



## Combining Data-driven Methods with Finite Element Analysis for Flood Early Warning Systems

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### Abstract

We developed a robust approach for real-time levee condition monitoring based on combination of data-driven methods (one-side classification) and finite element analysis. It was implemented within a flood early warning system and validated on a series of full-scale levee failure experiments organised by the IJkdijk consortium in August-September 2012 in the Netherlands. Our approach has detected anomalies and predicted levee failures several days before the actual collapse. This approach was used in the *UrbanFlood* decision support system for routine levee quality assessment and for critical situations of a potential levee breach and inundation. In case of emergency, the system generates an alarm, warns dike managers and city authorities, and launches advanced urgent simulations of levee stability and flood dynamics, thus helping to make informed decisions on preventive measures, to evaluate the risks and to alleviate adverse effects of a flood.

*Keywords:* IJkdijk, anomaly detection, one-side classification, levee monitoring, finite element modelling

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# 1 Introduction

Levee condition monitoring is an important national concern: large land areas are protected by levees (dikes). Cost of late detection of a ‘weak’ dike can be very high. For example, there were more than one thousand levee failures in the Netherlands between 1134 and 2006 [1]. Comprehensive analysis of various levee failure mechanisms can be found in [19]. Nowadays visual inspection is the general way of collection of information about levee condition. The problem is that often deformations that are visible at the surface mean that levee collapse is already in progress. It is important to get warning signals earlier. Remote sensing or installation of sensors inside the object (*in situ* monitoring) is usually applied. Installation of sensors can be more dangerous for the object but there are more parameters that can be collected by *in situ* monitoring.

Collected from the sensors measurements are transmitted to the data base (Figure 1). This can be done, for example, using the Common Information Space [2]. One of the most important problems is analysis of the collected data. Experts are usually not able to analyse in on-line all the measurements collected from the sensors. Delay in decision making can have severe consequences. Intelligent monitoring systems are required for analysis of the collected stream of measurements and for support in decision making. This paper is dedicated to development of an approach for support in decision making. There are several research projects related to this issue, e.g. Flood Control 2015 (<http://www.floodcontrol2015.com/>). Analysis of risks in case of flash floods can be found in [20].

Routine monitoring thousands of kilometres of levees requires significant computational resources. In critical situations (like storm forecast, heavy rains, or anomaly in the levee condition), increased sampling rate from sensors requires a truly "urgent" high-performance computing with high-priority resource allocation and extra simulations run on demand. Importance of such systems development was shown in [6].

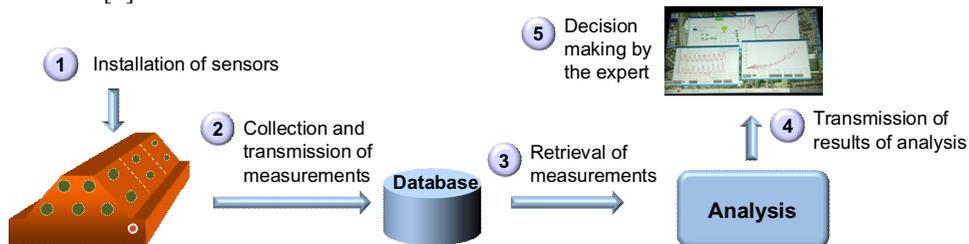


Figure 1. Scheme of sensor data analysis implemented in our research.

One of the general problems is that only patterns of normal behaviour are available. This complicates development of methods for detection of real anomalies in data that correspond to onset of levee collapse. Organisation of full-scale destructive experiments is required in order to verify that onset of levee failure is detectable.

The IJkdijk consortium (<http://www.ijkdijk.nl/>) organised in 2012 several full-scale levee destructive experiments (Booneschans, the Netherlands). Three levees (dikes) were constructed and were affected by abnormal conditions that led to collapse of these objects. Collected sensor measurements were analysed and visualised by several partners of the consortium. More information can be found in [4] and [5].

The planned experiments have been carried out at three levees: West levee piping experiment (21-26 August), East levee piping experiment (21-27 August), and South levee macro stability experiment (3-8 September). The East levee is presented before start of the experiment in Figure 2(a). The East levee collapsed on 27 of August (Figure 2(b)).

There are different types of sensors applicable for levee behaviour monitoring. Comprehensive overview of sensor technologies can be found in [13]. The pore water pressure sensors proved to be useful in levee stability analysis (e.g., detection of internal erosion) [10].

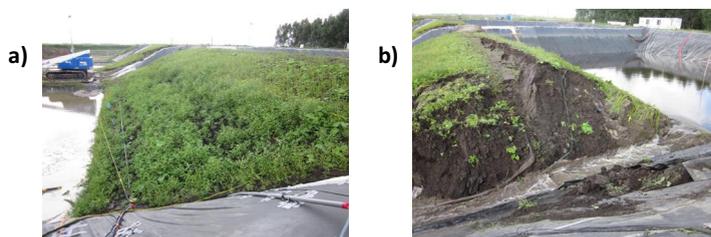


Figure 2. **(a)** Photo of East levee before start of the experiments (14 Aug 2012); **(b)** Collapse of East levee - 10:44 on 27 August 2012.

Pore pressure measurements were provided by Alert Solutions to the IJkdijk consortium in these experiments. There were installed 3 cross-sections with 2 sensors (GeoBeads) within each cross-section at different depth for the West levee, 5 cross-sections for the East levee. Locations of sensors are shown in Figure 3. Measurements collected from two sensors marked with red colour (AS 218 and AS 213) were used for further analysis.

GeoBeads consists of fully digital sensor modules (nodes). The set per node commonly includes a piezometer, an inclinometer and thermal sensors [14]. Pore pressure, inclination and temperature are measured as a result.

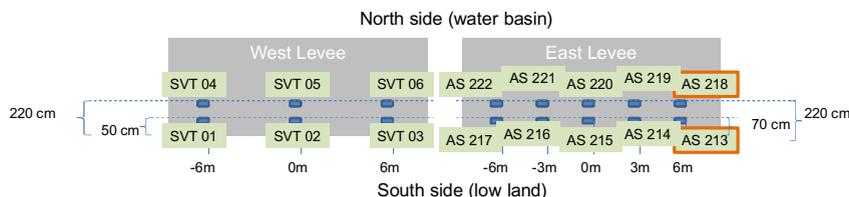


Figure 3. Alert Solutions sensors (GeoBeads) installed into the West-East levees (top view).

The research objective of this paper can be formulated as development of the approach for real-time levee condition monitoring based on combination of different types of models with sensor measurements collected from the monitored object. Validation of the developed approach during the full-scale destructive (IJkdijk) experiment is presented.

## 2 An Approach for Real-Time Levee Monitoring

There are two main classes of methods for levee behaviour analysis: *data-driven* (model-free methods) and *model-based* (numerical or physical modelling). The first class includes different techniques: machine learning methods (e.g., the artificial neural networks (ANN)), statistical methods (e.g., central moments, linear correlation, clustering), soft computing, data mining and others. Data-driven models do not require information about physical parameters of the monitored levee (slope geometry, soil properties etc.) as opposed to the physical modelling. This type of models requires only information collected sensors installed into monitored object or results of remote sensing. The corresponding block of the decision support system can be marked as Artificial Intelligence (AI).

We used one-side classification approach (Neural Clouds [8]) as the core method of this block. It is based on advanced k-means clustering algorithms: multidimensional points related to the previously known normal conditions are used to construct clusters of normal behaviour. The new points are checked: if they are outside of clusters of normal behaviour they are interpreted as anomalies that can be sign of onset of levee failure. In this case low *confidence values of normal behaviour* are produced as output of the Neural Clouds (close to 0). Points that belong to the clusters of normal behaviour

produce high confidence values of normal behaviour (close to 1). More details can be found in [15], [16] and [17].

Model-based approach (the second class of methods) requires information about the monitored object (e.g., initial geometry and soil properties); the constructed model will not depend on on-line measurements. Sensor values may be used for validation of the constructed model and as initial conditions for the modelling. Finite element method is widely used to simulate structural behaviour of dikes [3], [11], [12]. The corresponding block of the decision support system can be marked as Computer Model (CM). This class of models provides more information about the monitored object but it is hard to use these models for real-time behaviour assessment.

We presented first approaches to combine both classes of models in [18]. The possible variants of combinations are described below. There are two different opportunities: (1) computer model can be used for data generation or (2) for validation of the alarms generated by a data-driven model.

In the first case (Figure 4), the computer model can generate patterns of abnormal behaviour for testing of the developed anomaly detection approach. The computer model can generate normal data if there are no historical measurements but monitoring using data-driven methods has to be started immediately.

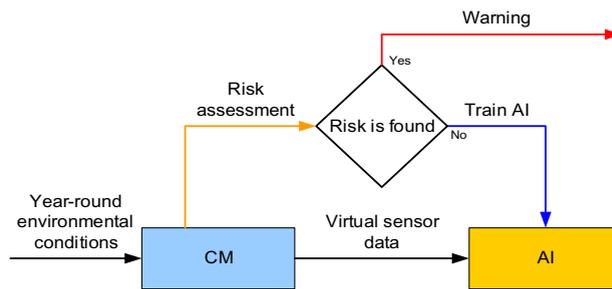


Figure 4. Training the artificial intelligence (AI) component using the virtual sensor data provided by computer modelling (CM).

In the second case (Figure 5), the computer model can be used for validation of the generated by the data-driven methods alarms: if the real alarm was detected it is verified. If the false alarm was generated, this can mean that new (previously unknown) state occurred, the component should be retrained including these new measurements.

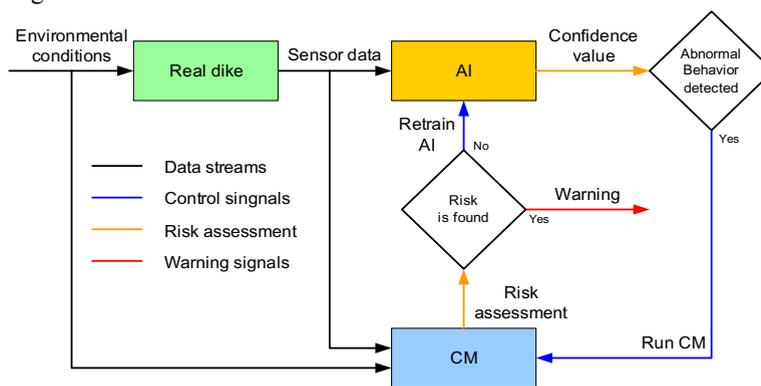


Figure 5. Combination of artificial intelligence (AI) and computer modelling (CM) components in one data processing chain.

The second option is suitable for real-time processing when all the components are built (trained) and the real object is monitored. We used in this paper the first option: computer model generated artificial data of normal behaviour that was used for training of data-driven methods. Results of computer modelling are presented in the next section.

Details about the second scheme details are published in [7].

### 3 Computational Model

The model that was constructed by the experts was based on documents and drawings provided by Deltares; finite-element method and finite-element software PLAXIS, which is oriented at studying of soil behaviour. The finite-element model is shown in Figure 6. East Levee consists of five main soil parts presented in Figure 6.

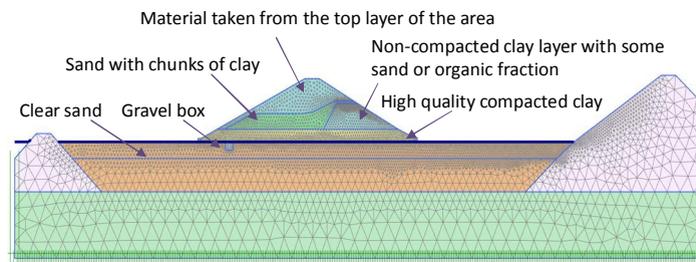


Figure 6. Geometry of East Levee.

Soils behave rather non-linear when subjected to changes of stress or strain. In reality, the stiffness of soil depends at least on the stress level, the stress path and the strain level. The Mohr-Coulomb model linear elastic perfectly plastic model was used for modelling. The linear elastic part of the Mohr-Coulomb model is based on Hooke's law of isotropic elasticity. The perfectly plastic part is based on the Mohr-Coulomb failure criterion that is formulated in a non-associated plasticity framework. Application of the Mohr-Coulomb model requires definition of four physical and mechanical properties of soil: Young's Modulus  $E_{ref}$ , Poisson's Ratio  $\nu$ , Cohesion  $C_{ref}$  and Friction Angle  $\phi$ . Researched part of levee consist of five soil layers.

15-nodes 2-D elements were used. Each model has about 300 000 degrees of freedom. Soil properties and geometry are nearly the same for whole levee. This means that construction of 2-D model for one cross-section is enough for analysis of behaviour of the whole levee [9].

### 4 Results of Finite Element Analysis

This section contains those results of numerical modelling which have been compared with the results of natural experiment with the aim of demonstration of applicability of finite element modelling (FEM) for prediction tasks. Sensors measuring pore pressure values were selected for comparison with results of numerical experiment (output of the FEM model). Hydraulic head (water level) was used as the input parameter for modelling.

Distribution of pore pressure (pressure of water inside the levee) at different stages of natural experiment is presented in Figure 7. It could be seen, that water rising at north side of the levee leads to increasing the value of pore pressure. Also it should be mentioned that high pore pressure front has non-linear shape under levee body and moves from north to south side of the levee (from right part to the left part of the cross-section in Figure 7) during the experiment.

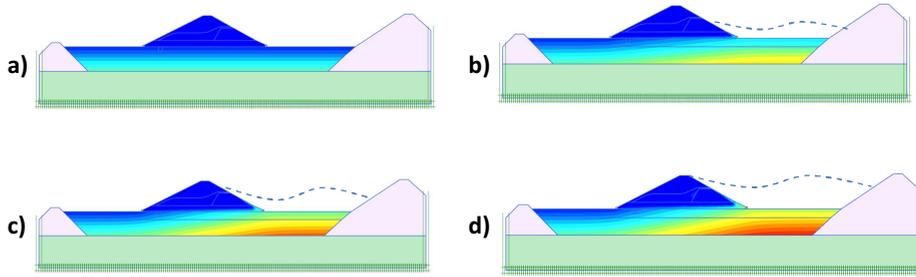


Figure 7. Distribution of pore pressure: (a) at initial state; (b) the water level is 1.6 m (approximate position is shown with blue dashed line); (c) the water head is 2.8 m; (d) the water head is 3.4 m. Blue color corresponds to zero value of pore pressure, red color illustrates maximum value of pore pressure during simulations.

Figure 8 shows comparison between results produced by the computer model (CM) developed by Siemens and measurements collected from the pore pressure sensors. The first virtual sensor is marked as ‘AS 213’, the second sensor – ‘AS 218’. Each step in time series reflects the increase of water level inside the levee. Small shifts between steps for real and virtual measurements are caused due to small offsets between initial planning and execution of the plan of the experiment.

For both sensors behaviour look similar till some point in the middle of Figure 8. Deviation between real sensor measurements and modelled values (after midnight on the 25<sup>th</sup> of August) can be used for identification of anomaly using data processing methods. Starting from this moment till the end experiment (collapse on the 27<sup>th</sup> of August) levee can be evaluated as ‘unstable’.

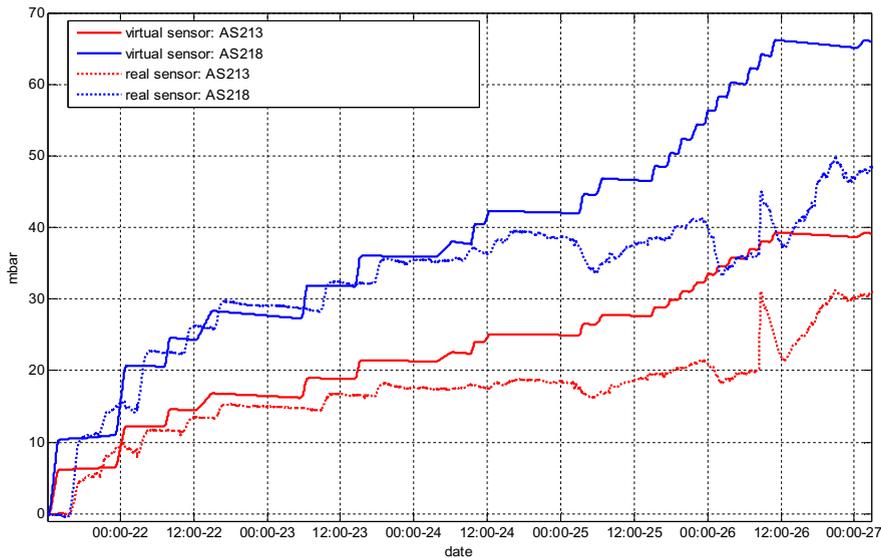


Figure 8. Comparison of virtual sensors (solid line) and real sensors (dotted line), AS 213 (red) and AS 218 (blue). X axis: date in format “hh:mm-dd”.

Figure 9 shows comparison of ‘virtual’ and ‘real’ sensors for hydraulic head parameter. In this case we mention under ‘real’ hydraulic head the real process of water pumping into levee; ‘virtual’ hydraulic head sensor shows the values that were used as input for FEM model according to the

initially planned course of the experiment. Hydraulic head (water level) measurements almost coincide for both of type sensors (virtual and real).

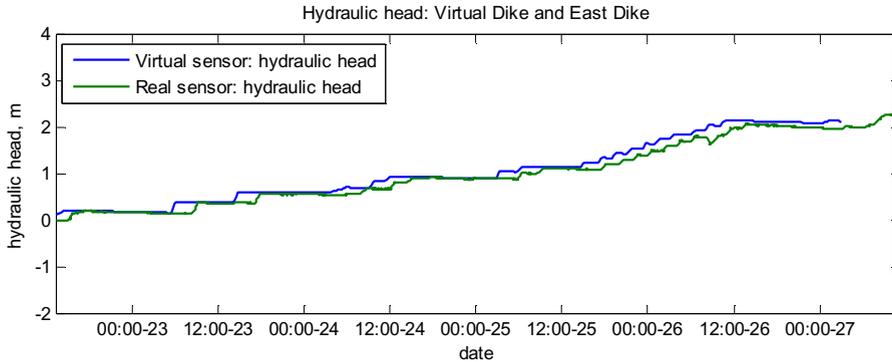


Figure 9. Comparison of virtual sensor measuring water level (blue) and real sensor (green). X axis: date in format “hh:mm-dd”.

### 5 Anomaly Detection on the Example of the East Levee

The Neural Clouds were trained on pair of virtual sensors (the whole available data set – blue colour in Figure 8 and Figure 9) and tested on a real sensor, AS 213, measuring pore pressure and Deltares sensor measuring hydraulic head (the whole available data set – green colour). Figure 10 presents clusters constructed on basis of virtual sensors. Black and red points are related to test set: black points are related to clusters related to normal conditions, red point are related to abnormal behaviour.

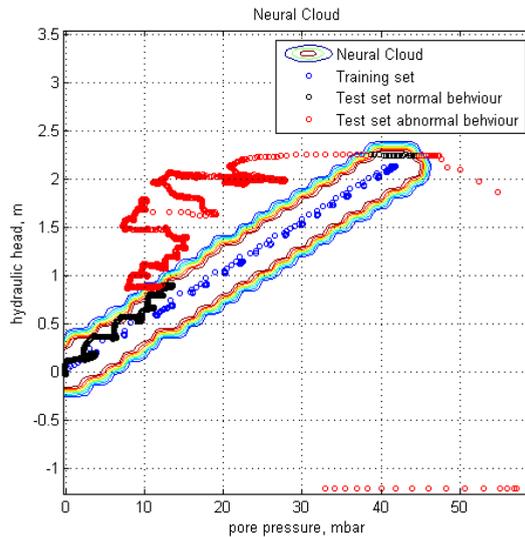


Figure 10. Constructed on basis of virtual sensors 2-D clusters of normal behaviour (X axis – pore pressure after air pressure subtraction, Y axis – hydraulic head) and results of the real sensor data testing (AS 213 and hydraulic head): blue circles – training set, black circles – test data related to normal conditions, red circles – data outside clusters related to abnormal behaviour.

In Figure 11(b) we depict the confidence value calculation based on results of clustering presented in the Figure 10. The root cause of low confidence value is the difference between real and virtual pore pressure values (Figure 11(a)).

First short alarm for 2 data points was identified at 24-Aug-2012 15:06:18. Start of the main alarm – 25-Aug-2012 02:06:18.

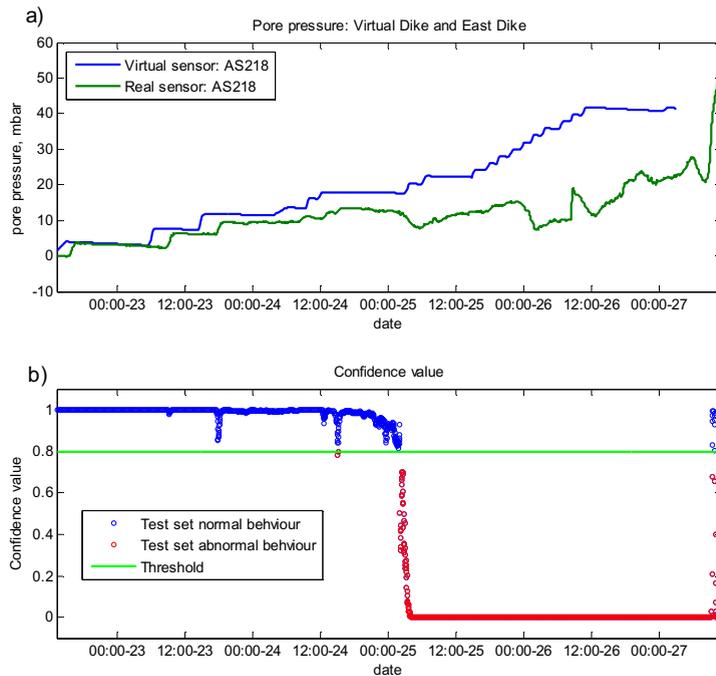


Figure 11. (a) Comparison of virtual sensor AS 213 (blue) and real pore pressure sensor AS 213 (green). (b) Confidence value calculated on basis of clustering presented in Figure 10. Blue points are related to normal conditions – higher than selected threshold of 0.8 (green line), red points – alarm situation. X axis: date in format “hh:mm-dd”.

## 6 Conclusions

This paper is dedicated to development a robust real-time levee condition monitoring system, based on a combination of data-driven anomaly detection with computational models. The computational models (e.g. finite element modelling) are precise enough for evaluation of the levee condition but it remains hard to be applied to real-time monitoring. Data-driven methods are based on measurements collected from sensors installed into monitored object. They provide fast response based on new data but they can easily provide false alarms due to different reasons (e.g. new normal state not presented in test set).

We show that *combination* of these two approaches is required for robust real-time condition monitoring as a part of the decision support system: in this case the operator of the monitoring system has to analyse only specific events detected by the system but not all the collected sensor data.

FEM was used for generation of virtual sensor data related to normal levee behaviour taking into account changing external conditions (water level). We used a one-side classification [8] approach for anomaly detection, this requires for training only data related to normal conditions. If the new point does not belong to the clusters of normal behaviour it is interpreted as anomaly.

Operability of the developed approach was validated during the full-scale destructive experiments organised in 2012 by the IJkdijk consortium. Computational models proved to be robust and issued and alarm in several before dike collapse, therefore providing valuable input for decision support.

The advantage of the developed approach that it is applicable to complex anomalies detection but in some easy cases like presented in this paper some other simpler methods can be used (e.g. threshold check).

The presented in this work anomaly detection approach can be applied for monitoring of various structures: it can be used for artificial (e.g., bridge, concrete dam, or building) or natural (e.g., levee) construction monitoring. The only requirement is installation of sensors that provide information about important parameters and availability of an on-line data stream for on-line analysis.

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