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Data-driven modelling for flood defence structure analysis

A.L. Pyayt, I.I. Mokhov, A.P. Kozionov & V.T. Kusherbaeva
Siemens LLC, Corporate Technology, St. Petersburg, Russia

B. Lang
Siemens AG, Corporate Technology, Munich, Germany

V.V. Krzhizhanovskaya
University of Amsterdam, Amsterdam, The Netherlands

R.J. Meijer
TNO, Groningen, The Netherlands

ABSTRACT: We present a data-driven modelling approach for detection of anomalies in flood defences (levees, dykes, dams, embankments) equipped with sensors. An auto-regressive linear model and feed-forward neural network were applied for modelling a transfer function between the sensors. This approach has been validated on a dike in Boston, UK—one of the pilot sites of the *UrbanFlood* project—that showed both normal and abnormal sensor behaviour. Comparison of the linear and non-linear models is presented. The suggested model-based anomaly detection approach will extend functionality of the developed Artificial Intelligence component of the *UrbanFlood* Early Warning System.

1 INTRODUCTION

One of the goals of the *UrbanFlood* project is the development of an Internet-based platform for flood early warning systems (Krzhizhanovskaya et al. 2011). Within this project, the early warning systems monitor several levees in The Netherlands, Germany and in the United Kingdom.

Different types of models are used for early identification of dike weakness: a finite element *Virtual Dike* model (Melnikova et al. 2011) and RELIABLE model from HR Wallingford, based on Limit State Equations and a probabilistic failure analysis based on Monte Carlo simulation. Data-driven methods are also applied to sensor data analysis: the main task of the Artificial Intelligence (AI) component is identification of anomalies that can indicate an onset of dike failure. The "anomaly" is detected as a deviation of current state of the dike from previously known "normal" behaviour.

Classification of anomaly detection approaches can be found in work of Chandola et al. (2009). Classification-based (Pyayt et al. 2011a,b) and model-based (Li et al. 2009) approaches were applied to dam behaviour analysis.

In classification-based approach the main goal of data processing is a selection of suitable features (or raw data) that will be checked for normality using some thresholds. This approach was applied for detection of anomalies for the Stammer dike in Amsterdam, The Netherlands (see Pyayt et al. 2011a). A combination of this approach with finite element *Virtual Dike* model was presented in (Pyayt et al. 2011b). One-side classification approach based on Neural Clouds (Lang et al. 2008) was used for dike behaviour assessment.

In this paper we present the development of a model-based approach (Isermann et al. 2005) applied to a dike in Boston, UK. The benefit of this approach is that a high-accuracy model can be constructed that predicts the "normal" behaviour of a complete sensor system. Deviation of sensor data from this "normal" model output can be easily detected. The disadvantage of this approach is that development of a high-quality model is a very challenging task.

The approach used in our work is called *Transfer Function (TF) modelling*. If an accurate model is constructed and input signal shows normal behaviour, the comparison of the model output with the sensor readings detects anomalies in the output real sensor (Fig. 1a). The same approach can be used for sensor modules that measure several physical parameters in the same point (Fig. 1b): in this case sensor measurements can be cross-validated.

Detected anomaly requires further analysis using expert models. Data pre-processing and processing procedures are presented in the next sections.

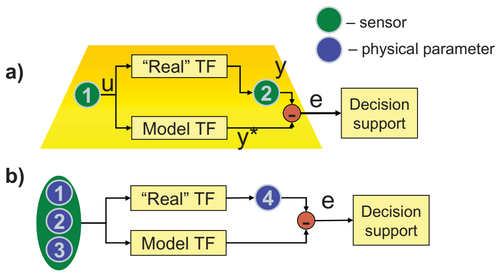

Figure 1. a) Transfer Function (TF) between different sensors; b) Transfer Function (TF) between physical parameters in one sensor module. **u** is input sensor signals, **y** is output sensor signals, **y*** is model output, **e** is output errors.

2 DATA PRE-PROCESSING

2.1 *General approach*

Pre-processing of raw dike measurements includes establishment of a *common time frame* and data *filtering*. Application of various methods for dike measurements filtering is presented in (Pyayt et al. 2011b).

Common time frame is required to provide stability of measurements rate, to fill the gaps, and to synchronize measurements. Jitters in rate can be caused by problems in communication lines; shifted values of sensors can be caused by polling of sensors; and gaps in data can be caused by technical problems.

2.2 *Example of gap filling for Boston dike*

Boston dike (Fig. 2) is one the pilot sites of the *UrbanFlood* project. Detailed description of sensor network installed into this dike can be found in (Simm, 2011).

This dike is equipped with different types of sensors, including pore pressure sensors. This type of sensors has clear periodic behaviour due to the sea tides and seasonal changes.

Selected models require stable rate of measurements without gaps. For model construction periods without gaps should be selected or gap filling procedure should be applied.

Due to large number of gaps gap filling procedure is required. Application of simple linear interpolation cannot sufficiciently reflect the dynamics of the signal in case of large gaps. Modified method of Hocke & Kampfer (2009) was applied (see Fig. 3) for gap filling of pore pressure measurements from sensor #501 (Fig. 2a).

Figure 2. a) Cross-section of Boston dike, circles with numbers show installation of pore pressure sensors; b) Photo of the Boston dike.

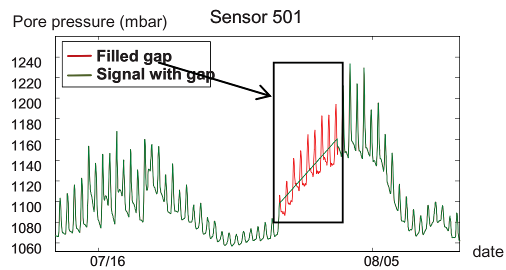

Figure 3. Example of gap filling for pore pressure sensor #501. The "reconstructed" signal is shown in red colour (inside the box). Measurement rate is once every 15 minutes.

3 TRANSFER FUNCTION MODELLING

The pre-processed data can be used as input parameters for linear or non-linear models.

3.1 *Polynomial autoregressive model*

The Autoregressive (AR) linear model is defined as follows (Box & Jenkins 1970):

$$
\begin{aligned}
&y(t)+a_1 y(t-1)+\ldots+a_{n_a} y(t-n_a) \\
&\quad = b_1 u(t-n_k)+\ldots+b_{n_b} u(t-n_b-n_k+1)+e(t) \qquad (1)
\end{aligned}
$$

where $y(t)$ is the output at time t; α_i, b_i $(i = 1{:}n)$ are the parameter of the model to be estimated; n_a is the number of poles of the system; n_b is the number of zeros of the system; n_k is the number of input samples that occur before the inputs affecting the current output; $y(t-1), \ldots, y(t-n_a)$ are the previous outputs on which the current output depends; $u(t-n_k), \ldots, u(t-n_b-n_k+1)$ are the previous inputs on which the current output depends; $e(t)$ is white-noise. Parameters n_a, n_b are called model orders.

The AR model can also be written in a compact way using the following notation:

$$A(q)y(t) = B(q)u(t) + e(t), \tag{2}$$

where

$$\begin{aligned} A(q) &= 1 + a_1 q^{-1} + \ldots + a_{n_a} q^{-n_a} \\ B(q) &= b_1 q^{-n_k} + \ldots + b_{n_b} q^{-n_b - n_k + 1}, \end{aligned} \tag{3}$$

q^{-1} is the backward shift operator, defined by

$$q^{-1}u(t) = u(t-1) \tag{4}$$

The following block diagram shows the AR model structure:

The *training* procedure of AR model is based on finding the best orders (n_a, n_b). The stopping criterion is Root Mean Square Error (RMSE):

$$\sigma_e = \left(\frac{1}{T} \sum_{t=1}^{T} (y(t) - y'(t))^2 \right)^{1/2} \leq threshold, \tag{5}$$

where y is a model output; y' is an expected output. RMSE gives the best value 0 when $y(t) = y'(t)$. It must be less than a threshold selected by the user.

Another approach for the best model selection is to use Akaike Information Criterion (AIC) (Akaike 1974):

$$AIC = \ln \sigma^2 + \frac{2d}{N}, \tag{6}$$

where σ^2 is a variance of model error (mean squared error), d is a model length, N is a length of training set.

The minimal value of AIC corresponds to the best model order. The advantage of AIC is that it imposes penalties on model length unlike MSE or RMSE.

3.2 *Artificial neural networks*

Artificial neural network is a non-linear approximator of input signal to output time series. In the current work we use a so-called Feed-Forward Neural Network (FFNN). The structure of FFNN is described in Figure 5.

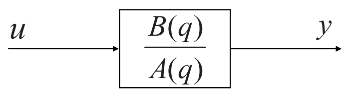

Figure 4. Autoregressive block diagram; u is input, y is output of the model, $B(q)/A(q)$ is transfer function.

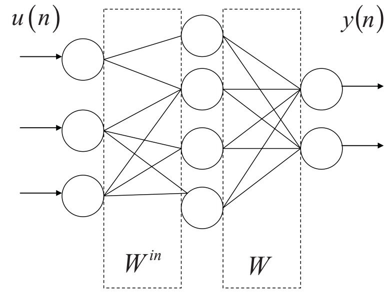

Figure 5. Structure of the three-layered (input, hidden and output layers) feed forward neural network that makes static nonlinear transformation of input $u(n)$ into output values $y(n)$. W^{in} and W—matrices of connections (weights) between layers.

Training of the NN is concluded in optimization of weights of the network so that for input signal the NN should produce right output signal. Inputs of the NN propagate through the input layer, hidden layers and the output layer. The following transfer function is used: $f(x) = tanh(u)$.

As the optimization algorithm, the gradient descent is used. Learning error function is defined as:

$$E = \frac{1}{2} \sum_{t=1}^{T} (y_t - d_t)^2, \tag{7}$$

where y_t—model output, d_t—target output, T—number of model and target instances.

For more information on FFNN refer to Haykin (1999).

The following types of models are considered and approximated using FFNN:

$$y_t = F(u_{t-k}, \ldots, u_t, y_{t-m}, \ldots, y_{t-1}), \tag{8}$$

where F is nonlinear function, u is input signal, y is model output signal, k is time-delay for input signal, m is time delay for output signal used as input to the model.

3.3 *Model quality assessment*

The quality of modelling can be characterized using the following quality measures:

1. The coefficient of determination R^2:

$$R^2 = 1 - \frac{\sum_{t=1}^{T} (y_t - d_t)^2}{\sum_{t=1}^{T} \left(y_t - \frac{1}{T} \sum_{t=1}^{T} y_t \right)^2}, \tag{9}$$

where y_t—model output, d_t—target output, T—number of model and target instances. This metric lies in the range of [1, −∞), where 1 corresponds to the best model fit.

2. Root-mean-square error—see Equation 5.

4 EXPERIMENTAL RESULTS

4.1 *Input sensors selection*

Pore pressure sensor data has been selected for modelling, since this parameter can be used for detection of different dike failure modes, like internal erosion or piping. Pore pressure sensor #506 (see Fig. 2a) was selected for output signal modelling. This sensor showed abnormal behaviour (see Fig. 6) starting from January 2011.

During the same observation period, sensor #501 was behaving normally (see Fig. 7).

At first for both sensors common time grid was created: red colour in Figures 6 and 7 marked with boxes shows the filled in gaps.

4.2 *Results of linear transfer function model (AR) application*

There are two ways for calculation of model output. In the *first* case, real sensor output values are used

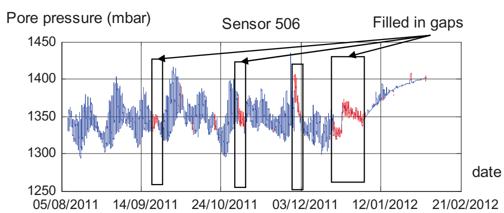

Figure 6. Pore pressure measurements (mbar) from sensor #506. Blue line—raw data, red line—examples of filled in gaps. Extended periods of filled gaps are marked with boxes.

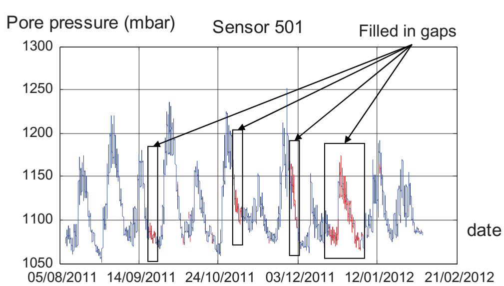

Figure 7. Pore pressure measurements (mbar) from sensor #501. Blue line—raw data, red line—examples of filled in gaps. Extended periods of filled gaps are marked with boxes.

$y(t-1), \ldots, y(t-n_a)$ (one-step forecasting)—this is the first linear model. In the *second* case, only previous model outputs are used, without real sensor outputs.

The first model provides a more accurate estimation of output according to RMSE and R^2 values for the training period (see Table 1). Weakness of this model is that can't detect trend change anomaly: RMSE and R^2 are the same for periods with and without anomalies (see also Fig. 8a): modelled values and real sensor measurements coincide for the whole observation period. This linear model is able to detect abrupt faults (Fig. 8b).

Second approach provides less accurate estimation of real output but allows to detect not only abrupt changes but also trend change (Fig. 9a,b). Divergence between real transfer function and model can be detected by RMSE (high value at period of abnormal behaviour) or R^2 (very low value at abnormal behaviour) (see Table 2). The problem of this approach is in difficulty of model estimation.

Table 1. Criteria of the *first* linear model quality for 3 periods: training period, test set with normal data only, test set with anomalies.

Criterion	Training set	"Normal" set	"Abnormal" set
RMSE	0.9209	0.9054	0.9729
R^2	0.9989	0.9986	0.9988

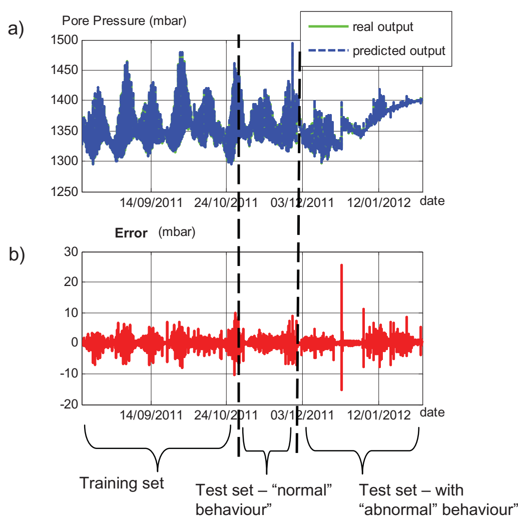

Figure 8. a) Results of one-step forecasting using the *first* linear model; b) Error of one-step forecasting.

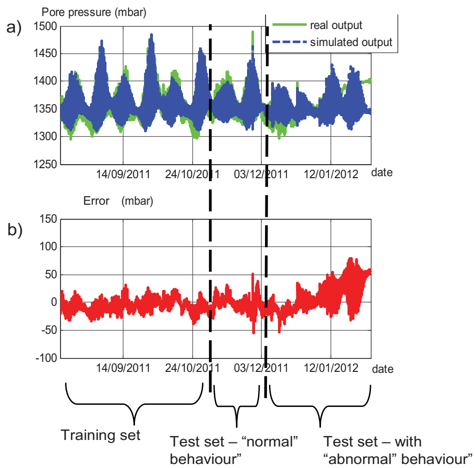

Figure 9. a) Results of one-step forecasting using the *second* linear model; b) Error of one-step forecasting.

Table 2. Criteria of the *second* linear model quality for 3 periods: training period, test set with normal data only, test set with anomalies.

Criterion	Training set	"Normal" set	"Abnormal" set
RMSE	9.4751	11.8003	27.9838
R^2	0.8182	0.7518	–0.2913

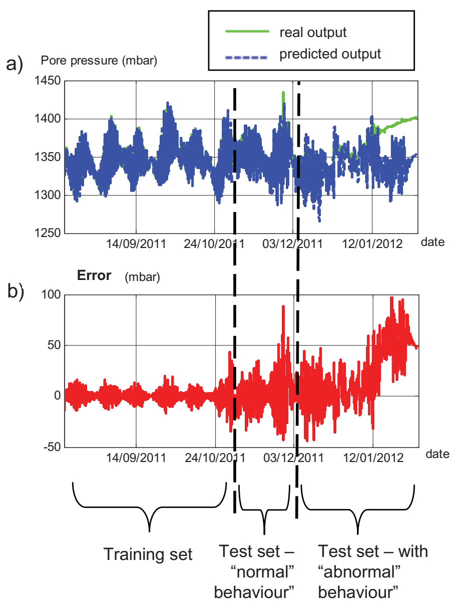

Figure 10. a) Results of one-step forecasting using the FFNN; b) Error of one-step forecasting.

Table 3. Criteria of the FFNN quality for 3 periods: training period, test set with normal data only, test set with anomalies.

Criterion	Training set	"Normal" set	"Abnormal" set
RMSE	1.1057	2.8746	14.0712
R^2	0.9970	0.9599	0.4147

4.3 *Results of non-linear transfer function model (FFNN) application*

Results of the FFNN model application for anomaly detection are presented in Figure 10a,b.

Plots in the Figure 10 show that the error of the model rises significantly on the test set with anomalies.

Analysis of Table 3 shows that quality of the constructed model on the training set and test set with normal behaviour is quite good.

As the result of the exhaustive search the parameters of the model described in Equation 8 are the following: $k = 50$ – number of delayed input values, $m = 20$ – number of delayed output values. The number of hidden layers is 2, the number of neurons at hidden layers is *10*. The number of epochs is 300, learning rate is 0.01. The filtering preprocessing procedure is Hodrick-Prescott filter.

5 CONCLUSION AND FUTURE WORK

5.1 *Current results*

In this work authors presented identification of anomalies in sensor measurements by application of model-based approach using data-driven models. It was suggested to identify anomaly in sensor measurements as a deviation of the model output from real sensor values.

This approach was applied for identification of anomalies in measurements gathered from sensor network installed into the Boston dike (UK). Sensor faults were in pore pressure sensor #506.

Comparison of non-linear model with the first linear model shows that accuracy of the linear model is higher than of the non-linear for test set with normal behaviour ($RMSE_{lin1} = 0.9054$, $RMSE_{FFNN} = 2.8746$, $R2_{lin1} = 0.9986$, $R2_{FFNN} = 0.9599$), but linear model couldn't detect sensor fault while FFNN did it: $R2_{lin1} = 0.9988$ (this means that is still good), $R2_{FFNN} = 0.4147$ that shows that the model output and real values differ significantly.

Comparison of the first and second linear models shows that the second model is of less accuracy ($R2 = 0.8182$), but finally this model provides detection of any type of anomaly: abrupt change and trend change.

It can be concluded that the first linear model is able to detect anomaly like abrupt change only and is not suitable for the task of anomaly detection in application to dikes; the second linear model allows to identify any kind of anomalies (abrupt change and trend change), requires only input data for the testing period (instead of real output values the estimated values are used), but it is a tough task to develop a stable and accurate model. The non-linear model construction requires even more efforts in comparison to linear models. It allows to identify both abrupt changes and trend change anomalies.

5.2 *Future steps*

Identification of anomalies in sensor measurements is very important for operational flood early warning systems. A more challenging problem is to distinguish between the onset of dike failure and sensor fault. To solve this problem, an expert knowledge or expert model is required.

One of the next steps is validation of the model-driven anomaly detection approach by application of the *Virtual Dike* model, in a way similar to our previous work (Pyayt et al. 2011b).

Cross-validation of feature-based and model-based approaches is another direction of our further research.

Finally, for automatic selection of model parameters, we plan to employ special optimization procedures.

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