GPS MONITORING OF THE FATIH SULTAN MEHMET SUSPENSION BRIDGE BY USING ASSESSMENT METHODS OF NEURAL NETWORKS

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ABSTRACT:

The second suspension bridge connecting the continents Asia and Europe, namely, Fatih Sultan Mehmet Bridge, has been monitored by using GPS technique. For this end permanent GPS observations with 0.1 seconds epoch interval were recorded for the same days of consecutive weeks. In addition to GPS observations, some other data belong to influencing factors such as traffic volume and weather conditions for the corresponding observation time were collected. At first step the time series of the respective point component displacements (deformations) were composed and linked to the data such as time, traffic volume and weather conditions. Then a detailed comparison of the individual observation days was investigated. Further on, an artificial neural network, from the family of soft computing methods is adapted in order to describe the deformation processes with respect to influencing factors. Such studies have been of special interest after the 17 August Earthquake in North Anatolian Fault Zone (NAFZ) since new earthquakes are expected. Therefore, monitoring of big engineering structures like bridges will bring important information for disaster management and risk analysis. The results present that artificial neural networks are efficient tools for modelling complex behaviours of deforming objects regarding the causing factors especially in case of continuous monitoring systems.

1. INTRODUCTION

Monitoring of engineering structures has become of importance particularly after the possibility of destructive natural catastrophes has been assumed to be increased. For this end, big engineering structures like suspension bridges, viaducts, tunnels and high buildings etc. have been subjected to continuously monitoring surveys. The technological developments in high precision point positioning systems together with no-human data transmission techniques without any atmospheric obligation have led to easily adapting such monitoring systems for the objects in question.

Fatih Sultan Mehmet Bridge is the second suspension bridge connecting the Asia and Europe. The construction has been completed in 1987 and since July 1988, it served as the second connection between Anatolian and European side for the Istanbul dwellers. Daily, an average of sixty thousand vehicles including automobiles, motorbikes, long vehicles, buses, minibuses and trucks pass over the bridge. This number shows how frequent the bridge is used. Therefore, any disaster which may ruin the bridge will not only bring structural loss but also many people will be damaged or even died.

It has long been a problem to geodesists to find efficient solutions to approximate functions that define geodetic deformations, especially when dealing with continuously monitored processes. A deforming object can be considered as a dynamic system (Pfeufer 1994, Welsch 1996, Heunecke and Pelzer 1998, Miima and Niemeier 2004) whereby, forces acting on the object (both internal and external loads) are regarded as input signals that lead to geometrical changes e.g., displacements and distortions as output signals. In most cases, mathematically description of a dynamic deformation process is very complex and using deterministic functions is not adequate to depict the behaviour of the deforming object. Up to now, many different methods were developed, it is however generally agreed upon that, there exist no single method that can satisfactorily describe the structural deformation as its underlying processes are normally so complex to be expressed by one simple expression.

The present study motivates the use of artificial neural networks for modelling the behaviours of deforming objects regarding the causing effects such as atmospheric conditions, traffic volume. Artificial neural networks are inspired from biological systems in which large numbers of neurons, which individually perform rather slowly and imperfectly, collectively perform extraordinarily complex computations that even the fastest computers may not match. This new field of computing method is recently widely used by different disciplines such as prediction and control engineering, image processing and identification, pattern recognition, robotic systems etc. It is very efficient tool for complex system identification in general.

2. STRUCTURAL DEFORMATION AS A DYNAMIC SYSTEM

A dynamic system, in general, is characterized by input signals, including all possible influences acting on the object leading to the output signals. In case of structural deformation, acting forces are regarded as input signals whereas the resulting changes in the coordinate components are output signals (Fig. 1).

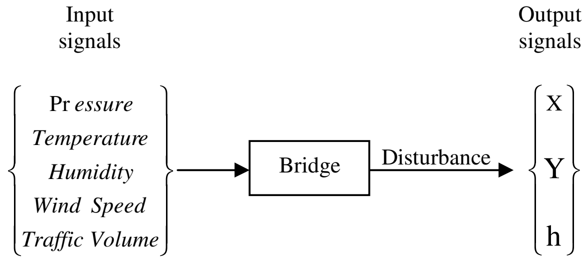


Figure 1. Schematic representation of the bridge as a system

Heunecke (1995) and Welsch (1996) have classified dynamic system identification models into three main types; parametric or white box, grey and non-parametric or black box models.
If the physical relationship between input and output signals, i.e. the transmission or transfer process of the signals through the object – in other words – the transformation of the input to output signals, is known and can be described by differential equations, then the model is called a parametric or white box model (Welsch and Heunecke 1999). Models using chosen a priori model structure or partially motivated physical analysis are the so-called grey box models whereas non-parametric or black box models experimentally identify the dynamic process. Artificial neural networks are from the family of black box models which can map input domain into any given output domain. Despite mapping of complex relationships between input and output signals is successfully provided, one can not make any inference just by looking at the transmission or transfer phase of the neural network. The following sections describe the neural networks and their use in deformation modelling.

3. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks are the simulation of human brain regarding the functional relationship between the neurons. A neuron is the basic processing unit in the human brain which have synaptic connections with other neurons in order to produce a decision or inference as the output signals. Biological systems are able to perform extraordinarily complex computations in the real word without recourse to explicit quantitative operations. This property of the biological nervous system has encouraged scientists to adapt the same structure as a mathematical tool for identification of complex systems. Indeed this idea was not quite new; the major improvement of artificial neural networks has begun in the last decades with the development in computer technology. The learning capability of organic neurons were then easily imitated by using computers, since the computations of the network parameters in an iterative procedure including derivatives and gradients of the performance functions was extremely difficult to handle. Figure 2 depicts the structure of a single neuron in an artificial neural network. The function of an artificial neuron is similar to that of a real neuron: it integrates input from other neurons and communicates the integrated signal to a decision making centre.

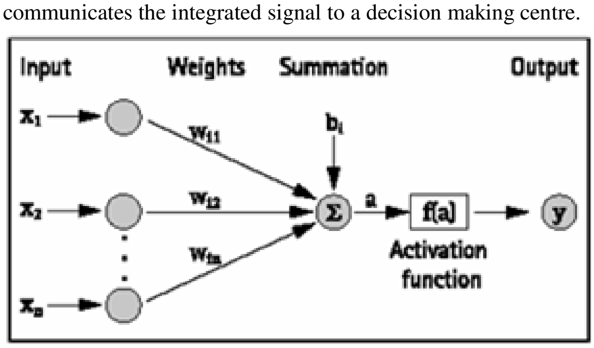


Figure 2. Single artificial neuron

The functional operation of a neuron is summarized as

$$y_i = f(a) = \frac{1}{1+\exp(-\beta a_i)}$$

(1)

with

$$a_i = \sum_{j=1}^{n} w_{ij} x_j + b_i$$

(2)

where y_i is the activity output of neuron i, a_i is the weighted sum of the neuron i from the input of the neurons in the previous layer, b_i is the bias term of the neuron i, x_j is the input from the neuron j, w_{ij} is the weight between two neurons i and j, and the constant β is threshold value which shifts the activation function *f(a)* along the x axis. An activation function is a non-linear function that, when applied to the input of the neuron, computes the output of that neuron. There exist various types of activation functions in neural computing applications such as hyperbolic tangent, Heaviside, Gaussian, multi-quadratic, piecewise linear functions, etc (Haykin, 1994). The one given in Eq. (1) is the most commonly used so-called sigmoid function.

3.1. Multilayer Networks

Multilayer networks are the most commonly known feed-forward networks. Neural networks typically consist of many simple neurons located on different layers and operate in cooperation with the neurons on the other layers in order to achieve a good mapping of input to output signals. The expression "feed-forward" emphasize that the flow of the computation is from input towards the output. There are three different types of layers in the concept of neural networks: the input layer (the one to which external stimuli are applied to), the output layer (the layer that outputs result), and hidden layers (intermediate computational layers between input and output). Theoretically, there is no limitation given for the number of hidden layers in a network configuration. That is, however have a great effect in the computation time as well as the number of neurons in hidden layers. Therefore, a compromise has to be found in order to achieve an optimal network configuration with an acceptable convergence time and quantitative precision.
Figure 3 gives a sample configuration of a multilayer feed-forward (MLFF) network with one input, one output and one hidden layer. Note that the network consists of five inputs and one output.

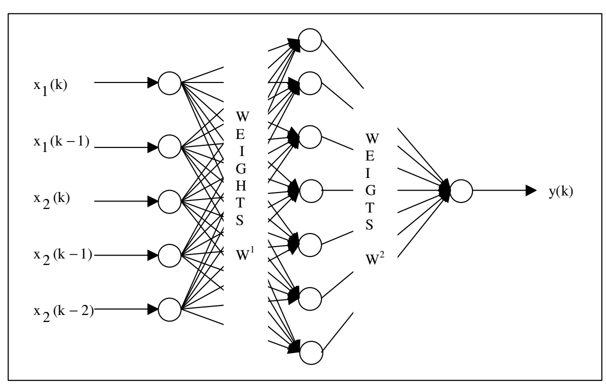


Figure 3. A schematic representation of a multilayer feed-forward (MLFF) neural network

3.2. Optimization of the network parameters

When a network configuration is fixed, the parameters of the network, i.e., the weights which link the neurons in consecutive layers has to be calculated so that a chosen function of the difference between the actual (desired) output and the output performed by the network is minimum. This function is usually called cost function or performance index. Most commonly used cost function is the sum of the squares of the residuals:

$$E = \sum \left(y_i(k) - y_i^{'}(k) \right)^2 \tag{3}$$

where $y_i(k)$, $y_i^{'}(k)$ and E are the actual output, network output and the corresponding cost function, respectively.

There is wide spectrum of different mathematical optimization tools like steepest gradient descent, Levenberg-Marquardt method, Gauss-Newton method etc. based on the iterative least-squares estimation of the network parameters. In order to respect the page limit, they are not discussed in detail. The reader is referred to standard text books like Haykin (1994) and Bishop (1995). The procedure for the optimization of the network parameters is usually called *learning* or *training* in neural computing literature.

4. APPROXIMATION OF STRUCTURAL BEHAVIOR BY NEURAL NETWORKS

In order to characterize the behaviour of the second bridge, Fatih Sultan Mehmet suspension bridge, under certain external forces, a satellite based continuous monitoring system was designed, and a multilayer feed-forward neural network using Levenberg-Marquardt learning algorithm was applied.

The steps of the entire study can be summarized as follows:

- Data collection and preprocessing
- Generation of the training patterns
- Identification of the network architecture
- Optimization of the network parameters and validation of the network by using test data set

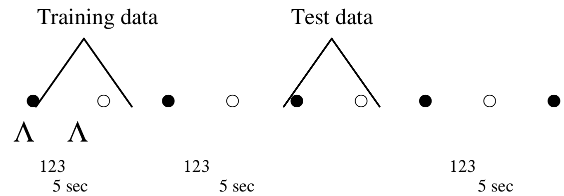
4.1. Data Collection and Preprocessing

In order to provide a continuous mapping of the bridges motion under the certain forces, a kinematic GPS survey with data sampling rate of 0.1 seconds was adopted. For this goal, two GPS receivers were set up: one on the top of the pole, and one on the platform that is located about the middle of the body of the bridge. Additionally, another receiver was set up as a reference station on the roof of ITU, Faculty of Civil Engineering. The GPS observations were processed using the software Leica SKI 2.1 and coordinate components for each observation epoch was derived. Hence, the time sequences of positions for each station located on the bridge were generated.

More over, hourly based corresponding atmospheric data as well as traffic volume statistics given in the left hand side of Fig. 1 were collected from the relevant institutions.

4.2. Generation of the training patterns

After processing of the GPS observations, they had to be coupled by the relevant causing effects, i.e., pressure, temperature, humidity, wind speed and traffic volume data which will then compose the input space of the network architecture. Wind speed is considered as a directed influence, and is divided into two components such that wind speed in the south-north and the east-west directions. Although the data sampling rate is 0.1 seconds, in order to reduce the size of data, solutions for every five seconds were considered. Since the atmospheric and traffic volume data is sampled in hourly basis, following assumptions have been adopted for coupling with the output data. The atmospheric values were assumed to be linearly varying values whereas the traffic volume was assumed to be equally distributed, between consecutive recording hours. Then the training and test data sets were generated in the following manner given in Fig. 4.



sequences.

The above given procedure was applied to all sequences both in input and output space of the network and matched to each other to be used in training and the validation of network parameters.

4.3. Identification of the Network Architecture

While the number of neurons in input and output layers is due to the number of acting forces and the resulting position component changes, the number of hidden layers and the number of neurons in these layers are the main concept of the determination of the network architecture. This is usually done by trials, however, some aspects have to be taken into account in order to achieve a successful and an efficient network. First of all, the number of layers and the neurons increase the training time. Second, a network that is too complex may fit the noise, not just the signal, leading to overfitting. Overfitting is especially dangerous because it can easily lead to predictions that are far beyond the range of training data, which yields poor generalization. The idea of partitioning the data set as training and test sets is for preventing network to fit the noise in the output sequences. Therefore, a compromise has to be found regarding the above mentioned criteria.

In this study, only the vertical motion of the bridge platform was investigated. As a sample study set, two different hourly data for each observation day was selected. Optimal network configuration has been found to be with multi layer feed-forward networks with two hidden layers. The number of neurons in each network varies from 10 to 20.

4.4. Optimization of the network parameters and validation of the network by using test data set

Although, this section is separately given, the training procedure has to be considered in combination with the content given in previous section, i.e. the network architecture. The number of neurons in hidden layers as well as the external

parameters of the network such as the learning rate has been determined by trials (Heine, 1999, Miima et al., 2001).
The optimization of the networks has been done by using Levenberg-Marquardt optimization method. The threshold values for the cost function was selected due to the mean standard errors obtained from the position accuracies determined by the adjustment of GPS measurements. The training was cut where the mean standard approximation errors reach minimum for both training and test data sets in order to avoid overtraining.
After successful training, the resulting weights for each signal were obtained as an intrinsic representation of the mapping function between inputs and output for the vertical motions of the bridge platform for respective time interval of each observation day. To validate the modelling process, a residual analysis of the modelling errors was performed. For this end, the *error mean* μ and the *coefficient of determination* r^2 for each model prediction were calculated for the residual signals as follows, respectively (Chatfield, 1975). Further on, the frequency content in residual signals is investigated by Fast Fourier Transform (FFT) in order to prove the randomness of the residuals.

$$\mu = \frac{1}{m}\sum_{i=1}^{m}\left(y_i(k) - y_i'(k)\right) \tag{4}$$

$$r^2 = 1 - \frac{\sum_{i=1}^{m}\left(y_i(k) - y_i'(k)\right)^2}{\sum_{i=1}^{m}\left(\overline{y}_i(k) - y_i'(k)\right)^2} \tag{5}$$

where $\overline{y}_i(k)$ and m denotes the mean of the actual output vector and its size, respectively. For a perfect approximation, the mean error and the coefficient of determination should be 0 and 1.

5. SAMPLE RESULTS

Modelling results for the vertical motion of the platform in July 2 2001 between 7:20 – 8:20 and 10:15 – 11:15 are given in Fig. 5 and Fig. 6, respectively.

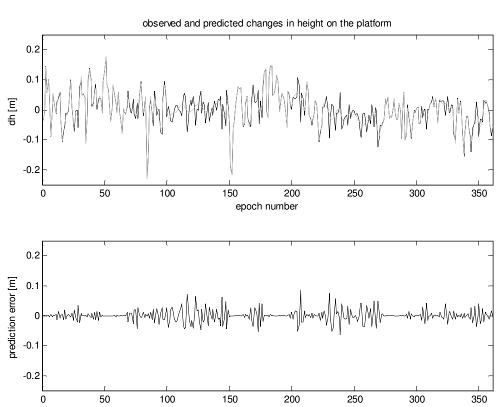


Figure 5. Actual (black) and predicted (grey) height changes (top) and corresponding prediction errors in July 2 2001, between 7:20-8:20

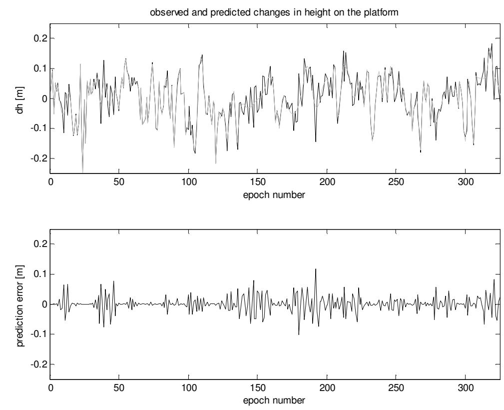


Figure 6. Actual (black) and predicted (grey) height changes (top) and corresponding prediction errors in July 2 2001, between 10:15-11:15

Some information about the prediction quality for the time spans given in Fig. 5 and Fig. 6 are summarized in Table 1.

July 2, 2001		
	7:20 – 8:20	**10:15 – 11:15**
μ (m)	0.000	0.000
r^2	0.853115	0.840395
Mean abs. error (m)	0.013	0.018
Standard deviation (m)	0.020	0.027
Max. error (m)	0.086	0.118
Min. error (m)	-0.066	-0.102

Table 1. Quality measures of the prediction results for July 2, 2001.

Fig. 7 and Fig. 8 show the prediction results for the date July 9, 2001 between 7:20 – 8:20 and 10:15 – 11:15, respectively.

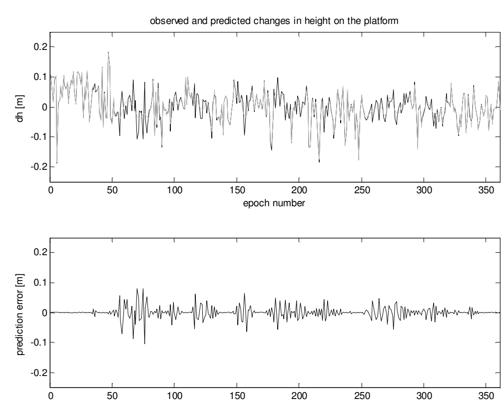


Figure 7. Actual (black) and predicted (grey) height changes (top) and corresponding prediction errors in July 9 2001, between 7:20-8:20

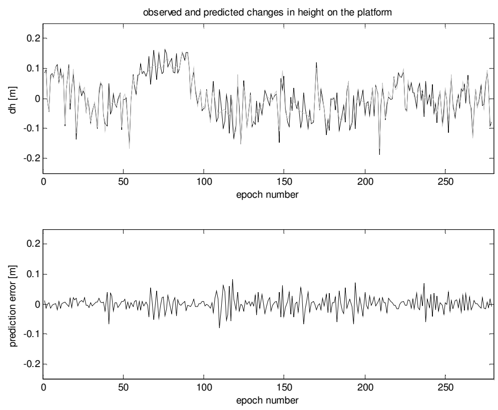


Figure 8. Actual (black) and predicted (grey) height changes (top) and corresponding prediction errors in July 9 2001, between 10:15-11:15

Note that the epoch numbers given in both days at 10:15 – 11:15 interval are less than those at 7:20 – 8:20 intervals. These data gaps are due to the inconvenient satellite constellation resulting with unsuccessful integer ambiguity solution for the relevant epochs of kinematic GPS observations.

The quality measures of the predictions for the relevant time spans in July 9, 2001 are given in Table 2.

July 9, 2001

	7:20 – 8:20	**10:15 – 11:15**
μ (m)	0.000	0.000
r^2	0.844668	0.845583
Mean abs. error (m)	0.012	0.018
Standard deviation (m)	0.020	0.025
Max. error (m)	0.079	0.082
Min. error (m)	-0.105	-0.080

Table 1. Quality measures of the prediction results for July 2, 2001.

The resulting standard deviations are obtained as the same values with the mean square errors of the point heights derived from the adjustment of GPS observations. Recalling the figures 5, 6, 7 and 8, there are some parts of time sequences very precisely estimated whereas a very small part are slightly less precisely predicted. This is due to the sampling rate of the input values which were assumed to be either linearly varying or constant values during each hourly period. However, in general very good approximations were achieved.
In addition to the criterion given in Table 1 and Table 2, the remaining residual sequences are investigated by using fast fourier transform in order to examine the frequency content of the residuals. Fig. 9 shows the frequency content of the remaining residual series of the approximations.

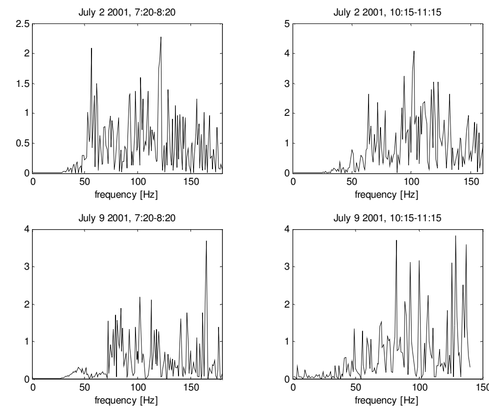


Figure 9. The frequency content of each neural approximation residuals. Note the chaotic form of the residual frequencies for all four models.

The frequency content in the remaining residual reflects a wide spectrum of frequencies exist which approve that the resulting prediction errors are highly normally distributed random errors with zero mean and variances equal to the mean variances of adjusted heights from GPS observations (See Table 1, Table 2).

6. CONCLUSIONS

The use of artificial neural networks for modelling deformation process of engineering structures as well as natural hazards such as landslides offers geodesists a good alternative for the description of resulting deformations as a function of causing effects which are generally more or less non-geodetic observations. In case of neural modelling, the determined parameters, i.e. the weights between consecutive neurons implicitly describe the mapping between the inputs and outputs, but cannot be used in any other way as representing a typical mathematical function for deformation process.
One has to note that the results from the neural network are particularly depend on the selection of inputs and outputs, and the architecture of the network to be used as they are capable of learning anything. One disadvantage of neural network applications is that there is no single similar solution to any given input-output data set as the estimated parameters of the network depends on various settings, which are especially considered during learning process. In most cases, these settings are selected by personal human judgement. Therefore, the solution of neural network is referred as sub-optimal solution. This means that the obtained solution is just the one among other solutions which provide the similar precision of approximation and/or prediction.
In this study, Matlab Version 6.5 Neural Toolbox is used for computations. During the network architecture and learning process, the number of layers and the neurons in each layer as well as the number of training run has been cared to be kept as minimum as possible in order to avoid overfitting and overtraining.
The results given in Table 1 and Table 2 show that a very good approximation can be succeeded even if the input data sampling rate is very low, i.e. every one hour, a measurement of input data has been used to generate the input matrix of training and testing data sets. The more frequently the input data is measured the better approximation can be obtained by using neural network methods. On the other hand, the more accurate output

data, in other words the less noise in output data would increase the approximation quality as well.
Neural networks can be considered as efficient tools for the description of deformations, especially in continuous monitoring of engineering structures where there is no *a priori* knowledge on the underlying deformation processes or where the relations between the acting forces and the behaviour of the monitored object is very complex to be described by conventional mathematical tools.

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