



UvA-DARE (Digital Academic Repository)

Finite element analysis of levee stability for flood early warning systems

Melnikova, N.B.

Publication date
2014

[Link to publication](#)

Citation for published version (APA):

Melnikova, N. B. (2014). *Finite element analysis of levee stability for flood early warning systems*. [Thesis, fully internal, Universiteit van Amsterdam].

General rights

It is not permitted to download or to forward/distribute the text or part of it without the consent of the author(s) and/or copyright holder(s), other than for strictly personal, individual use, unless the work is under an open content license (like Creative Commons).

Disclaimer/Complaints regulations

If you believe that digital publication of certain material infringes any of your rights or (privacy) interests, please let the Library know, stating your reasons. In case of a legitimate complaint, the Library will make the material inaccessible and/or remove it from the website. Please Ask the Library: <https://uba.uva.nl/en/contact>, or a letter to: Library of the University of Amsterdam, Secretariat, Singel 425, 1012 WP Amsterdam, The Netherlands. You will be contacted as soon as possible.

Chapter 7 Artificial intelligence system training⁶

One of the main objectives of this research was development of a numerical dike model able to reproduce complex behaviour of real dikes, particularly under failure conditions. Validation cases analyses presented in chapters 4-6 have proved that the module realistically simulates sensor dynamics in normal modes (for Livedike, Boston dike) and at failure (the IJkDijk experiment). Reaching this high level of realism and accuracy allowed us to implement an innovative hybrid approach of combining FE modelling with artificial intelligence (AI) analysis, so that simulated virtual sensors data was used as training sets for the AI system. This hybrid method has been proposed and implemented for the *UrbanFlood* EWS, in cooperation with Alexander Pyayt, a researcher and developer of the AI module (Pyayt et al., 2011a) and successfully tested on a full-scale Livedike prototype model, for a simulated strong storm with very high water level. The artificial intelligence module detected the onset of dike instability after being trained on the data from the *Virtual Dike* finite element simulation.

7.1 Comparison of numerical approaches to dike failure prediction: data-driven analysis, model-based prediction, hybrid method

A data-driven approach to dike failure prediction is bounded by various numerical methods of processing raw sensor data registered by dike monitoring systems. Data processing can be real-time or pre-computed. The data-driven methods include machine learning methods (neural networks), statistical methods (central moments, linear correlation, clustering), soft computing and others (see (Solomatine and Ostfeld, 2008), (Jaksa et al., 2008) for an overview of data-driven methods). Implementations of this approach for various cases can be found in (Baars, 2005), (Noortwijk et al., 1999), (Khan et al., 2010).

A model-based approach (in geotechnics, it's typically represented by limit equilibrium methods and by finite element analysis) requires information about physical properties of a monitored object. A model-based approach based on finite element analysis of dike stability has been thoroughly described all over this thesis. The constructed finite element models are independent of on-line measurements, while sensor measurements (e.g., water level and pore pressure) define external loadings and boundary conditions for the computational model. During construction of the model, historical sensor data are used for calibration of soil parameters and overall validation of the model. In a model-based approach, high risk of failure is detected if factors of safety computed are close to 1 (or lower than 1).

Data-driven methods are highly dependable on availability of sensor data, both for normal conditions and for abnormal (failure) modes. If such data are not available for a

⁶ Parts of this chapter have been published in (Pyayt et al., 2011a)

particular dike, a model-based approach can simulate sensor response to use as input for the AI training, including pattern recognition and classification tasks.

The idea of combining FE with AI brought us to an innovative hybrid approach, which had a successful numerical validation on a prototype model of the Livedike.

7.2 Virtual Dike Simulation Results

For testing the proposed hybrid AI+FEM model approach, we designed a prototype dike similar to the LiveDike, a sea dike protecting in Groningen (see Chapter 4). The geometric configuration and boundary conditions of the prototype model are similar to those of the LiveDike, while material properties have been artificially weakened to obtain a more pronounced plastic zone under the condition of a simulated flood.

A prototype model is composed of homogeneous sand. A two-dimensional plane stress structural problem is solved on second-order triangular finite elements. The problem size is 29788 degrees of freedom. Boundary conditions are: (a) roller constraint on the dike's base (allowing x-movement only) and roller constraints on the vertical cuts in the sand (allowing y-movements); (b) water pressure acting both on the seaside and landside. The landside is subjected to water pressure because of the channel behind the dike.

In order to generate a training set for the AI component, an abnormal behaviour of the dike has been simulated. Flood condition has been modelled by linearly increasing the water level from a Mean Sea Level (MSL) to the artificially extremely high level of +6.6 m above the MSL. The top of the dike is at 9 m.

Time dynamics of stresses in the dike are non-linear due to the plastic deformation. This nonlinearity is illustrated in Figure 7-1a, which shows principal stresses acting in cross-section plane for six "virtual sensors" located at the land-side slope of the dike (Figure 7-1b).

Plastic yield function defined by formula (2.9) has naturally been considered as a scalar stability criterion: the function indicates occurrence of plastic yielding in a material point, and plastic yielding is a local instability. When large areas of the dike are captured by plastic yielding, a global instability and failure of the dike occurs.

Stability criterion dynamics during the flooding is shown in Figure 7-1c. The criterion values become negative when plastic deformations occur. Similar to curves shown in Figure 7-1a, a change of trend in stability criterion dynamics occurs with intensive plastic deformations development.

A distribution of stability criterion in the dike is presented in Figure 7-2 for two flood phases (namely, for water levels 0 m and 6.6 m above NAP). Pore pressures in the dike grow with the height of water level, which reduces the magnitude of effective normal stresses, compressing the sand. Zones of plastic yielding grow as water level increases. Plastic zones are shown as dark red areas in Fig. 9. When water level reaches 6.6 m above the reference level, the stiffness matrix becomes singular. This means that a significant part of the dike has yielded to plastic deformation, which may indicate the onset of a failure process.

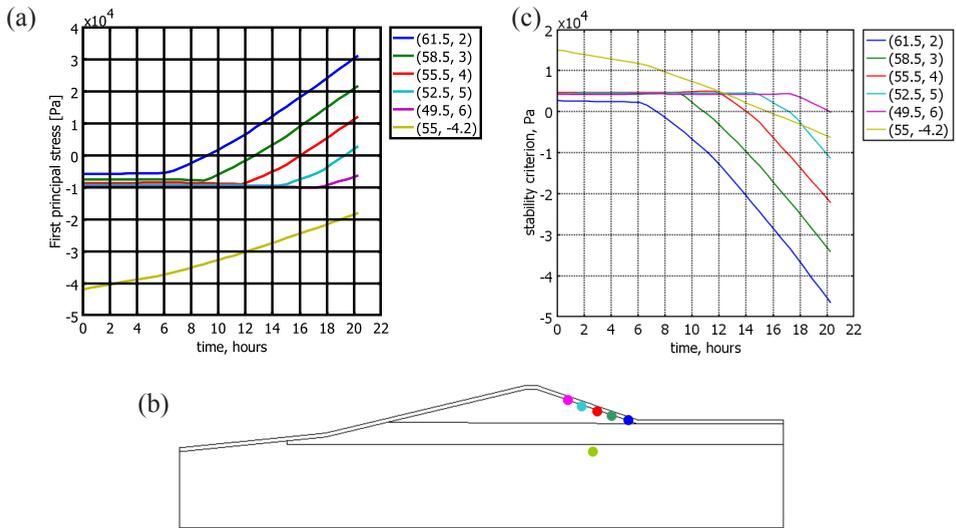


Figure 7-1. Simulated dynamics for six "virtual" sensors measuring principal stresses and simulated dynamics of stability criterion: (a) signals of six virtual sensors; (b) locations of the virtual sensors; (c) stability criterion dynamics

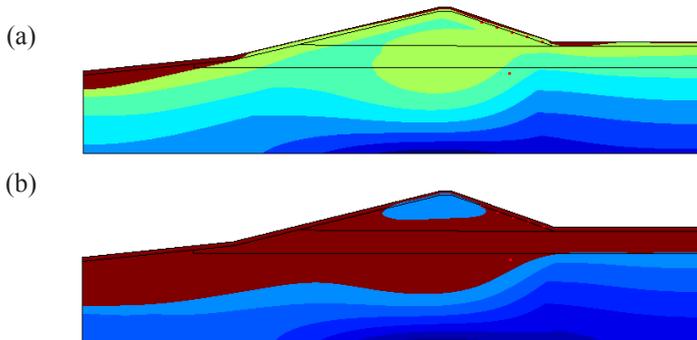


Figure 7-2. Stability criterion distribution, for different load steps: (a) zero water level; (b) critical state, water is at 6.6 m above reference level. Plastic zones are shown with dark red

7.3 Detection of Artificially Generated Anomaly by the Artificial Intelligence Component

The first principal strain and X deformation measured by the virtual sensor located at point ($X=55$ m, $Y=-4.2$ m) were used as input parameters for the one-side classifier by Neural Clouds (Lang et al., 2008). Figure 7-3 shows input variables and time dynamics of the confidence value. Vertical red line in Figure 7-3 shows the moment when confidence value went down from the values close to 1 (normal behaviour) to zero (detected anomaly).

Figure 7-3 demonstrates the ability of Neural Clouds to detect anomaly: confidence value went down to zero at the moment when the stability criterion changed the slope angle. The dike failure can occur when the stability criterion becomes zero and lower. In Fig. 12 it happens around the time step 1100, which means that the AI detected the onset of forthcoming dike instability over 600 time steps earlier (Pyayt et al., 2011a).

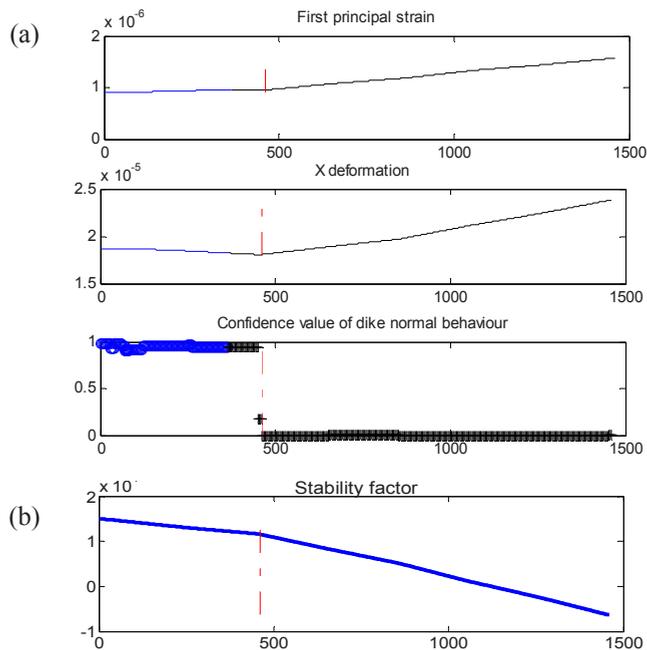


Figure 7-3. Detection of anomaly using the Neural Clouds (NC) approach: (a) - training data set (first principal strain and X-axis deformation) and calculated confidence values. Blue lines indicate the training period (time steps 1-460), black lines indicate the testing period (times steps 461 and further); (b) Stability criterion calculated by the *Virtual Dike* finite element model (Pyayt et al., 2011a)

7.4 Conclusions

An innovative hybrid approach for the assessment of monitored dikes' stability has been proposed and implemented in the present research, in cooperation with the AI system development team of the *UrbanFlood* project (Pyayt et al., 2011). The approach combines the finite element modelling with the artificial intelligence methods for real-time signal processing and anomaly detection. This combined method has been developed for the *UrbanFlood* early warning system and tested on a numerical model of a large-scale sea dike, under strong storm conditions, with very high water level.

In the *Virtual Dike* module, plastic deformation of a sand dike subjected to flood loading has been simulated. Stability of the dike has been analysed and a critical water level detected as a margin of dike stability.

After training, the artificial intelligence module successfully detected the onset of dike instability. The AI module showed a very sharp drop of the dike safety confidence

value from 1 (normal behaviour) to zero (anomaly). After this anomaly detection, it took another 640 time steps (about 10 hours) to develop real dike instability as evaluated by the stability criterion calculated in the Virtual Dike model.

A natural direction for further research on hybrid modelling would be training AI on a FE simulation of a real experimental dike collapse (for example, the IJkDijk South Levee slope failure simulation), with subsequent validation of the AI failure prediction against the actual observations.