Modeling the Deformations of a Lock by Means of Neuro-Fuzzy Techniques

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Key words: Deformation Measurement, Engineering Survey, Fuzzy Inference System, Prediction, Deformation, Neuro-Fuzzy Modeling

SUMMARY

The survey and modeling of the deformations of large structures is a major task in engineering geodesy. In this paper, a new procedure to describe and predict the deformations is presented and discussed which is based on Neuro-Fuzzy modeling. Neuro-Fuzzy methods are data driven; they deduce the model directly from the data. Hence, they are mostly convenient if there are no physical models available. They allow the automatic derivation of interpretable rules and the data based simulation of complex processes. In particular, the Adaptive Network based Fuzzy Inference System (ANFIS) technique is used here. It represents a fuzzy inference system which is implemented in the framework of adaptive networks. It is based on a supervised learning algorithm to optimize the parameters of a fuzzy inference system.

In this study, the procedure of ANFIS is outlined. The corresponding way of modeling is studied based on geodetic data collected at the lock Uelzen I. This lock is located in Northern Germany at the Elbe-Seiten-Kanal which connects the river Elbe with the Mittellandkanal. The surmounted height difference is about 23 m. The lock has a length of 190 m and a width of 12 m. The size of the flood gate is 12 m x 11 m. Since 1978 the Geodetic Institute of the University of Hanover (GIH) has carried out numerous measurement campaigns at the lock Uelzen. The data used for this study were collected during the last campaign in 2004. They comprise time series of several types of geodetic observations. In this study, data of plummet records and of the water level are used to derive different ANFIS models which are discussed in order to exemplarily show the handling and the benefit of Neuro-Fuzzy modeling.

ZUSAMMENFASSUNG

Die Erfassung und Modellierung von Deformationsprozessen an großen Bauwerken ist eine der Hauptaufgaben der Ingenieurvermessung. In diesem Beitrag wird eine neue Methode zur Beschreibung und Prädiktion von Deformationen vorgestellt und diskutiert, die auf der Neuro-Fuzzy-Modellierung beruht. Neuro-Fuzzy-Methoden sind datengetrieben, d. h. ein Modell wird direkt aus den Daten abgeleitet. Dies ist hauptsächlich dann von Vorteil, wenn keine physikalischen Modelle vorliegen. Neuro-Fuzzy Methoden erlauben eine automatische Ableitung interpretierbarer Regeln und die datenbasierte Simulation komplexer Prozesse. Im Speziellen wird in diesem Beitrag das ANFIS-Modell (Adaptive Network based Fuzzy Inference System) verwendet. Das ANFIS-Modell ist ein Fuzzy-Inferenz-System, welches in

ein adaptives Netz eingebettet ist. Die Systemparameter können so mit Hilfe eines Trainingsalgorithmus optimiert werden.

In diesem Beitrag wird die Arbeitsweise von ANFIS beschrieben und eine Datenmodellierung basierend auf Daten durchgeführt, die an der Schleuse Uelzen I gewonnenen wurden. Die Schleuse Uelzen I befindet sich im Norden Deutschlands am Elbeseitenkanal, der die Elbe mit dem Mittellandkanal verbindet. Der zu überwindende Höhenunterschied beträgt 23 m. Die Schleuse hat eine Gesamtlänge von 190 m und ist 12 m breit. Das Schleusentor hat eine Größe von 12 m x 11 m. Das Geodätische Institut der Universität Hannover führt seit 1978 regelmäßig z. T. kontinuierliche Überwachungsmessungen an der Schleuse Uelzen I durch. Die Daten, die für diese Studie verwendet werden, stammen aus der letzten Messkampagne im Jahre 2004. Die gewonnenen Zeitreihen stammen aus GPS Beobachtungen, terrestrischen Messungen, Lotungsmessungen und Informationen über den Wasserstand. Die beiden letztgenannten Datentypen werden zur Aufstellung von ANFIS-Modellen verwendet und abschließend kritisch diskutiert.

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1. INTRODUCTION

The survey and modeling of the deformations of large structures is a major task in engineering geodesy. In this paper the occurring deformations of a lock chamber during a ship is passing through are modeled by using the Neuro-fuzzy method ANFIS. Here the focus lies on the short term prediction of the lock chamber motion due to changing water levels. The paper is organized as follows. In the subsequent sections the lock Uelzen I and the ANFIS method are described. Afterwards the models derived by ANFIS are introduced and discussed.

2. THE LOCK UELZEN I

2.1 Object Description

The lock Uelzen I (Fig. 1) is located between Hamburg and Hanover in the northern part of Germany. It was built at the Elbe side channel which connects the river Elbe with the Midland channel. It is one of two buildings which surmount the height difference of 61 m. The lock Uelzen I transcends a height difference of 23 m. The lock is composed of 11 u-shaped blocks and has an overall length of 190 m. The lock chamber has a width of 12 m and the size of the flood gate is 12 m x 11 m. The water level inside the chamber varies from 42 m to 65 m. The sink rate of the water level is 2.15 m per min and the climb rate is 1.94 m per min. It takes 30 min to bring a ship through the lock. Due to the changing loads of 54,000 t of water, deformations of the underground and the lock chamber can be detected. Approximately 100 ships per day are passing through the lock. Within the last 20 years the Geodetic Institute of the University of Hanover has carried out several deformation measurement campaigns at the lock. One task was to determine the deformations which are caused by the periodically changing water level inside the lock chamber.

Fig. 1: Aerial view of lock Uelzen I

2.2 Plummet Measurements

Since 1989, a Hanover plummet measurement system is installed at the eastern tower of the tail-bay. The system consists of ten inductive transducers which allow a contact-free measurement of the motion of the plummet wire. The x-axis is parallel to the axis of the lock in North-South direction. The change of the plummet-wire position is registered as a frequency changing. To transform the frequencies into elongations, a calibration function determined with a polynomial approach is used. The frequency ranges between 4400 and 8400 Hz. With a thickness of the plummet wire of 3.8 mm and a distance of the transducers of 20 mm a measurement range of approx. 16 mm is obtained. The sampling rate is usually 10 minutes and the water level is registered in dm intervals with every plummet measurement.

The data used in this paper are registered every minute for two days and one night. Linear interpolation closes gaps in the time series. The information about the water level and the movement in x-direction of the two transducers in a height of 3 and 27 meters, respectively, are used for the calculations.

3. ADAPTIVE-NETWORK-BASED FUZZY INFERENCE SYSTEMS (ANFIS)

The ANFIS (Adaptive Network based Fuzzy Inference System) is a combination of a fuzzy inference system (FIS) with learning techniques derived from neural networks (adaptive networks, AN). Here only a short overview is given due to the limited space; for a detailed description of ANFIS in the geodetic context see (Akyilmaz and Kutterer 2004) who applied it to time series of Earth orientation parameters. Note that (Miima 2002) presents a study of ANFIS in bridge monitoring which is related to the work presented here. Our study is more comprehensive concerning the various possibilities of modelling.

FIS are integrated inference structures: (antecedent, premise) → (rule base, inference base) → (consequent, decision). They consist of several units to transform input quantities (cause parameters, independent variables) into output quantities (effect parameters, dependent variables) by means of fuzzy logic. The *fuzzification interface* maps the real-valued input quantities on fuzzy input sets (membership functions). The *rule base* contains several *if…then rules*. The *data base* defines the membership functions of the fuzzy rules. The *decision making unit* and the *knowledge base* map the fuzzy input sets on fuzzy output quantities. The *defuzzification interface* transforms the fuzzy output sets into unique real-valued output values which can be used for decision and control purposes.

There are several types of fuzzy inference systems which have been proposed in literature, respectively. These types differ in the inference and hence in the consequent part. Typically the so-called Mamdani type is used as it directly represents the basic, intuitive idea of fuzzy logic and fuzzy control. Note that throughout this paper the so-called Takagi-Sugeno type is considered as it allows – in contrast to the Mamdani type – an automated training and optimization of the inference system in a rather easy way. The output of each rule is a linear combination of the input variables plus a constant term. The final real-valued output is the weighted average of each output rule with the weights calculated either by minimum or product fuzzy intersection.

An AN is a superset of all kinds of feed-forward neural networks with supervised learning capability (Jang 1993). It is a network structure of nodes which are connected by directional links. Furthermore, parts or all of the nodes are adaptive. That means that their outputs depend on one or more parameters pertaining to these nodes, and a learning rule specifies how these parameters should be modified to minimize a given error measure. The basic learning rule of adaptive network is based on the gradient descent and the chain rule. In order to achieve a desired input-output mapping, the parameters of the network are updated according to given training data and a gradient-based learning procedure.

ANFIS as the combination of AN and FIS is a supervised learning algorithm and is used to optimize the parameter set of FIS. The following exemplary description outlines the principal way of inference. Suppose that the FIS under consideration has two inputs x and y and one output z. The rule base contains two fuzzy if…then rules of Takagi-Sugeno type:
Rule 1: if x is A_1 and y is B_1; then $f_1=p_1x+q_1y+r_1$
Rule 2: if x is A_2 and y is B_2; then $f_2=p_2x+q_2y+r_2$

Here, A_1, A_2, B_1, B_2 are fuzzy sets which can be represented by their membership functions. Actually A_1 and A_2 (and B_1 and B_2 as well) are two different linguistic variables of the fuzzy set A (and B, respectively). Example: Let A = "length of a distance"; then A_1 = "small distance" and A_2 = "long distance". During the training of the network the parameter values are derived which quantify, e.g., a "long distance" based on the data.

Typically in ANFIS the membership functions $\mu_{A_i}(x)$ and $\mu_{B_i}(x)$, respectively, are chosen as bell-shaped functions

$$\mu_{A_i}(x) = \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{b_i}} \tag{1}$$

where a_i, b_i, c_i are the free parameters of the (input membership) function which have to be optimized during the network training. Note that other continuous and piecewise differentiable functions like trapezoidal or triangular-shaped membership functions can also be used. In the next step the values of the input membership functions for a particular rule are multiplied yielding the so-called firing strength w_i of each rule. The normalized firing strengths are derived as

$$\overline{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1,2\ . \tag{2}$$

The final defuzzification is obtained in a very natural way as the weighted average of the values of all rules

$$\text{output} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}\ . \tag{3}$$

4. PREDICTION OF DEFORMATIONS BY ANFIS

In this study the motion of the plummet measurement point at the height of 27 meters should be predicted. Therefore the ANFIS editor of the Matlab© Fuzzy Toolbox is used. Before starting the calculations and the modeling, the data have to be arranged as input and output pairs. The three time series which are discussed in this paper consist of 1711 values with a sampling rate of one minute. They cover two days and one night.

Let wl(t) denote the value of the water level at time t, x(t) the corresponding motion of the plummet at a height of 3 meters in x-direction and z(t) the motion of the plummet at a height of 27 meters in x-direction. The parameter t indicates the time. Fig. 2 shows the three time series. The indicated peak signals are caused by the lockage process; they show a quite irregular temporal pattern.

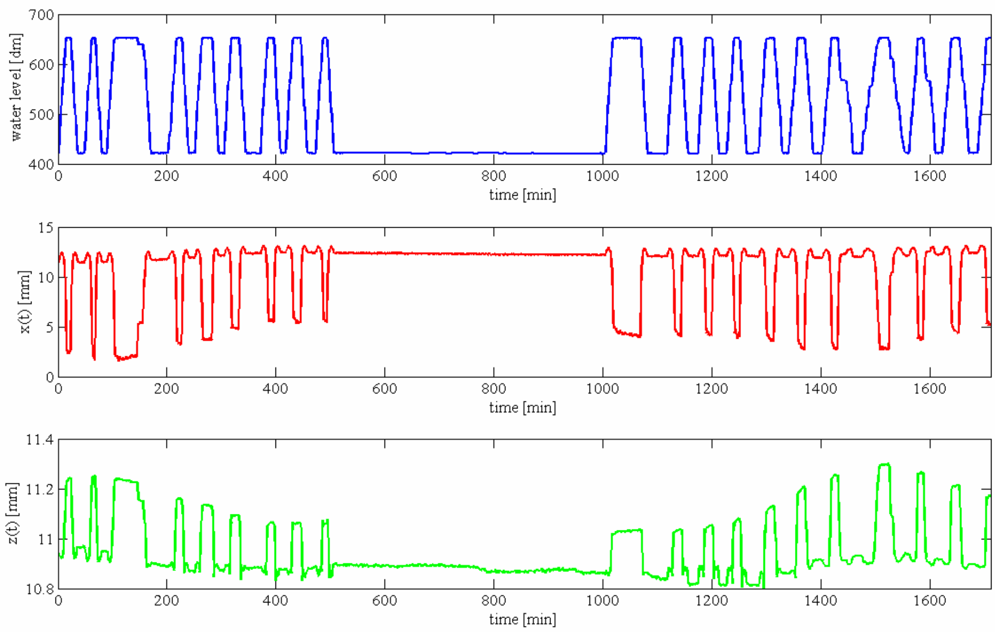

Fig. 2: Time series of …

As seen in the figure above, the water level and the two plummet measurement points are highly correlated. The correlation coefficients of the water level and the plummet wire at 27 m is 0.80 and of the water level and the plummet wire at 3 m is -0.81. The transducer measurements are correlated with -0.92. Regarding the correlation coefficients for the training and validation set separately, they show the same magnitude, the ones for the validation data set are a little smaller. For this reason good modeling results are expectable.

The basic idea of modeling in this paper is that the state of the parameter z at time t is predictable from a subset of the states of x, z and wl at the same and at previous times. Hence all discussed models have the same consequent z(t) to be predicted; the patterns differ in the numbers and the type of input variables. This can be understood as a joint model of causal parameters and observations of the object state. The following eight patterns are discussed.

	input		output
1.	$\{z(t\text{-}4k), z(t\text{-}3k), z(t\text{-}2k), z(t\text{-}k)\}$	$\longrightarrow$	$\{z(t)\}$, k=1,2, …, 10
2.	$\{x(t\text{-}k), wl(t\text{-}k), x(t), wl(t)\}$	$\longrightarrow$	$\{z(t)\}$, k=1,2, …, 10
3.	$\{x(t\text{-}k), wl(t\text{-}k), z(t\text{-}k), x(t), wl(t)\}$	$\longrightarrow$	$\{z(t)\}$, k=1,2, …, 10
4.	$\{x(t\text{-}k), wl(t\text{-}k), z(t\text{-}k)\}$	$\longrightarrow$	$\{z(t)\}$, k=1,2, …, 10
5.	$\{x(t\text{-}k), wl(t\text{-}j\text{-}k), x(t), wl(t\text{-}j)\}$	$\longrightarrow$	$\{z(t)\}$, k=1; j=1,2, …, 10
6.	$\{wl(t\text{-}k), wl(t)\}$	$\longrightarrow$	$\{z(t)\}$, k=1,2, …, 10
7.	$\{wl(t)\}$	$\longrightarrow$	$\{z(t)\}$
8.	$\{x(t), wl(t)\}$	$\longrightarrow$	$\{z(t)\}$

The parameter k indicates the epoch in future which has to be predicted, and j is the number of the epochs by which the time series wl is shifted against x. Each individual variable in the input space is represented by two bell-shaped membership functions according to Eq. (1). The time series are used to compose the respective matrices of input quantities and the corresponding output vector. With Pattern 1 the motion of the plummet wire in 27 meters (time series z(t)) is predicted only using the information about the previous motion of this plummet wire itself. Pattern 2 uses information from x(t) and wl(t) at two different epochs. It does not use any previous information about the time series z(t).

In addition, Patterns 3 and 4 introduce previous information about z; Pattern 4 uses only previous information, Pattern 3 also present information on x and wl. In Pattern 5 the time series wl shows an additional offset compared to x but no information about z is used. In contrast, Pattern 6 uses only information from the water level wl; note that two different epochs are considered. Hence it represents a purely causal model. Finally, Patterns 7 and 8 are somehow different to the others as they use just data from the present epoch. Hence, these two models have to be understood as for spatial or structural prediction of the state of z. The time component does not play any role in the prediction. Note that the more input variables are modeled the higher is the model complexity and thus the computational costs.

For setting up the ANFIS models, the first half of the time series is used as training data (model optimization) and the second half as validation data (independent check of the model) See (Akyilmaz and Kutterer 2004) for details. The patterns are then shifted against the time series. The predictions are made for the first ten epochs in the future.

The here applied error measure is the one introduced in (Schuh et al 2002) as

$$\mathrm{RMS}_e = \sqrt{\frac{1}{\mathrm{n}}\sum_{i=1}^{n}\left(\hat{l}_e^i - l_e^i\right)^2} \tag{4}$$

where $\hat{l}_e^i$ is the predicted value of the ANFIS network for epoch *e*, l_e^i is the actual value z(t) of the transducer at the height of 27 meters, and n is the number of predictions made for the different epochs. Approximately 860 predictions starting at different dates in the training or validation set were made for each epoch to calculate the RMS error. Some results are given in Fig. 3, the RMS of the training data sets for Patterns 1 to 6 for the prediction of ten epochs in future on the left side and the RMS for the corresponding validation sets on the right side. Note, that the two diagrams have different scales on the vertical axes.

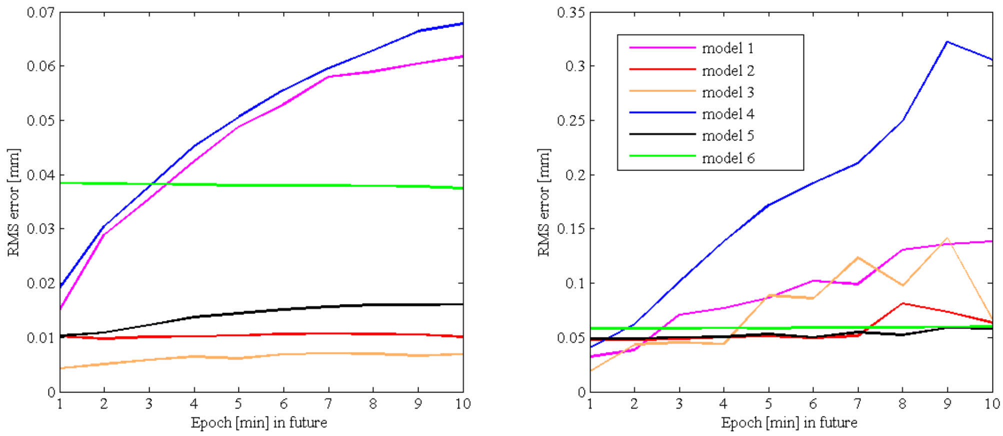

Fig. 3: RMS values for
the trainings data set the validation data set

The RMS values for Patterns 7 and 8 are not shown in Fig. 3 because they are only calculated for the actual epoch. For Pattern 7 the RMS error for the training data set is 0.039 mm and for the validation data set it is 0.058 mm; for Pattern 8 the corresponding values are 0.015 mm and 0.049 mm.

5. DISCUSSION

In the following, some results of the ANFIS prediction of the object motion expressed in the time series z(t) are discussed. The following figures consist of two subplots. On the top, z(t) (blue) is compared to the ANFIS prediction (green). The corresponding prediction errors are depicted at the bottom; the color respective the model color in Fig. 3.

The results of Pattern 1 which is only composed of the time series z(t), are shown in Fig. 4. The prediction was made for the 9th epoch. This first example is presented in order to indicate some limits of ANFIS modeling. Actually, the prediction just from the considered time series seems to be rather promising. However, the ANFIS prediction does not fit well with the measured time series even in the trainings space. This is due to the rather irregular structure of the lockage process; it is problematic to use data which were observed too far in the past.

These results are comparable to the ones obtained for Pattern 4 which only uses the values of the past of all three times series; the characteristics of the RMS values are nearly the same.

Just for short-term prediction (first two epochs in the future) set model performs quite well; it is comparable to Pattern 3 with five input parameters.

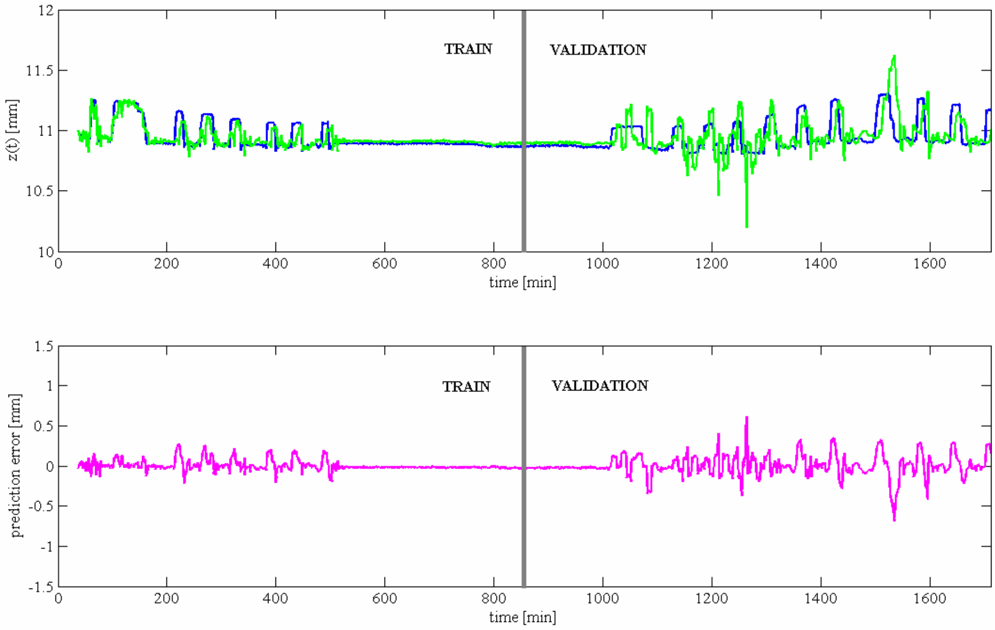

Fig. 4: Model 1, prediction for k=9

Fig. 5 shows the results of the calculations with Pattern 2, $\{x(t-k), wl(t-k), x(t), wl(t)\}$, for k=1 (prediction for the next epoch). The input variables are the water level and the time series x(t) at actual time and at previous times. Regarding the prediction error it is obvious that the long periodic changes are not modeled. This effect can be explained because the input time series wl(t) and x(t) do not contain any information about these long periodic changes. It is the same with Pattern 5 $\{x(t-k), wl(t-j-k), x(t), wl(t-j)\}$, and Patterns 6, 7 and 8 which do not use values of z(t) as input. But there are nearly the same small RMS values from Pattern 2 for the training data set for all k. The peak in the RMS value for the training data in the 8th epoch could not be explained yet.

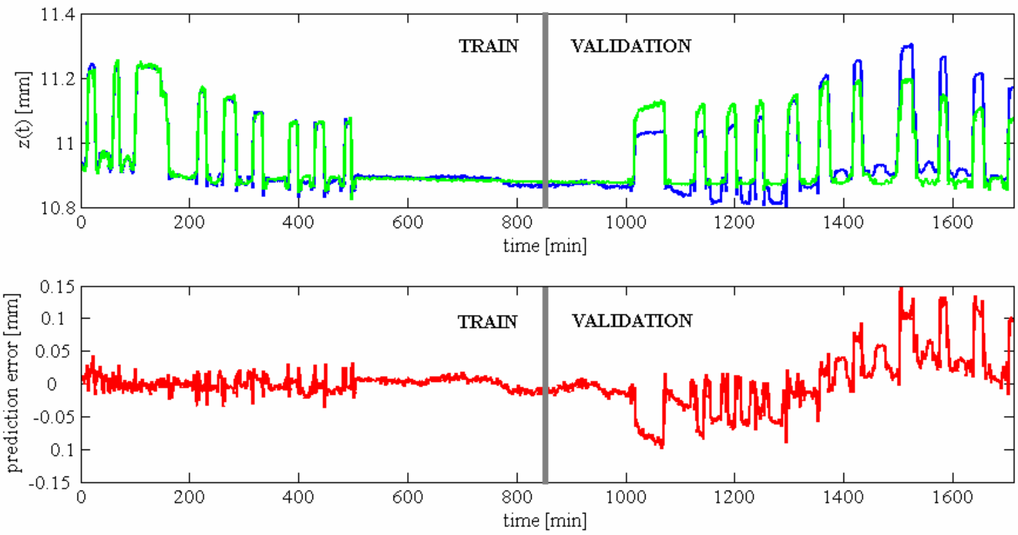

Fig. 5: Model 2, prediction for k=1

Fig. 6 shows the result of the ANFIS prediction of z(t) for the 1^{st} epoch (k=1) in future with Pattern 3, $\{x(t\text{-}k), wl(t\text{-}k), z(t\text{-}k), x(t), wl(t)\}$, which is the most complex one as it uses input data from all three times series and from the present epoch and from one previous epoch. The corresponding prediction error is depicted at the bottom (orange). This model leads to the best results for the training data set and (for the first epoch in future) for the validation data set. The absolute prediction error does not exceed 0.13 mm and the corresponding RMS for the validation set is about 0.02 mm. The long periodic effects are modeled much better than with Pattern 2 and Patterns 5 to 8. The peaks in the validation set always occur at the steep flanks of the time series.

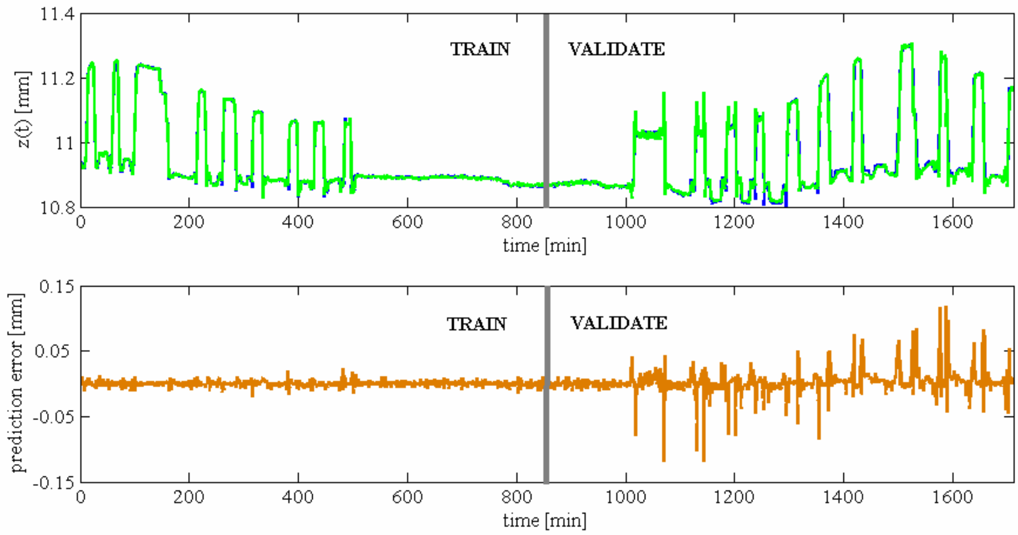

Fig. 6: Model 3, prediction for k=1

The results of Pattern 4 with the 3 input variables $\{x(t\text{-}k), wl(t\text{-}k), z(t\text{-}k)\}$ with values from a previous state yields the worst results; they are not shown here. The RMS of the training and the validation data set, except the RMS value for k=1, is always significantly higher than the results of the other models; see Fig. 3. A time offset emerges both in the training and the validation data set and the model is not suited for the prediction of z(t).

In Pattern 5 not only the time series are shifted against each other but there is also an offset j between the water level and the motion of the plummet wire at 3 m, $\{x(t\text{-}k), wl(t\text{-}j\text{-}k), x(t), wl(t\text{-}j)\}$ (Fig. 7). It does not use any information about the time series z(t). The RMS values are comparable to Pattern 2; they are slightly worse for the training data but best for the validation data.

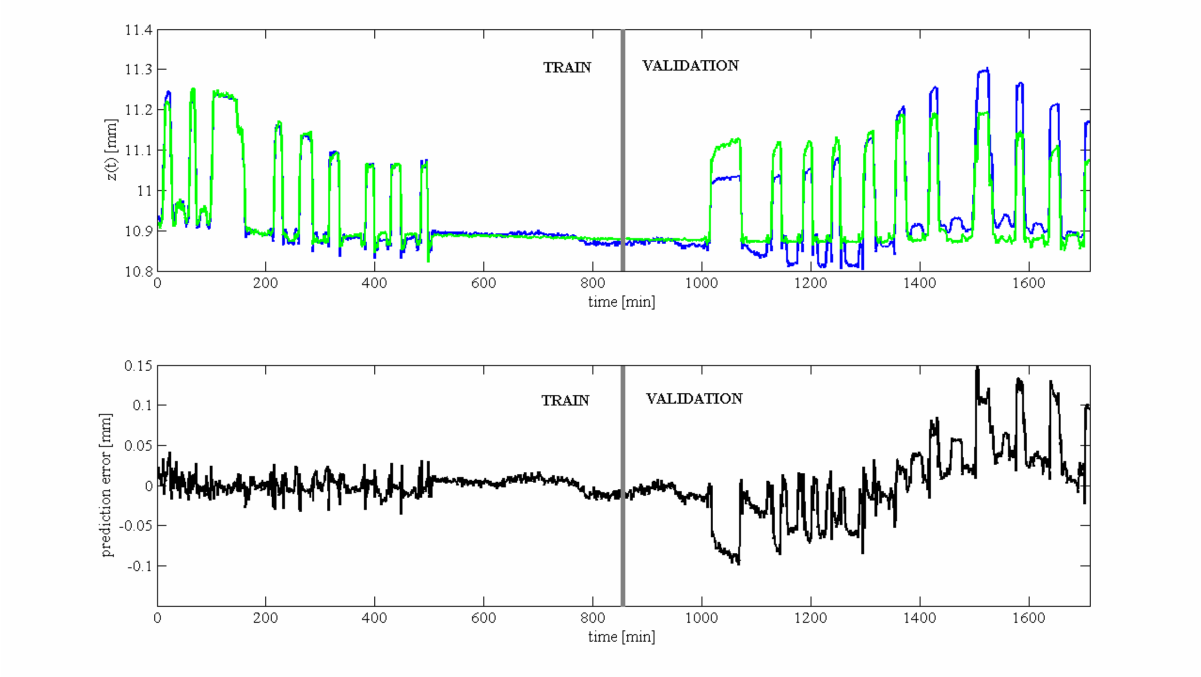

Fig. 7: Model 5, prediction for j=1

Pattern 6 with $\{wl(t\text{-}k), wl(t)\}$ uses only the information of the water level at different times for the prediction of z(t). As seen in Figs. 8 and 9 there is no big difference to Pattern 7 which uses only the present water level $\{wl(t)\}$.

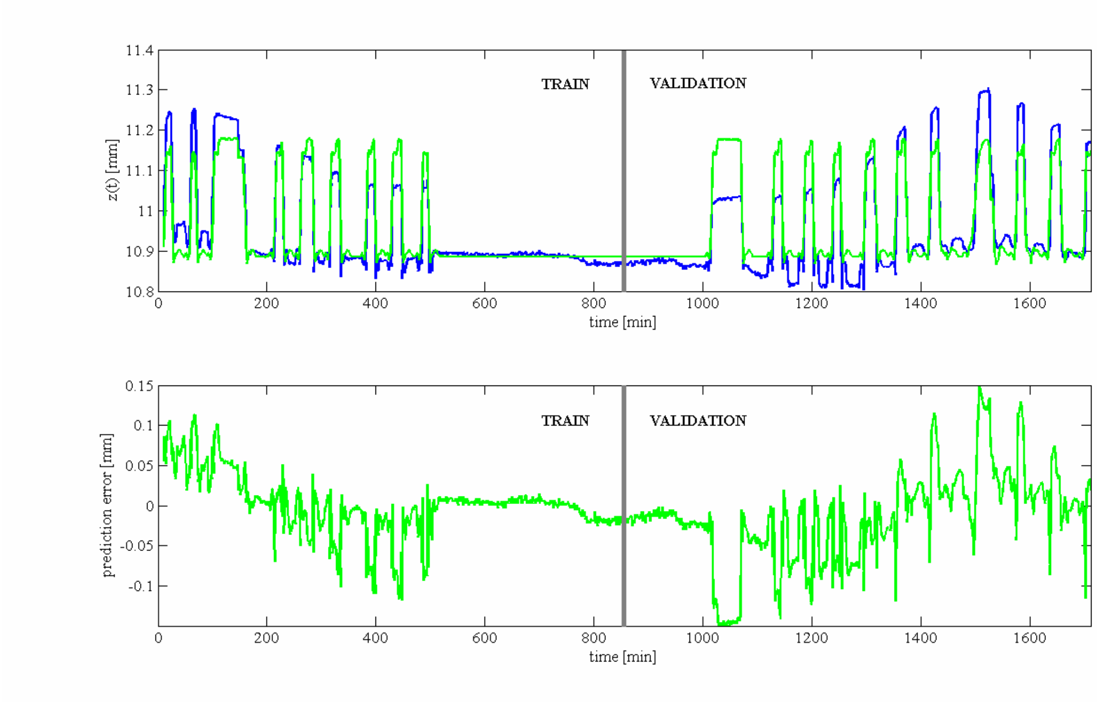

Fig. 8: Model 6, prediction for j=10

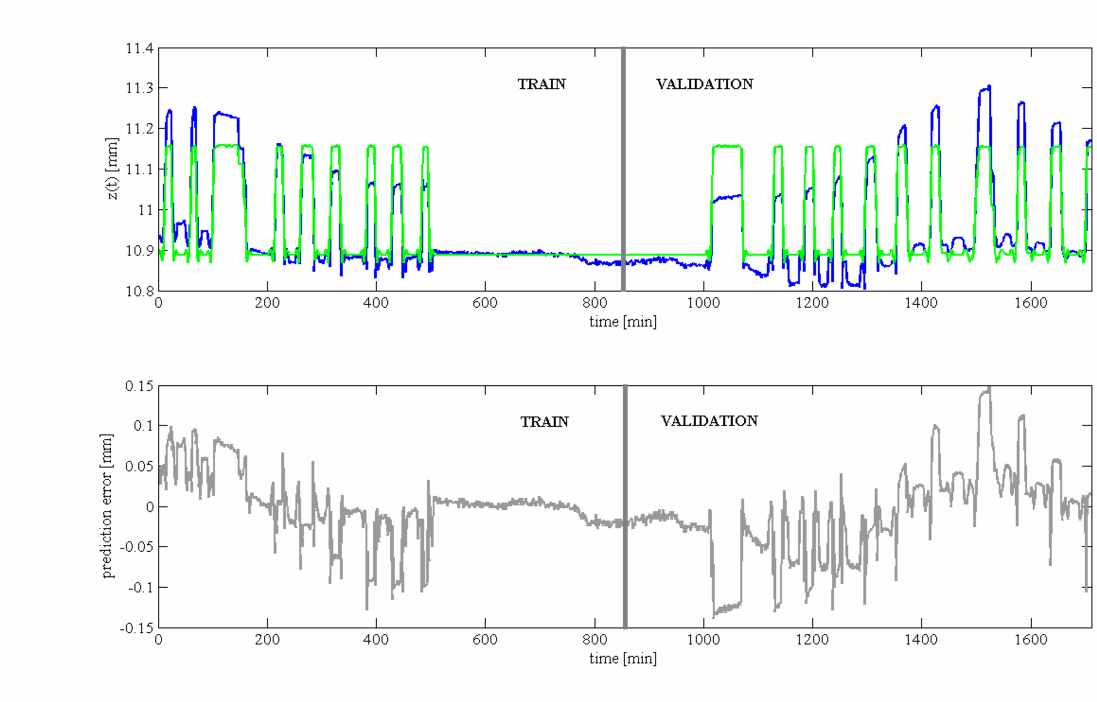

Fig. 9: Prediction with model 7

Fig. 10 shows the ANFIS prediction for Pattern 8 with $\{x(t), wl(t)\}$. Here, the state of the variable z is predicted from the states of x and wl at the same time. This can be understood as spatial but time-independent prediction like with Pattern 7. Thus, the RMS values are calculated only for the value z(t). For the training data there is RMS=0.0146 mm and for the validation data RMS=0.0485 mm. The validation data set shows a long-periodic signal which was not described by the model.

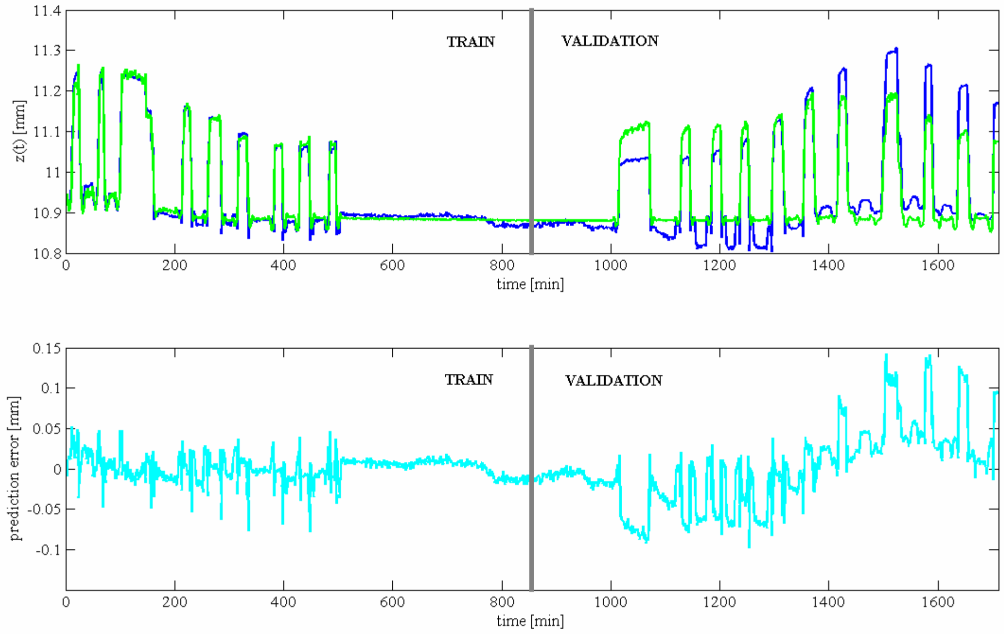

Fig. 10: Prediction with model 8

6. CONCLUSIONS

The Adaptive Network based Fuzzy Inference System ANFIS is purely data-driven. Hence this technique can be used in case of unclear relations between variables which describe the motions and deformations of a structure such as a lock. This paper presents results of a first study on the dedicated and systematic application of ANFIS to kinematic and dynamic modeling in engineering geodesy for, e.g., monitoring purposes and deformation analysis.

In total eight input patterns were considered in order to model structural deformations expressed in one particular quantity. On the whole Pattern 2 with the water level wl(t) and the plummet wire observations at 3 meters x(t) at different times as input parameters lead to the best results. Pattern 5 with the additional temporal offset between wl(t) and x(t) performed only slightly worse. Concerning the long-periodic signal component the best results were obtained for Pattern 3 which is the most complex as it uses the information about wl, x and z (at a previous state).

The first results on the use of ANFIS in engineering geodesy are promising. Our next steps will focus on more complex models which use also information of other sensors like GPS measurements and terrestrial observations. Besides, the relation between purely causal models and models which also use geodetically observed effects will be studied in more detail. Some effort has to be put into the ANFIS modeling of the different signal scales which are contained in the time series. The potential of the interpretability of the fuzzy rule base has not been used yet. There will also be comparative studies on alternative data-driven modeling strategies such as regression analysis.

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