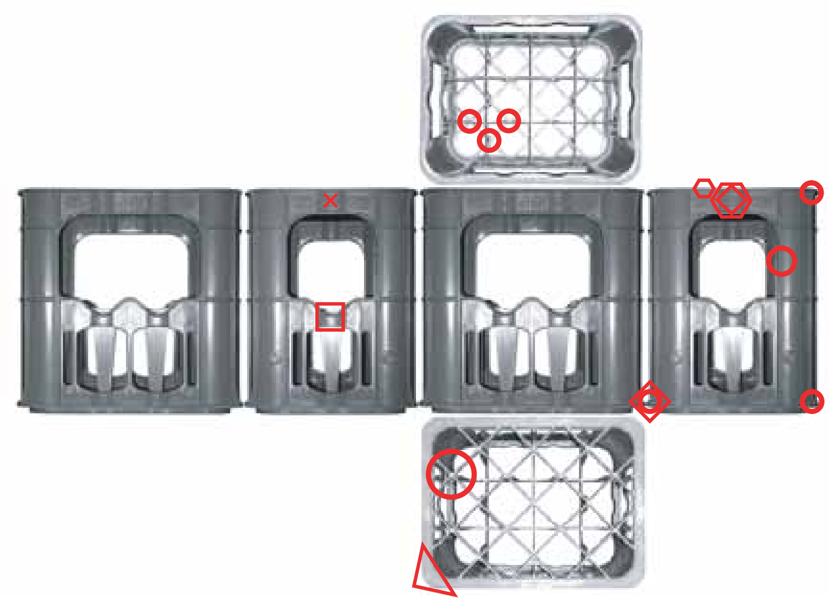

Fig. 11 Locations of hard-detectable damages on the crate (5 different cases marked with different geometric forms)