INVESTIGATION OF DYNAMIC THERMAL EFFECTS WITH NON-PARAMETRIC AND 'PARAMETRIC' DEFORMATION MODELS

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Abstract: The Viennese theatre 'Etablissement Ronacher' was founded in 1871 and is one of the oldest theatres in Vienna. Since 1987 the listed building is integrated in the 'Vereinigte Bühnen Wien' cooperation and serves for the presentation of musicals. Increasing numbers of spectators and the necessity for modernisation of the infrastructure require a complete rehabilitation which started in 2006 and is finished in spring 2008. The stability control of the theatre demands a permanent geodetic monitoring for the whole construction process. Especially the theatre ceiling is affected by significant mechanical and thermal loads.

The first part of the paper contains a short description of construction process, permanent monitoring system for the ceiling (based on tacheometer measurements) and the principal strategy for automated alerting via e-mail or SMS.

The second part of the paper deals with the investigation of the displacements in selected material points. A special focus is set on the quantification of thermal effects caused by changes of the temperature gradient between roof truss and auditorium. It is shown that 'black box' models (e.g. Artificial Neural Networks, Fuzzy Methods etc.) as well as 'grey box' models (e.g. analogous spring-damp-systems identified by Kalman-filtering) are suitable to quantify and predict the deformation behaviour. Advantages and disadvantages of the different applications are discussed.

1. MONITORING THE 'RONACHER' THEATRE

As a result of new safety aspects in connection with the development of early warning and alarm systems, geomonitoring has a gaining significance. The basic concept is to collect repeated (Δt = days to years) or 'continuous' (Δt = msec to hours) measuring data from the observed objects (e.g. natural objects like regional and local earth crust, geological and geotechnical structures and artificial objects like dams, buildings, machineries during their construction and / or operating phase). Mostly, geodetical, geotechnical and geophysical measuring methods are used and implemented in an integrated online warning / alarm concept.

For the years 2006-2008, our institute was authorised to install a geodetic monitoring system in the Viennese theatre 'Etablissement Ronacher' (see Figure 1). One of the main tasks was to monitor the whole construction process, especially the vertical mechanical and thermal deformations of the 600 sqm theatre ceiling (see Eichhorn et al., 2007).

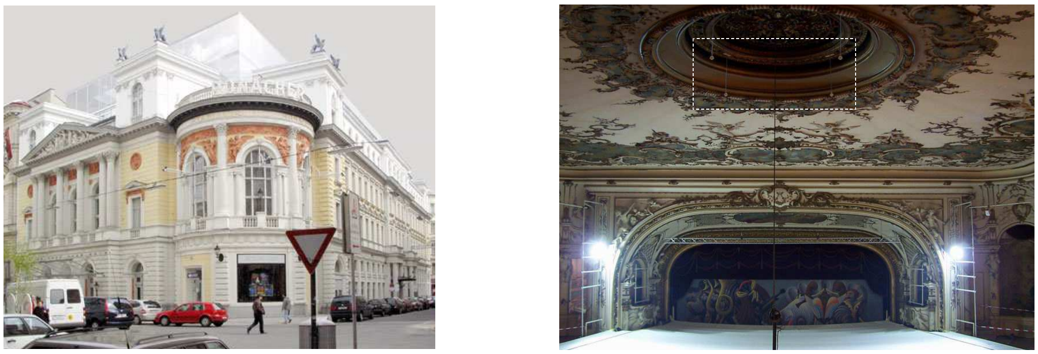

Figure 1 - Etablissement Ronacher and study object theatre ceiling.

Four selected object points (O_i) were continously monitored with a measuring rate of Δt = 10 min, six additional reference points (FP_i) with a rate of Δt = 60 min. The monitoring system and the measuring design are shown in Figure 2.

The system contains an automated alarm function (by email or SMS) if predefined tolerances $T_{\mathrm{I}} = \pm 25$ mm in construction phase I (reallocation of the ceiling) and $T_{\mathrm{II}} = \pm 12$ mm in phase II (roof finishing) are exceeded. T_{I} is the maximum tolerable vertical deformation of the ceiling related to a balanced condition at the beginning of the construction process. T_{II} is related to a balanced state at the end of phase I (Eichhorn et al., 2007).

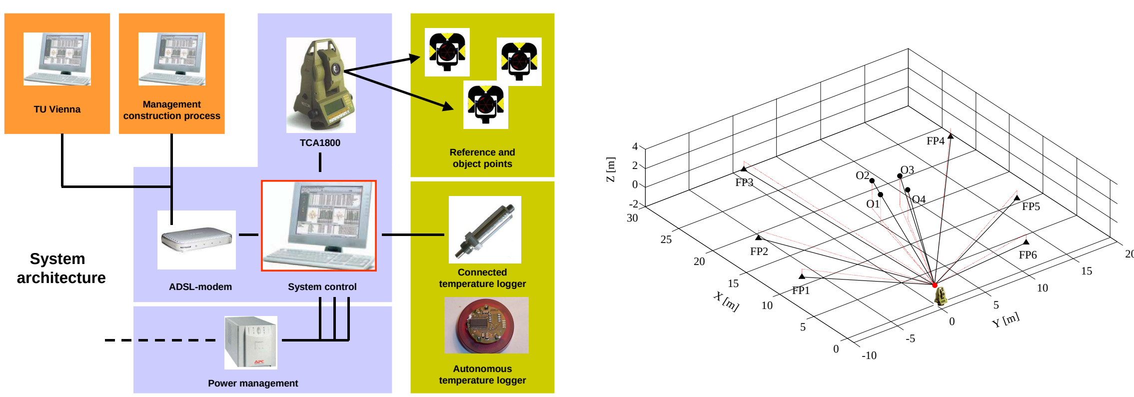

Figure 2 - Monitoring system and measuring design.

2. THERMAL DEFORMATIONS OF THE THEATRE CEILING

Apart from the dominant mechanical deformations, the sensitive and reliable alarm function has also to consider the influence of temporal variations of the vertical temperature gradient between roof truss and auditorium (see Figure 3). Naturally, the thermal influence is not a risk for the stability of the building. Nevertheless, thermal stress may cause cracks in plaster and stucco and requires periodical reparation. In this respect, the investigation is considered as part of the full deformation analysis. Two temperature sensors are logging the air temperatures in the roof truss (*T*o) and the auditorium (*T*u) with a measuring rate Δt = 10 min.

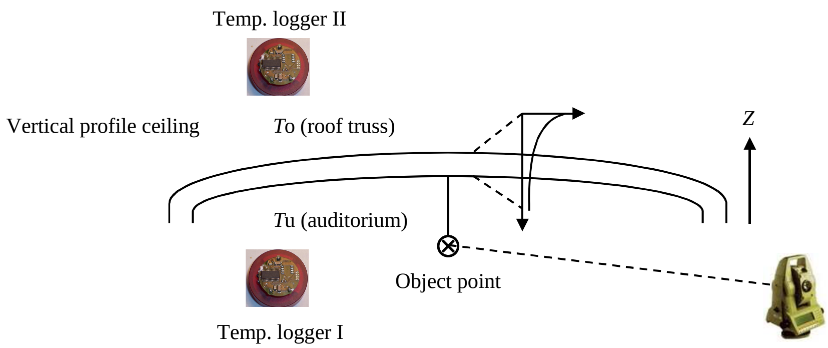

Figure 3 - Monitoring of thermal deformations.

3. NON-PARAMETRIC DEFORMATION MODELLING ('BLACK BOX')

The main problem for deformation modelling is that nearly nothing is known about the inner structure of the old ceiling. It is inhomogenous and maybe consists of a mixture of cement, wood and straw. So first of all it is decided to use non-parametric dynamic deformation models (e.g. 'black box', see Welsch et al., 2000) for the investigation of the causal chain:

change of vertical temperature gradient => change of vertical displacements.

The following methods are presented for object point O1 and can be classified as SISO (= Single Input Single Output, e.g. Unbehauen, 1980) models with the temporal progress of the temperature gradient ΔT_k as input (dynamic load) and the vertical displacements Δz_k as output. The basic principle is shown in Figure 4.

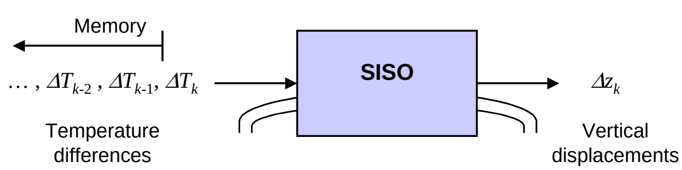

Figure 4 - Creation of SISO deformation models.

3.1. Neuro-Fuzzy approach

Fuzzy systems are an approach to handle and process data according to the human way of thinking. With fuzzy systems, input and output variables are defined by so-called 'membership functions'. E.g. the variable 'temperature' can be described by the linguistic membership functions 'low', 'medium' and 'high'. The corresponding values are in most cases overlapping intervals to consider the inherent fuzziness of the transition of e.g. 'low temperature' to 'medium temperature'. The human expert knowledge of the application's processes must be modelled by IF-THEN-rules and stored in a rule base, which represents the connection between input and output. In some complex applications, it is not possible to model the behaviour of a system by rules, defined by a human expert.

ANN (= Artificial Neural Networks, see also Section 3.2) are usually used to model a system without having knowledge of the underlying processes. A big disadvantage of this method is that ANN are 'black box' systems, i.e. the system can not be analysed or interpreted.

So a combination of fuzzy systems and ANN seems to be a useful approach to benefit from the advantages of both strategies, disregarding the several disadvantages. These neuro-fuzzy methods are based on the following approach: Within the specification of the input and output variables, the membership functions for both groups have to be defined. In most systems it is possible to predefine an initial state for the membership functions, but it is also possible to start from scratch. Within the training phase, training data is used to define and optimise the membership functions and the rule base, using the learning component of ANN. After a checking phase, the resulting fuzzy system can be used for prediction or control. Detailed information on neuro-fuzzy systems can be found e.g. in Jang (1993) and Borgelt et al. (2003).

The data investigated consists of temperature and position measurements of 9 days in July 2006 for the object point O1. In Figure 5 the original measuring data of the height component (Z coordinate) of O1 is shown in blue. Apart from a periodical structure, the signal is also overlaid by a non-stationary part.

Goal of the neuro-fuzzy application is the prediction of the temperature-induced movement of the object point O1, so the output variable is the Z coordinate of O1. Two input variables are used for modelling:

- $\Delta T = T_o - T_u$: difference between the measured temperatures at the roof truss (T_o) and at the auditorium (T_u)
- ΔT with a time delay of 6 hours

It is evident that thermal deformations are not only dependent on the actual temperature but also on the temperature some time ago. The time delay of 6 hours was empirically found to be able to represent the form and amplitude of daily thermal variations. Other time delays tested here (e.g. the delay of 4.7 hours found by cross correlation or another delay of 12 hours) gave almost equal or worse results.

For calculation the Matlab® Fuzzy toolbox was used. For both input variables, three membership functions of type 'Gaussian bell function' were defined. The parameters and the shape of these membership functions were optimised during the training phase. Here, an hybrid training algorithm combining least-squares method and a backpropagation gradient descent method was used for the 950 pairs of input and output training data.

Within the checking phase, the remaining data was processed to get an idea of the quality of the prediction capabilities of the resulting system. In Figure 5 the measured output is shown in blue and the calculated output is shown in red, both for the training phase (left part) and the checking resp. prediction phase (right part). The lower figure shows the differences between the measured and the calculated *Z* values; the maximum difference within the prediction phase is 0.28 mm. It is obvious that there is a stronger increase of the *Z* coordinate at the transition between training and prediction phase. This situation could not fully be reproduced by the neuro-fuzzy system so that there is a remaining rather constant offset of about 0.15 mm.

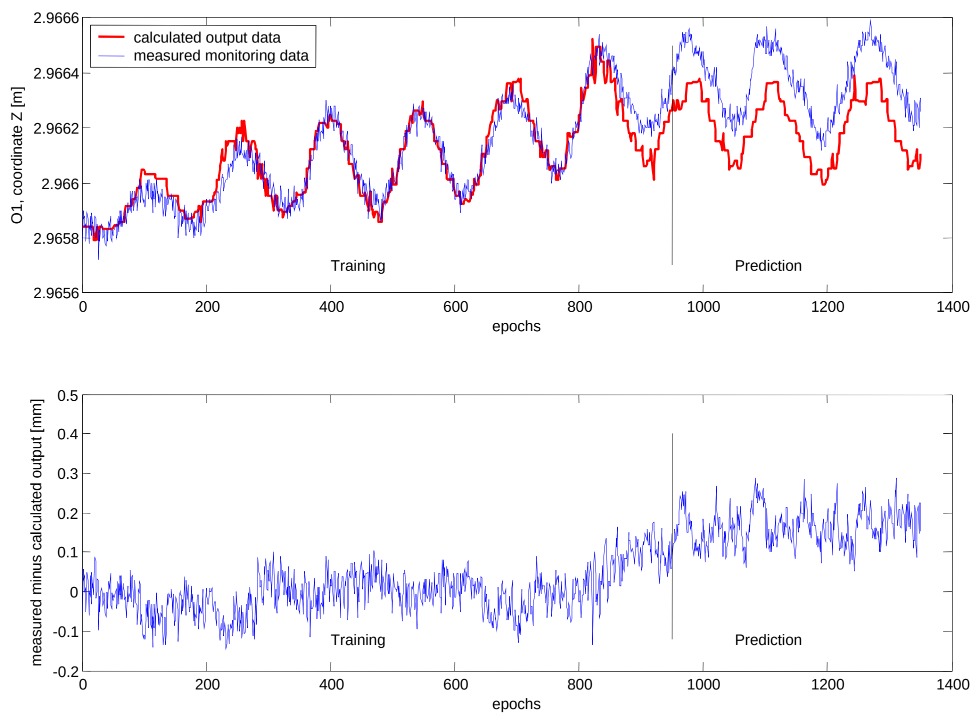

Figure 5 - Upper figure: measurements (blue) and predictions (red). Training and prediction phase are separated by a vertical line at epoch 950. Lower figure: residuals between the measurements and the calculated output.

3.2. Artificial Neural Network

ANN are using a different approach of problem solving in comparison with conventional computer software – they process information in a similar way the human brain does. The basis of an ANN consists of a set of highly interconnected processing elements, the so-called 'neurons'. The disadvantage of such an approach is that the network finds out how to solve the problem by itself, therefore the user receives no declaration how the problem was solved. Furthermore neural networks operations can be unpredictable.

An ANN can be seen as a simple clustering of artificial neurons. Each network is subdivided into single layers, which are then connected among each other. Basically, all artificial neural networks have a similar structure and consist of three types of layers: (1) input layer represents the first interface to the real world (to receive the inputs); (2) output layer represents the second interface to the real world (to provide the network's outputs); (3) hidden layer represents the rest of the network (to transform the information from the input layer to the output layer).

The single artificial neurons are connected (normally unidirectional) via a network of paths. Each neuron receives inputs from many other neurons, but produces a single output, which is communicated to other neurons. There exist different types of connections between neurons (fully connected, partially connected and others) – we use a 'fully connected feed forward network', by which each neuron on the first layer is connected to every neuron on the second layer. The neurons on the first layer send their output to the neurons on the second layer, but they do not receive any input back form the neurons on the second layer. More detail about artificial neural networks and their application can be found in Zell (1994) and Bishop (1995).

For our application the number of input and output units is fixed by the number of correspondent parameters – for our example 2 input units for the temperature logger (To and Tu) and 1 output unit for the coordinate Z (each coordinate X, Y and Z will be modeled by a separated neural network – in the following we will focus our report on Z). The input layer was extended to an input array of 2×10 units to simulate a memory (Z_i, Z_{i-1}, Z_{i-2}, ...). The number of hidden-units is directly related to the capabilities of the network. For the best network performance an optimal number of hidden-units must be properly determined – we have chosen a hidden layer of 10×10 units.

The processed data consists again of temperature and position measurements of 11 days (1589 epochs) in July 2006. The data has been divided into two parts: a training data set (start at day 49) and one for testing (start at day 54). Both have been pre-processed in such a way that they are limited to an interval of 0-1 (normalization).

The network was trained by means of the 'backpropagation algorithm' and by means of 800 epochs of trainings samples – each sample consisting of 2×10 input samples and the appropriate output sample. To ensure optimal results and to avoid an overtraining we have used several criteria for controlling the training process. First of all the threshold for the Sum Squared Error (SSE) of the learning function was fixed to a value of 0.01. Secondly, the maximum training cycles were set to 1000. After having trained the ANN, the second part of the data set (789 epochs) was used for testing – the result is shown in Figure 6. The maximum difference between predicted and measured Z is 0.27mm.

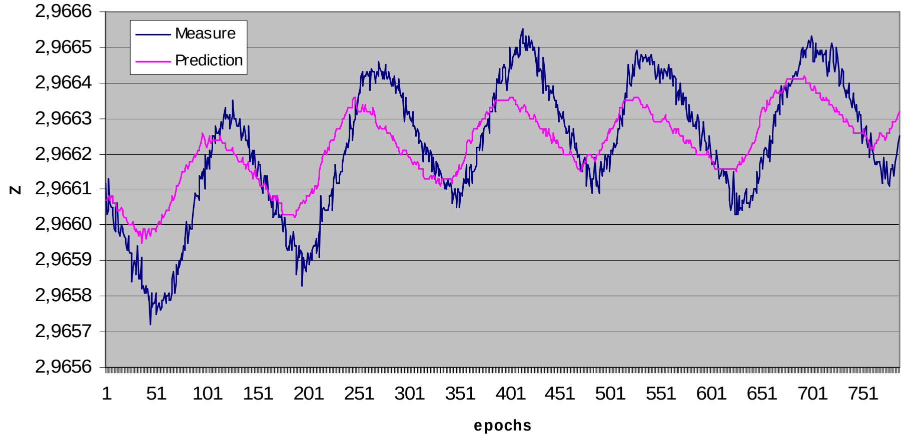

Figure 6 - Neural network in prediction mode: measurements (blue) and predictions (magenta).

4. 'PARAMETRIC' MODELLING ('GREY BOX')

4.1. 'Parametric' model and adaptive Kalman-filtering for identification

For an improved modelling also of the non-stationary thermal effects in the deformation signal in object point O1, the ceiling is assumed to show a visco-elastic behaviour in a certain operational range around a state of equilibrium (in the following, thermal induced deviations from the balanced state are quantified with Δz_k). In this case the thermal deformation model can be prepared with a 'spring-damp system' as mechanical analogous model (Kelvin material, e.g. Pelzer, 1977 and Heunecke, 1995). According to Welsch et al. (2000) such a model can be classified as a 'grey box' model, this means it is situated somewhere between non-parametric and real parametric models.

The configuration of the spring-damp system is shown in Figure 7, with γ the spring constant and β the damping. The system is 'activated' by the vertical temperature gradient $\Delta T_k = To_k - Tu_k$ (see also Figures 3 and 4).

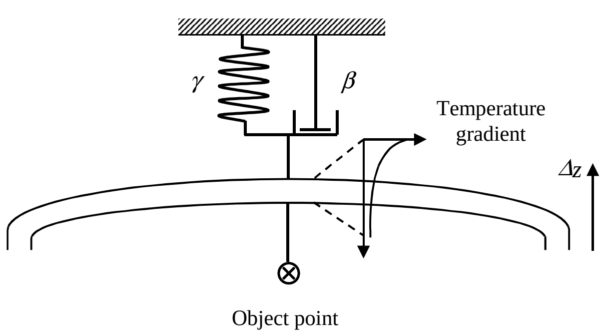

Figure 7 - Principle of the mechanical analogous model 'spring-damp-system'.

The adaptation of the spring-damp model to reality is part of the experimental system analysis (system identification, see Isermann, 1988) and contains the determination of the initial values and the physical parameters γ and β. The identification is realised with an adaptive Kalman-filter (e.g. Eichhorn, 2005). The basic filter equations are shown in (1) and (2).

$$
\begin{aligned}
\Delta\tilde{z}_{k+1} &= e^{-\frac{(\tilde{\gamma}_k + w_{\mathrm{p},\gamma,k})}{(\tilde{\beta}_k + w_{\mathrm{p},\beta,k})}\Delta t}\,\Delta\tilde{z}_k + \frac{1}{(\tilde{\gamma}_k + w_{\mathrm{p},\gamma,k})}\left(1 - e^{-\frac{(\tilde{\gamma}_k + w_{\mathrm{p},\gamma,k})}{(\tilde{\beta}_k + w_{\mathrm{p},\beta,k})}\Delta t}\right)\Delta\tilde{T}_k \\
&\quad + \frac{1}{(\tilde{\gamma}_k + w_{\mathrm{p},\gamma,k})}\left(1 - e^{-\frac{(\tilde{\gamma}_k + w_{\mathrm{p},\gamma,k})}{(\tilde{\beta}_k + w_{\mathrm{p},\beta,k})}\Delta t}\right) w_{\Delta T,k} \\
\tilde{\gamma}_{k+1} &= \tilde{\gamma}_k + w_{\mathrm{p},\gamma,k} \\
\tilde{\beta}_{k+1} &= \tilde{\beta}_k + w_{\mathrm{p},\beta,k}
\end{aligned}
\tag{1}
$$

$$
\tilde{L}_{\Delta z,k+1} = \Delta\tilde{z}_{k+1} \tag{2}
$$

In the system equations (1) the state vector contains $\boldsymbol{x}_k = (\Delta z_k,\ \gamma_k,\ \beta_k)$. The quantity $w_{\Delta T,k}$ represents a stochastic disturbance influence, which quantifies the deficiency of the model. The physical parameters are integrated into two random walk processes, whereby $w_{\mathrm{p},\gamma,k}$ and $w_{\mathrm{p},\beta,k}$ are the stochastic disturbances. The state quantity Δz_{k+1} is directly observed, which leads to the simple measuring equation (2).

The filter strategy is defined according to Eichhorn (2005) for dynamic deformation processes with high sampling rates. This means e.g. the use of reduced random walks to guarantee a stable progress and convergence of the estimation results.

4.2. First Filter results for O1

The following investigations are divided into two phases: training and pure prediction phases. The training phase contains the model identification. The pure prediction phase is the calculation of the model output (Δz) using only the identified deformation model and the measured temperature gradient (ΔT) as input. Like in Section 3 the comparison calculated output versus measured output is again a good indicator for the model quality.

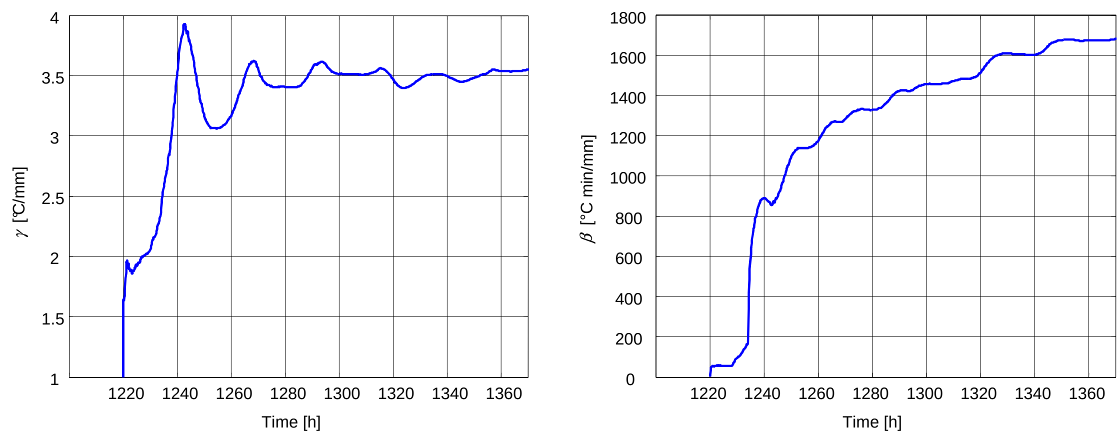

Figure 8 - Identification results for spring (γ) and damping parameter (β).

Because of summer time and no significant construction activities, the period July, 2nd – July, 11th 2006 (see also Section 3) shows a clear thermal deformation signal which is not overlaid by any changes of mechanical deformations and is selected as training period. Figure 8 shows the identification results with a filter progress of Δt = 10 min. Starting from totally arbitrary initial values ($\gamma_0 = \beta_0 = 1$), the estimation of the spring constant γ converges to γ= 3.55°C/mm (with σ_γ= 0.2°C/mm) and the damping to β= 1681°C min/mm (with σ_β= 50°C min/mm). The relative errors of 5% and 3% show a homogenous accuracy level. Nevertheless the damping is more difficult to determine because of lower correlations with the observations $L_{\Delta z}$ (Eichhorn, 2005). This results in a nearly twice as long identification time.

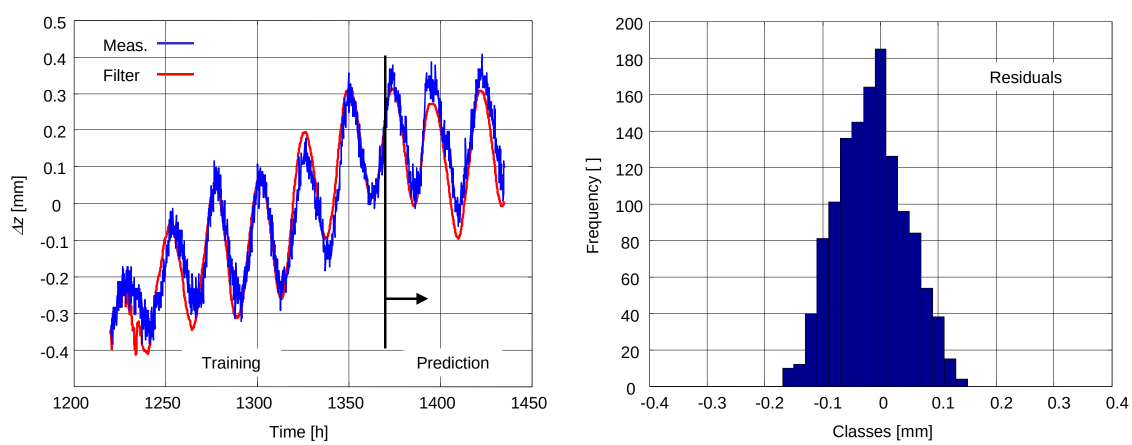

Figure 9 - Training and prediction phase of thermal deformations Δz in O1.

The filtered deformation signal Δz is shown in Figure 9. The pure prediction phase reaches from t = 1370 h to 1435 h. Within the 65 hours (2.7 days) the predicted deformation (red line) follows well the measured deformation (blue line). The residuals are in a maximum range of ca. ± 0.15 mm. Their *r.m.s.*-value is 0.06 mm. Because of remaining small systematic errors, the distribution shows a certain skew symmetric behaviour. In total, it can be stated that the identified model describes well the main characteristics of the thermal deformation process.

5. CONCLUSIONS AND OUTLOOK

The comparison of the 'black box' (Neuro Fuzzy and ANN) with the 'grey box' model (spring- damp-system) clearly shows that the 'grey box' approach obtains the best prediction results when the thermal deformation signal is overlaid by non-stationary parts. The results are summarized in Table 1.

	Neuro Fuzzy	ANN	Spring-Damp
r.m.s. [mm]	0.15	0.17	0.06
Characteristics	No phase shift Offset	Phase shift Scale factor	No phase shift Small offset

Table 1 - Residuals of deformation prediction.

Because of the deviations between all three models and the real physical behaviour of the ceiling, also the validity of the spring-damp-system remains restricted to a narrow range (approximately up to 1cm) around the balanced state in July 2006. Another working point requires a re-calibration. To extend the validity a modification of the model will be required. In this case maybe a dynamic Finite Element representation could improve the results. But taking into account the 'poor' discretisation of the ceiling with only four object points and the unknown inner structure, this approach will have only a low chance to succeed.

Consequently, further investigations will preliminarily be focussed on a further development of Neuro Fuzzy approaches and the ANN.

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