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Controlling flow-induced vibrations of flood barrier gates with data-driven and finite-element modelling

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ABSTRACT: Operation of flood barrier gates is sometimes hampered by flow-induced vibrations. Although the physics is understood for specific gate types, it remains challenging to judge dynamic gate behaviour for unanticipated conditions. This paper presents a hybrid modelling system for predicting vibrations by combining machine learning with physics-based modelling so that critical situations can be avoided. In the outlined data-driven approach gate response data is acquired by sensors and stored in a database. For an underflow gate under submerged flow conditions, gate opening and "reduced velocity" are the attributes for classification into safe and unsafe situations. Results from physical scale model tests are used to illustrate the proposed technique. A finite-element model for computational fluid-structure interaction simulations, presently under development, is applied to provide complementary input to the system's database. The system described in this paper contributes to safer gate control and can become a useful aid in flood barrier management.

1 INTRODUCTION

Many flood defences contain barrier structures with movable gates. Large sector gates are built to close off waterways during storm surge events. Coastal sluice structures use hydraulic gates to provide protection from high sea levels and to regulate the discharge of river flow to sea. These gated engineering structures are for instance found in The Netherlands and in Saint Petersburg, Russia, where a large dam with multiple gates protects the city from floods. Optimal control of hydraulic gates and prevention of gate failure are crucial for reliability and safety of flood defences.

Flow-Induced Vibrations (FIV) pose a threat to hydraulic gate operation. Exposure to impermissible forces can lead to downtime, unexpected maintenance, or even failure during emergency situations. Traditional ways of investigating gate vibrations are physical scale model experiments in the laboratory and analytical studies combining hydrodynamics and structural mechanics (Kolkman 1984, Jongeling 1988). Relevant experimental research is collected in Naudascher & Rockwell (1994).

A compromise between several requirements, the design of a barrier gate may contain sub-optimal characteristics with respect to dynamic loads. Physical model tests greatly improve principal response properties, but cannot in all cases rule out the emergence of unwanted vibrations completely (Thang 1990). The issue of FIV is sometimes underestimated or overlooked—until operational difficulties arise in the early life of the structure. Unforeseen field measurements are then carried out to determine the gate behaviour and to find the cause of vibrations. Continuous gate monitoring and smart use of acquired data is the suggested alternative that reduces the risks associated with FIV of gates.

An increase in available computing power in the last two decades has promoted the usage of Computational Fluid Dynamics (CFD) in environmental engineering projects (Bates et al. 2005). CFD models have become household tools for solving problems in hydrology (Solomatine & Ostfeld 2008), coastal management (Roelvink et al. 2009) and river morphology (Van Rijn 1987, Mosselman & Sloff 2008). Moreover, they are being used in operational systems in those areas. Only few examples of model applications exist in which vibrations of barrier gates are simulated (Lupuleac et al. 2008). Flow around hydraulic structures involves complex three-dimensional free-surface hydrodynamics. Additionally, inclusion of the interaction between structure and flow adds to an even greater complexity.

For the large storm-surge barriers in The Netherlands, construction of the most recent barrier was completed in 1997, no CFD analyses were performed to simulate and assess the FIV loads on the gates. Instead, the hydraulic design conditions were determined and physical scale model tests of the structure design were made accordingly to check and improve the gate dynamics. For the barrier in Saint Petersburg, Russia, construction finished in 2010. For this barrier, CFD simulations were involved to study the effect of FIV of the gates (Lupuleac et al. 2008).

Parallel to development of physics-based models, a growing use of sensors and data processing tools has led to applications of Data-Driven Modelling (DDM) in hydrology and hydraulic engineering. Solomatine & Ostfeld (2008) give an overview of DDM trends in river basin management. Machine Learning (ML) techniques are frequently used in connection with DDM to handle the large amounts of data from measurements and numerical simulations, with the goal of making it easier to come to (automated) decisions (Pyayt 2011, Krzhizhanovskaya 2011).

Several research groups and international projects are working on the design and implementation of decision support systems for flood control. The EU project Urban Flood (2012) elaborates on the idea of using an Artificial Intelligence (AI) environment as a central component in an early-warning system that checks the states of flood barriers and detects anomalies. The Leading Scientist Programme comprises the development of an Advanced Computing Laboratory (2012). Its goal is to develop a computational infrastructure to study complex systems and provide decision support, among others for the control of flood defences.

The problem that the present work sets out to solve is as follows. Given the fact that the FIV response of a flood barrier gate is not fully known (due to limited physical tests or none at all), how can its operational safety be improved? This problem is tackled using data-driven modelling complemented with numerical physics-based simulations. FIV has been investigated numerically for quite some time, but numerical studies on FIV of gates are rare and tend to focus on problem solving for a specific gate (e.g. Lupuleac et al. 2008). This study gives an account of a generic yet applicable method that is in line with recent developments on control and decision support systems mentioned above.

Section 2 introduces the overall set-up of the system. Subsequent sections then cover all components in more detail. Sections 4.2 and 4.3 test a part of the system on experimental data.

2 SET-UP OF A HYBRID SYSTEM

The proposed system consists of a sensor environment complemented by simulations and enclosed in a control loop. The role of the components and the data exchange between them is presented in this section. We consider a single underflow gate with submerged flow, see the cross-sectional sketch in Figure 1, but the ideas hold equally for (or are easily translated or extended to) other gate types and free flow. The starting point is the gate itself, which holds a certain position that is assumed to be described by its gate opening a. The "data acquisition" module collects data from sensors installed on the gate. Apart from constant registration of the gate opening $a(t)$, the acceleration in time is measured by a number of sensors $x_i''(t)$. Also, the water levels on either side of the gate are registered: $h_1(t)$ and $h_2(t)$.

Figure 2 shows the functional block diagram of the system. The shaded grey rectangle marks the components that are discussed in more detail in subsequent sections. The acquired signals are input for the "primary data analysis" module. It consists of appropriate signal processing methods (e.g. Fast Fourier Transform computations) to derive the dominant frequency f_{dom} and mean displacement amplitudes $x_{dom,i}$ from the acceleration signals of the most recent, sliding time window. The hydraulic head difference Δh and mean gate opening a during this time are calculated. Also, a cross-correlation matrix A_{corr} is made of all combinations of acceleration signals.

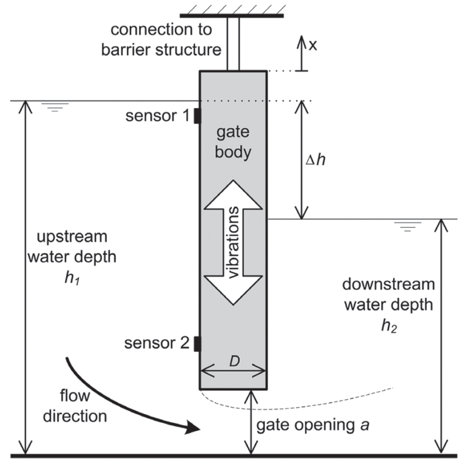

Figure 1. Sketch of the cross-section of an underflow gate with the most important definitions.

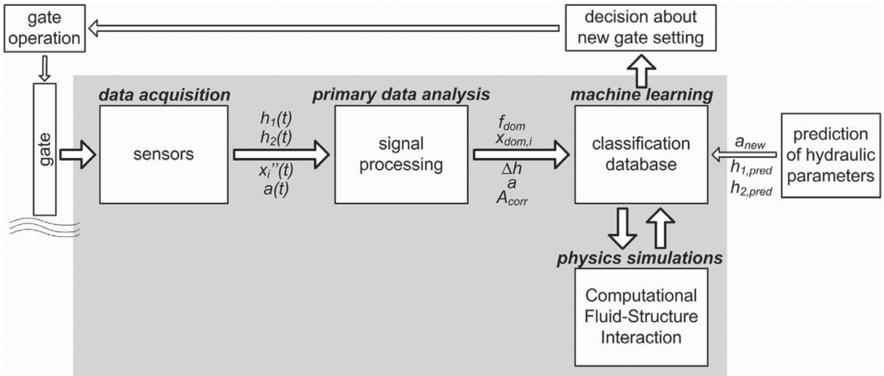

Figure 2. Schematic overview of the control system of gate dynamics. The components inside the shaded rectangle are discussed in this paper.

The central module is the “Machine Learning” (ML) module which consists of a large database plus a set of artificial intelligence algorithms that classify and interpret data. The ML module receives data from several sources. It receives input about the most recent situation (hydraulic conditions and gate status) from the “primary data analysis” module. Furthermore it receives the latest predictions of water levels on both sides of the gate $h_{1,pred}$ and $h_{2,pred}$ and the proposed new gate setting a_{new} from a large external modelling system that produces water level predictions (and possibly also other hydraulic parameters, e.g. related to water quality). If it is possible to draw a conclusion about the stability of proposed new gate settings based on available data already present in the database, no “physics simulation” is needed and a decision can be made about this new gate setting. If this is not the case, the system will perform a Computational Fluid Structure Interaction (CFSI) simulation to assess gate stability of the proposed gate setting.

The control loop starts with a decision support module which evaluates the safety of a new gate setting based on the input from the ML block. The gate is operated to execute that decision (upper arrow leftwards) and the gate will attain a new situation. This situation is monitored by the sensors and analysed by the modules that have been discussed above. Initially, the proposal to move the gate to another position comes from a large prediction model (not treated in this paper) of expected water levels. This proposition only becomes a decision to actually move to that setting when the ML module has confirmed its safety, or after it has modified it to a safer alternative operation.

The system adopts a straightforward way of vibration control: avoidance of critical parameter range. This is done by adjusting settings of gate opening, by selection of starting time of the operation, or by adjusting the speed of the gate movement. However, one can also use the system to track the exact conditions under which vibrations occur and use this knowledge to improve the present gate design. In some cases, relatively simple additions or modifications to the gate (e.g. the material used for seals) are enough to influence flow separation in a beneficial way (Kolkman 1980).

3 DATA ACQUISITION AND PRIMARY DATA ANALYSIS

The sensors should provide accurate and useful information on gate dynamics. We propose to make a permanent installation of acceleration sensors on the gate. Acceleration can be measured easily and has direct physical relations with gate movement and forces. The displacement amplitude is derived from the acceleration amplitude by simply integrating twice with respect to time.

In Figure 1 only two sensors are drawn, but in reality one accelerometer is needed for each degree of freedom in which the gate can move as a whole. Additional accelerometers should be placed such that elastic deformations of the gate itself are also captured. Gates with considerable longitudinal spans can suffer from bending vibration modes (Ishii 1992).

The water level measurements need to be done by permanent installations not too close to the structure (so as not to be influenced by contraction or outflow turbulence), but also not too far so they are no longer representative of the gate flow.

The main features that shall be extracted from the raw sensor data to be used for further analysis are the frequency and amplitude of the acceleration signals. The primary signal analysis consists of a Fast Fourier Transform that produces spectra of all acceleration signals from which dominant frequencies are deduced. There are different ways to determine frequencies and amplitudes. Various (combinations of) filtering techniques may be applied if necessary. Erdbrink (in prep.) describes data analysis of a laboratory vibration experiment. Precise choices for filter settings and running averages, for instance, depend on specific situations.

4 MACHINE LEARNING MODULE

4.1 *Classification based on reduced flow velocity*

Machine Learning (ML) is a popular branch of artificial intelligence that applies computational algorithms to all conceivable data sets with the purpose of executing classifications, uncovering patterns or learning a specific skill. See Rogers & Girolami (2012) for an introduction to ML. The sensory data and the numerical model provide the database module with labeled data points. All ML operations on this data are therefore in the realm of supervised learning, more specifically, they are classification operations.

The 'reduced flow velocity' Vr is commonly used to signify and interpret gate vibrations. See for instance Thang & Naudascher (1986). This dimensionless quantity allows descriptions of flow-induced vibrations in terms of different regimes, hence enabling comparisons between different gates. The 'reduced velocity' is defined as

$$Vr = \frac{U}{fL} = \frac{\sqrt{2g\Delta h}}{fD}, \tag{1}$$

where U is a characteristic flow velocity, for which the mean velocity of the accelerated flow cross section under the gate is used. f denotes gate vibration frequency, L is a characteristic length of the vibrating object for which the thickness of the gate D will be used (see Fig. 1), g is the gravitational acceleration constant and Δh is the water level difference across the gate. We derive U from Δh, via (1), as is common approach (e.g. Thang, 1990).

Gate vibration data (measured or calculated) may be presented in three-dimensional space, see for instance Figure 3. For different gate openings a_1 and a_2, the gate response is quantified by displacement amplitude as function of the Vr-number. In this example, the strongest vibration at gate opening a_2 is found at about $Vr = 2.5$. Now, the problem that the control system should tackle is shown in the lower plot of Figure 3. Suppose the gate has a constant position, so that the a-dimension drops out, and the head difference increases so that the dynamic state moves from Vr_1 to Vr_2. The question

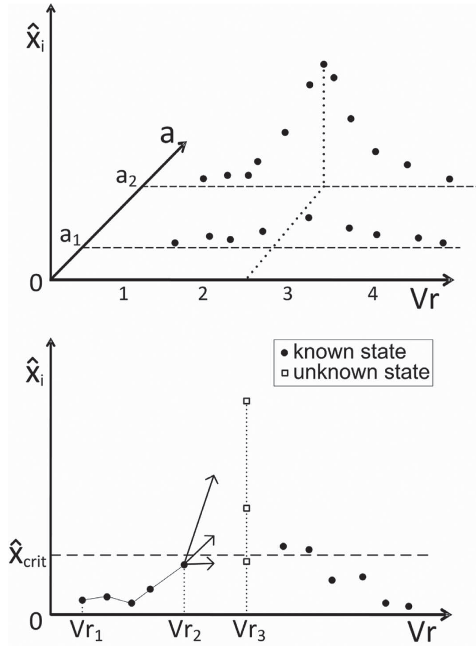

Figure 3. Upper plot: typical results of vibrations measurements of a single underflow gate (after Thang 1990). Vr is 'reduced velocity' (eq. (1)), a is gate opening, x_{crit} is gate displacement amplitude detected by sensor i. Lower plot: the problem of predicting gate response for increasing Vr at constant gate opening. In this figure and in Figure 4, fictional data is used for illustration purposes.

is then what response is expected if Vr continuous to grow to Vr_3. The empirical data points of the recent states between Vr_1 and Vr_2 and the known states for $Vr > Vr_3$ (from measurements or numerical modelling) may be wrong indicators of the unknown state at Vr_3. Obviously, interpolation between the nearest known states in the (Vr, x)-plane will not predict the state at Vr_3 correctly.

To enable the use of efficient artificial intelligence, we introduce a critical mean amplitude threshold x_{crit} (see Fig. 3), below which the gate is said to be in a safe condition and above which vibrations are harmful. This allows a transformation of the problem into a binary classification problem: all data points belong either to a 'critical state' c.q. 'unsafe' class ($x > x_{crit}$) or to a 'safe state' class ($x \leq x_{crit}$). This is in essence a projection onto the (Vr, a)-plane.

Figure 4 shows the binary data points in the new plane. In this form, closure or opening under constant head difference is a vertical line. A changing head difference in time at fixed gate opening is shown as a horizontal line in this plane.

The projected binary data points constitute a 'training set'. In a classic machine learning approach, the 'training objects' are characterized

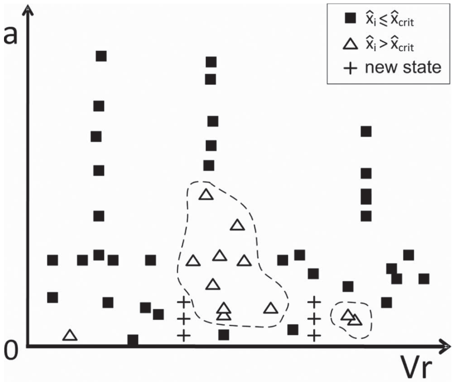

Figure 4. Example of measured data points in the (Vr, a)-plane. Vibrations above the critical limit are indicated with triangles and vibrations below the critical limit with squares. This data is used as training data for classification of new states (+).

by two 'attributes' (Vr and a) and one 'label' ("safe" or "unsafe"). Most entries will be safe situations and in certain regions islands of critical vibration states are found. A suitable classification algorithm is required that is capable of making accurate predictions to which class a new point is most likely to belong to. There exist many such algorithms. A basic choice is the 'K-Nearest Neighbours' (KNN) algorithm. This non-probabilistic classification method associates a new point with a class based on the majority of the K nearest points. See Rogers & Girolami (2012). The value of K can be determined by cross-validation, i.e. by repeatedly using different parts of the training set as validation data.

A typical question the system should provide an answer to is whether it is safe to open a gate under certain conditions. First, Vr should be determined using measured Δh and response frequency f estimated from nearby available data or using the gate's natural frequency. Figure 4 shows two options of opening scenarios that the system needs to evaluate indicated by +´s, these are new points that require classification. In the case of opening in the lower of the two Vr-conditions, the system may give advice to wait with gate operation until Vr is reduced, in order to stay clear from the unsafe zone. Alternatively, the system may decide to open the gate at a faster rate, so that the critical zone is visited briefly.

4.2 *Results of experimental data classification*

The operations introduced in the previous section are applied to vibration data from a recent laboratory experiment on cross-flow vibrations of an underflow gate (Erdbrink, in prep.). The data set used for the classification consists of 145 distinct dynamic gate situations of a rectangular flat bottom gate. Figure 5 shows this data set in the same way as depicted by Figure 3. The data represents measurements at various gate openings. During each test (corresponding to one data point in Figs. 5 and 6), the discharge, gate opening and hence water levels were kept constant.

Figure 5 shows the dominant amplitude of the measured vibration forces in the gate suspension. Clearly, there are two regions of Vr at which the vibrations grow in size considerably: $2 < Vr < 4$ and $Vr > 8$. The tests were done under fully submerged flow conditions. A threshold at 2 Newton divides the data into two classes named "vibrations" and "no vibrations". The signals below this threshold are noisy or contain irregular vibrations of small amplitude, above it more regular vibrations are found. Using this binary division and gate

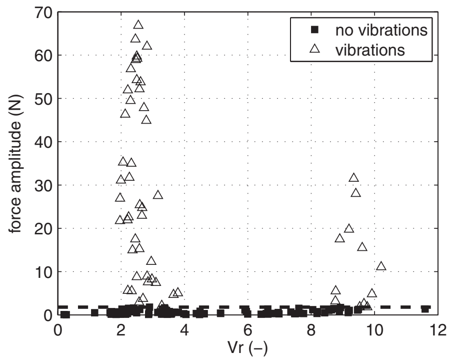

Figure 5. Experimental vibration data of a rectangular underflow gate from physical scale model (Erdbrink, in prep.). The plot shows vibration force amplitude as a function of 'reduced velocity' for steady-state conditions. The data set is divided into two classes using a threshold at 2 Newton.

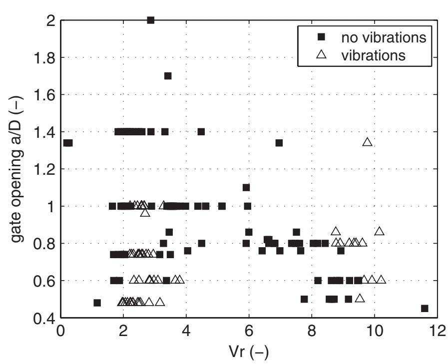

Figure 6. Identifying vibration regions. The 'reduced velocity' is plotted versus dimensionless gate opening.

opening label, the data can be plotted as shown in Figure 6.

It can be seen from Figure 6 that vibrations are found for specific regions of Vr in combination with certain gate opening ranges. The gate opening a is here presented in dimensionless form by dividing it by gate thickness D. While obviously the limited amount of data does not give the full picture, it is shown that vibrations in the region $2 < Vr < 4$ are not significant when the gate is opened up to 1.4 times the gate thickness and further. The same cannot be concluded (based on the available data) for vibrations detected at $Vr > 8$.

To classify this data, it is nominalized to scales from 0 to 1. This is done to enable application of a universal KNN-algorithm. A twenty-fold cross-validation was done on the value of K, which showed that $K = 3$ is the choice with minimal error in this case. The codes that were used are adaptations from Matlab scripts b Rogers & Girolami (2012).

Machine learning is used here as an automated tool for tracking critical gate conditions. The result of a well-trained data set is a number of classification decision boundaries that represent the contours of vibration regions up to a certain accuracy. The purpose of this technique matches the general goal of physical vibration tests, but automates and hence accelerates the identification of significant dynamic response regions.

Application of the vibration classification to real experimental data has shown that the method works in principle and could thus be used as a basis for decisions towards use of that particular gate type.

4.3 *Application challenges*

A challenge for the classification algorithm is that the training set is very asymmetric, because there will always be many more data points for safe situations where no vibrations occur than vibration data points. The experimental data set of the laboratory experiment by Erdbrink (in prep.) is in this respect not representative of real-life monitoring data at full scale, as the experiment focused on finding and recording vibrations. An aspect that is similar to a full-scale situation, however, is the occurrence of more than one vibration regime. In other words, there are multiple regions (fixed by values of 'reduced velocity' and gate opening) in which significant vibrations are found. These vibration regions may have different physical causes and indeed different excitation mechanisms.

The rate at which the database is filled with data points of critical situations depends on chosen critical limits (threshold) and occurrence of flood events. Not unlike the experimental data set that is shown in Figure 5, collected vibration data of real barrier gates will not be distributed in such a way that determining the regime boundaries is straightforward. In particular, water level variations and gate openings are usually not varied sufficiently to get a complete view on all possible vibration states. Dedicated measurement events in which gate openings are prescribed when specific hydraulic heads occur are useful, if not necessary, to collect validation data for the simulations. See section 5.2.

In the application of the classification operation, the challenge is to make suitable choices for the threshold value of the binary split, and of the parameters of the classification algorithm (in case of KNN-algorithm, this is K).

5 SIMULATION MODULE

5.1 *Set-up of the FEM model*

The goal of employing a simulation model in this control system is to provide the database with training data points, so that sensible extrapolation can be made in areas where no site data is available. Setting up and applying a Computational Fluid-Structure Interaction (CFSI) model is quite a challenge even today (Jongeling & Erdbrink 2010). Note that, from a physical viewpoint, the study of gates is a rather specific subset of the FIV field, which itself can be seen as a subset of Fluid-Structure Interaction (FSI). CFSI is a research field that employs numerical simulations to model FSI.

The model should predict instabilities of the gate as a whole due to unstable flow separation. A flat bottom shape is known from past research to show the characteristics of cross-flow gate vibrations excited by a mechanism of instability between the gate and the flow that separates from the upstream edge of the gate bottom (described in for instance Naudascher & Rockwell 1994). The spring-mounted gate interferes under certain flow conditions with the separated shear layer, which may initiate a cyclic process of interaction between flow and structure that can lead to significant vibration amplitudes and associated forces on the supports of the gate.

The physical working of this mechanism dictates the requirements of which physical aspects need to be simulated explicitly and which aspects need not be. The model has to represent the time-varying pressures directly underneath the gate and the structural response that is the result of these pressures. Prevalent features recognised as necessary physical elements needed to get realistic pressures are: flow convection under and past the gate, the wall roughness of the gate bottom, and turbulence. Fluctuations of the downstream water surface and flow resistance from bottom friction are examples of physical aspects that are considered to be of less importance.

We consider a two-dimensional domain defined by a vertical cross-section through the gate section from one water body (e.g. lake) to the other (e.g. sea), see Figure 1. The model consists of two domain types: a flow domain (flow past the gate) and a solid domain (the gate body itself). A rigid rectangular gate with a flat bottom is modelled. It is given one degree of freedom for movement in the vertical direction. Figure 7 shows a part of the flow domain. Here the gate is not yet explicitly included.

The Reynolds-Averaged Navier-Stokes (RANS) equations for incompressible flow are the basis for the simulations. The external force component forms the coupling with the movement of the structure. We consider a rigid object; elastic deformation of the gate structure itself is not simulated. The movement of the rigid gate is modelled by the damped mass-spring equation with one degree of freedom.

The upstream flow boundary consists of a prescribed velocity profile (constant discharge), with a shape that is in equilibrium with the roughness of the bottom wall, which has a no-slip boundary. The downstream flow boundary is a prescribed hydrostatic pressure profile. Because strictly submerged flow conditions are considered, the water surface is modelled as a horizontal 'rigid lid' (free-slip boundary). As an initial condition, a uniform flow velocity equal to the upstream boundary is applied everywhere in the domain.

An unstructured, triangular computational mesh is used with refinements near boundaries and in areas of high velocity gradients. The application of the Arbitrary Langrangian-Eulerian (ALE) method enables deformation of the computational mesh due to movement of the structure.

The package Comsol Multiphysics is chosen to simulate the gate. This Finite Element Method (FEM) solver is applied to solve the RANS equations, using the SPOOLES method for solving the set of discretized equations. The k-epsilon model is used for turbulence closure.

The modelling strategy is to start with a CFD simulation of a steady-state flow past a fixed gate that should produce correct vertical pressure distribution on both sides of the gate and a rotational cell (recirculation zone) downstream of the gate. The flow field resulting from the steady-state run is applied as initial values for a time-dependent flow run, still with a rigid and fixed gate, that should give reasonable turbulence features and show a correct separated shear layer. The solid domain can first be studied in Comsol in a separate model of the gate and suspension (without surrounding water) that determines the eigenfrequency. Then, a rigid and fully submerged gate is modelled by giving it a prescribed vibrational displacement inside a still water domain. If successful, this movable gate can be added to the time-dependent flow model to obtain a full FSI. The idea behind this multi-step approach is twofold. It enables the modeller to identify numerical obstacles and carry out validation devoted to specific (physical) elements.

5.2 *First simulation results*

Figure 7 shows a time frame from one of the first time-dependent flow model runs with a fixed gate. The downstream boundary lies outside the range of the shown figure. As expected, the flow separates from the upstream bottom edge. The separated shear layer can be seen to come close to the downstream edge. A small downward movement of the gate might therefore initiate an unstable gate response. Incorporating this effect is the next step in the simulation process.

Ongoing efforts focus on obtaining a robust model application. Experiences so far indicate that the gate bottom boundary is a main point of attention for achieving successful simulations. Not only does this boundary provide the transfer of forces between fluid and solid, but it should also accurately represent the effect the gate movement has on the local flow behaviour. After all, both these

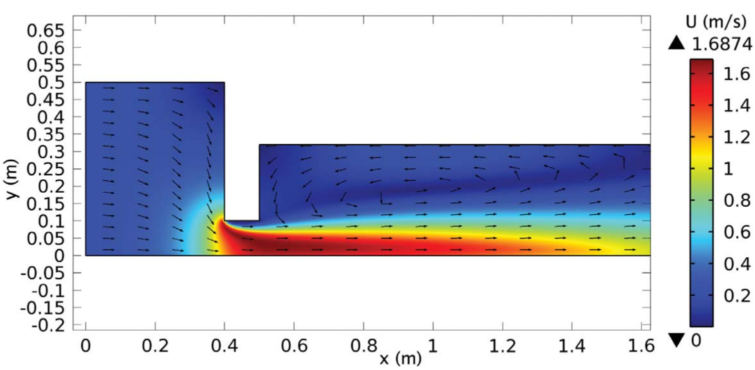

Figure 7. Simulation snapshot of a steady-state CFSI model run with Comsol showing separated flow under a fixed gate. The flow vectors are normalized. The figure shows the basic idea of the simulation and does not represent an obtained final result.

things directly influence the pressures that reign the interaction process.

5.3 *Use of data in simulation module*

Data flowing to and from the simulation module take different forms. Four distinct data flows are mentioned, corresponding to subsequent stages of model use:

1. *Validation runs*
   Every predictive model needs to be validated. To validate the CFSI gate model, recent results from physical scale model experiments of vertical-lift gate vibrations (Erdbrink, in prep.) will be used. Over 300 tests collected data of cross-flow vibrations for a wide range of suspension stiffness and for various hydraulic conditions. Two essentially different gate bottom geometries were applied. The resulting data set clearly shows the different dynamic responses of the gate for different settings.

   The present Comsol simulation attempts to reproduce this experiment. This is done by using similar domain dimensions and by applying the same flow discharge. The first validation step is to look at the steady submerged flow situation: the simulated pressure profiles away from the gate are compared to measured water levels (for a given combination of discharge and gate opening) and the simulated velocity under the gate is compared to analytical values. The second validation step is obviously to compare the simulated frequencies and amplitudes of the gate movement resulting from the interaction with the flow, with the experimental values. The reduced velocity *Vr* parameter may be used to cover different vibration response regimes during validation. Note that the multi-step model development mentioned above allows for use of several other validation parameters not explicitly treated here.
2. *Set-up of the system: database runs*
   After confidence has been gained by validating the CFSI model for the small-scale gate of the laboratory experiment, the same numerical model (with the same settings) can be applied to a real-life gate. Gate geometry and direction of movement are necessary for this and preferably also information on structural stiffness and damping. Data input going into the model will consist of a variety of expected water levels. Several runs are made for different gate positions. The data going out of the model consists of gate response characteristics.

   These runs are intended to generate vibration data to fill the database of the ML module. It is assumed that the database is empty at this stage and no sensory data is available yet. At first, the frequency and amplitude predictions from the CFSI model may be quite inaccurate, yet the training data set thus generated makes ML estimates possible—presumably leading to better insights than the complete uncertainty of gate response that one faces otherwise.
3. *Operational runs*
   When the system is fully operational, the database is growing with data from the continuous gate vibration measurements. The CFSI model is used for predictions only for cases that are not yet found in the database and that are not reliably interpolated from measured data. The data inflow and outflow of the FSI model are the same as described above.
4. *Calibration based on achieved measurements*
   Every time that a gate condition is achieved that was previously simulated by the FSI model, the measured gate response data will be used to check and incrementally improve the FSI model. This is in fact a calibration of the CFSI model for these specific conditions. The next time that the system asks the model for predictions in the neighbourhood of these conditions, the simulations will be more accurate.

6 CONCLUSIONS AND FUTURE WORK

This study has provided a new view on how to apply numerical modelling to control flow-induced gate vibrations effectively. The presented system is generic and makes use of both measurements and computational modelling without disregarding physical insights from past studies.

An outline is given as to how machine learning can be applied to classify gate response data, with the goal of predicting whether a future gate state is safe or not. Application of the K-nearest-neighbour-algorithm to experimental data from laboratory measurements of gate vibrations has shown that the approach is feasible and has identified a number of application challenges. A computational fluid-structure interaction model is employed to provide additional input for the database to cover situations where sensory data is lacking.

Future extensions to the signal processing could include wavelet methods for detection of transitions between different dynamic conditions. The CFSI model needs to be further developed so that the full interaction between flow and gate is simulated. The gate bottom boundary is identified as a crucial element in achieving this. Model validation can be done by comparison with the experimental data set of Erdbrink (in prep.). For the machine learning module, improvements can be made by attempting various other classification algorithms. Also, the threshold value need not be a constant. It should be fine-tuned to accurately distinguish noisy and irregular fluctuations from vibrations that are capable of growing to harmful levels.

The system has direct practical implications, since it follows an engineering approach towards tackling the problem of gate vibrations that plays a role not only in new structures, but also in the renewed gate operation in existing barriers (e.g. in relation with new ecological requirements or safety regulations). Implementation of the system depends on recognition of its usefulness and efficiency by barrier managers. The proposed system has potential in identifying the risks of vibrations and improving gate operation of large flood defence structures.

ACKNOWLEDGEMENTS

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