PROBABILISTIC DESCRIPTION OF SEDIMENT PLUME REQUIREMENTS AT THE ØRESUND FIXED LINK DREDGING PROJECT

M. Nieuwaal MSc[1,3], P.H.A.J.M. van Gelder PhD[2] and K.G. Nipius MSc[3],

Abstract: In an increasing number of dredging contracts, environmental requirements concerning sediment plumes have to be met. The required frequency of measurements to check if the actual turbidity or concentration of suspended solids complies with the limits, varies largely per contract. When measurements are taken continuously the probability that the limits are exceeded without registration by measuring are small, but continuous measurement methods are very expensive. The objective of this study is to optimise the number of measurements at a location, i.e. the number of ship crossings through a sediment plume, given the costs and the accuracy of the turbidity measurements, by a statistical data analysis.

Data from the Øresund Fixed Link project in the Baltic Sea is used for the case study. Turbidity was measured 24 hr/day throughout this project. The measurements of one day, 15 January 1996, were used for the data analysis. The measurements were carried out from a vessel that sailed perpendicular across the sediment plume, at a distance of 200m from the dredger, collecting current and turbidity data. Upstream turbidity was measured for baseline values.

Turbidity is assumed to be a random variable. Currents, dispersion, turbulence, and the amount of suspended sediment released by dredging influence the process of turbidity and make it inherently uncertain. The turbidity data are assumed to come from a Binomial-Exponential (BE) distribution. The data contain natural background values as well and the BE distribution separates the background values from the extra turbidity. To check whether data fit well in the distribution function a χ-square method was used. The BE distribution has two distribution parameters: p is the percentage of zero's measurements (background values) and m is the mean value of the non-zero's of the turbidity.

The uncertainty of these parameters depends on the number of ship crossings. The uncertainties were quantified by the coefficient of variation values (CV). These values were derived analytically as function of the number of ship crossings and tested by a numerical parametric statistical estimation method.

An optimised number of ship crossings can be determined by an optimisation of the total costs. The total costs consist of the costs of ship crossings and the gains of having a smaller CV-value. Results are shown for the Øresund project together with a sensitivity analysis of the cost parameters.

[1] Delft University of Technology, P.O.box 5048, 2600 GA Delft, The Netherlands, mnieuwaal@hotmail.com

[2] Delft University of Technology, P.O.box 5048, 2600 GA Delft, The Netherlands, fax +31 15 27 85 124, p.vangelder@ct.tudelft.nl

[3] Royal Boskalis Westminster, P.O.box 43, 3350 AA Papendrecht, The Netherlands, k.g.nipius@boskalis.nl

INTRODUCTION

In an increasing number of dredging contracts, environmental requirements concerning sediment plumes have to be met. The required frequency of measurements to check if the actual turbidity or concentration of suspended solids complies with the limits, varies largely per contract. When measurements are taken continuously the probability that the limits are exceeded without registration by measuring are small, but continuous measurement methods are very expensive. The objective of this study is to optimise the number of measurements at a location, i.e. the number of ship crossings through a sediment plume, given the costs and the accuracy of the turbidity measurements, by a statistical data analysis. Other work in this field has been performed by Cicero et al, (2001), and Gotz et al (1998).

Section 1 describes the Øresund Fixed Link projects to provide background information on the used turbidity measurements. To be able to use the turbidity data of the project for a statistical analysis, simplifications were made on the raw data. This is described in Section 2 and Section 3 considers the statistical analysis of the simplified data. In Section 4 a method is proposed to optimise the number of ship crossings on the basis of a cost optimisation.

1 PROJECT

The used data come from the Øresund Fixed Link project. Figure 1 shows the location of the Øresund Fixed Link. Dredging works at this project included a trench for the tunnel, work harbours, navigation, construction and access channels and compensation dredging (deepening of certain parts of the Øresund to maintain the overall exchange of water; the zero solution). Reclamation works included the artificial peninsula at Kastrup on the Danish coast and the artificial island south of Saltholm.

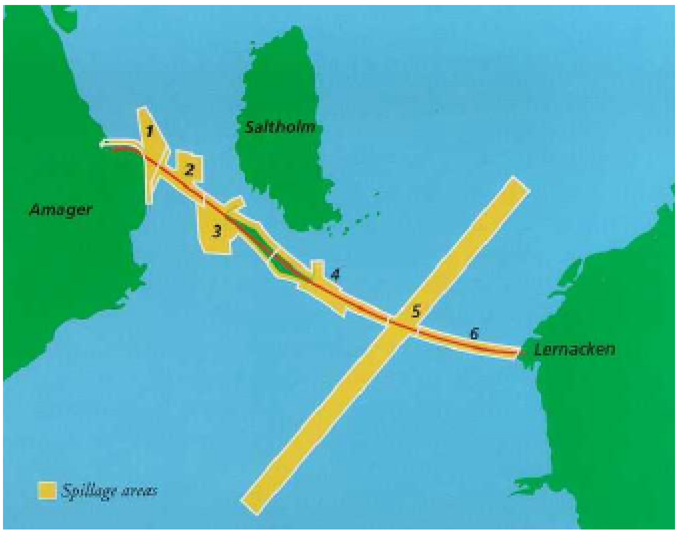


Figure 1 The location of the Øresund Fixed Link

1.1 Sediment Spill

The limits at the project are sediment spill limits. An overall spill limit of 5% (by weight) of the design quantity to be dredged and more detailed limitations, weekly and daily percentages of spill were prescribed. The contractors are contractually obliged to measure spillage and are responsible for monitoring the amount of spillage.

Spill is defined as the portion of dredged or excavated material brought in suspension during dredging, transport or filling, which leaves the work zone or land reclamation areas. The work zone is the area that has to be dredged plus a surrounding 200m zone. Spill is measured by dry weight of suspended materials (kg). The sediment spillage by the dredge will appear as plumes travelling in the direction of the current, away from the dredging area. Figure 4 shows an examples of sediment plumes.

Essential data for the calculation of the spill are the current and turbidity values within the plume leaving the workzone. The spillage measurements are carried out from vessels that sail across the plume from ‘clear water’ to ‘clear water’ at right angles to the current, collecting current and turbidity data. At the reclamation areas the outflow from the sedimentation basins is measured inside pipelines.

1.2 Methods of Measurement

Depending on the waterdepth, the current velocity is measured by acoustic (ADCP) or electro-magnetic current measurements. Four Optical BackScatter (OBS) sensors measure the turbidity, one mounted at the front of the vessel, three placed on a streamer cable with an output in FTU (Formazin Turbidity Unit). Figure 2 shows the spillage monitoring.

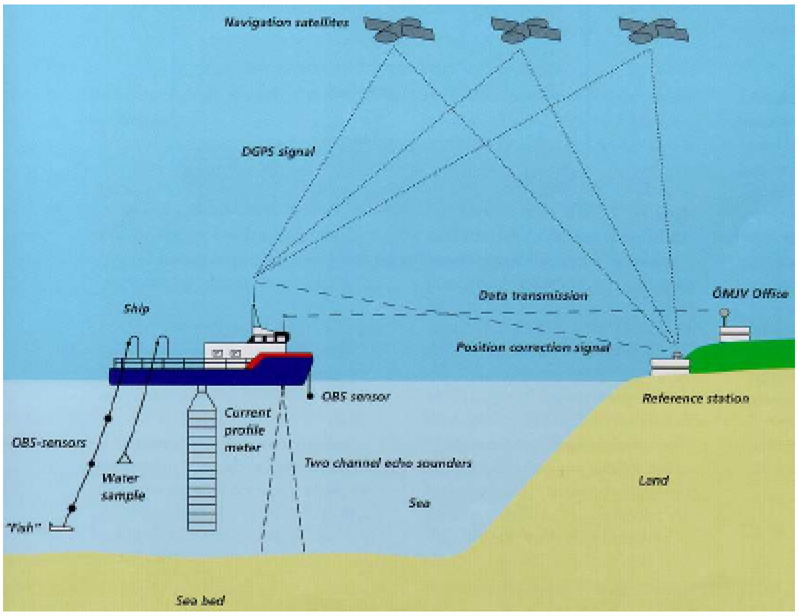


Figure 2 Spillage monitoring

Since the amount of spill was calculated in terms of weight the turbidity measurements were translated into concentrations of suspended sediment. For each area a correlation between turbidity and concentration of suspended sediment was calculated on the basis of water samples taken during the measurements.
The concentration of suspended sediment converted to (kg/m^3), multiplied by the current velocity (m/s) integrated in spaces gives a spill flux or intensity, F_s (kg/s). The amount of spill can then be calculated by integration of all transects in time. At the end of every day an average amount of (kg/day) was calculated.
This set-up was used during the whole project. The costs of the monitoring program were very high. At the Øresund Fixed Link project the employer was willing to pay these costs to be sure the Swedish and Danish authorities' environmental requirements were met.

2 DATA

2.1 Turbidity Data of the Øresund Project

The used data are turbidity measurements of one day; 15 January 1996. The tidal influence in the Øresund is low; currents are mainly wind driven. During this day the wind velocity was 4,6 to 6,2 m/s (wind-force 3 to 4) and the direction was south to southeast. Background values were low; approximately 0,1 FTU. The dredged material consisted of clay and limestone. The dipper dredger 'Chicago" was dredging a work harbour on the west side of the artificial island. This location falls under spillage area 3 (Figure 1). The 'Chicago' (Figure 3) has a dipper bucket capacity of 22 m^3 and a daily maximum production between 2.000 and 8.000 m^3. The dredge loaded 2.000-ton material barges to be towed to the reclamation areas for offloading behind stone revetments.

The vessel 'Coastal Flyer' was measuring the spillage. Figure 4 shows a picture of the 'Chicago' and the 'Coastal Flyer' at work and an overview of the main sailed lines and the position of the dredge is given in Figure 5.

Figure 3 Dipper dredge 'Chicago'

Figure 4(right) 'Chicago' and 'Coastal Flyer' at work

During 15 January 1996, the measuring vessel sailed 72 ship crossings in 24 hours. There were 58 ship crossings at line 1 (Figure 5) and the rest of the crossings was divided over the other lines. Under influence of the wind driven current, the sediment plume travelled to the north-east and turbidity in the plume was measured at line 1. At line 3 and 5 upstream background turbidity was measured.

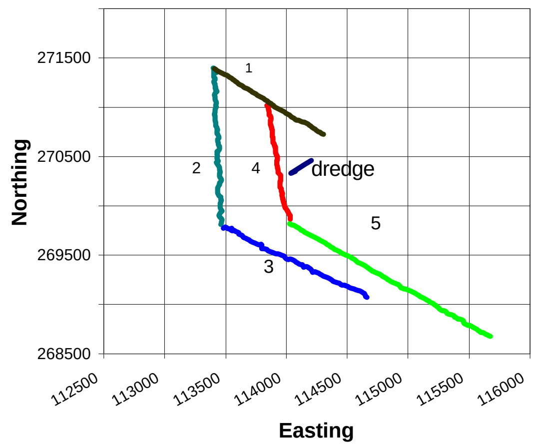


Figure 5 Co-ordinates (m) of the sailed lanes by 'Coastal Flyer' and the position of the dredge

2.2 Simplification of the Data

To be able to describe the turbidity process structure in the cross section in time the structure of the data is adjusted. To restructure the data assumptions were made:

- At every ship crossing the vessel measures at the exact same locations in distance and depth. Therefore only the part of crossing line 1 with a reasonably constant depth of the seabed is used for the data analysis.
- All measurements in one cross section are taken at the same time.

This results in a data structure with the format:

$n, x_j, d_1, d_2, d_3, d_4, t_1, t_2, t_3, t_4,$ with:

n : number of ship-crossings [1:58]

x_j : distance (m), at j=1,2,…,30 [0, 17, 34,…,493]

d_k : depth (m), at k=1,2,3,4 [0.5, 1, 2.5, 4.5]

$t_{n,j,k}$: turbidity at location (j,k) at ship crossing n

The ship makes 58 crossing from j=1 (x = 0m) to j=30 (x = 493m) (Figure 6).

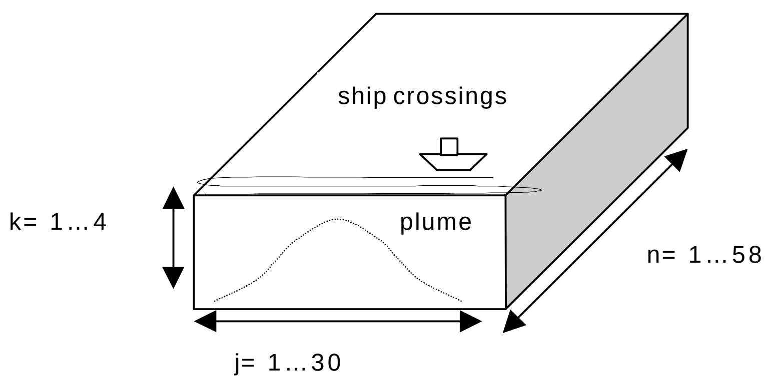
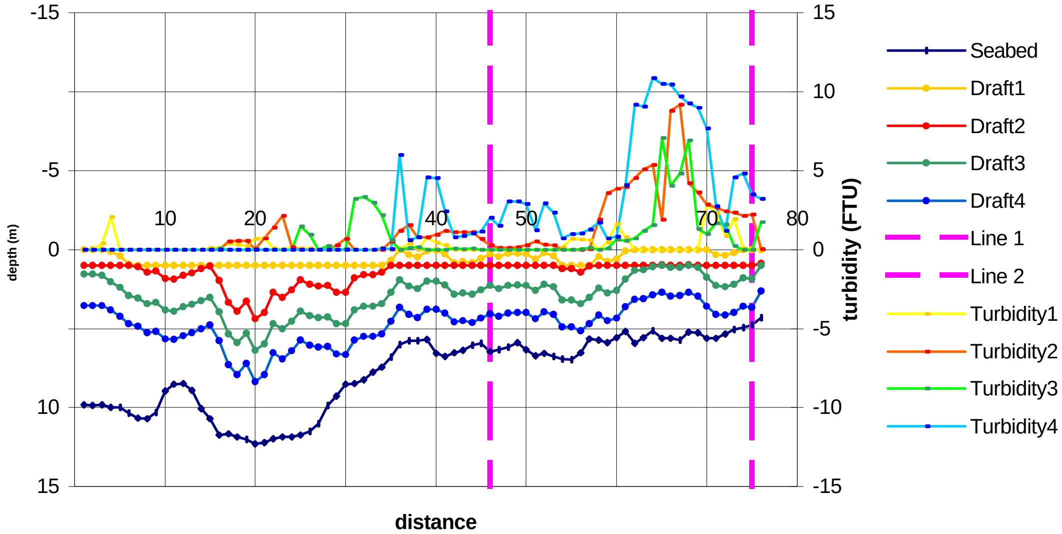


Figure 6 An overview of the data. During one ship crossing the vessel measures the turbidity 30 times at 4 depths. The vessel makes 58 crossings

During 24 hours the sediment plume passes by and turbidity is measured 58 times at each location (x,d). Figure 7 shows an example of the simplification at ship crossing 1. In the graph the part that was used for the data analysis is marked with vertical lines. The depth between these lines is assumed to be constant. The second graph shows the simplified data, used for the statistical data analysis.



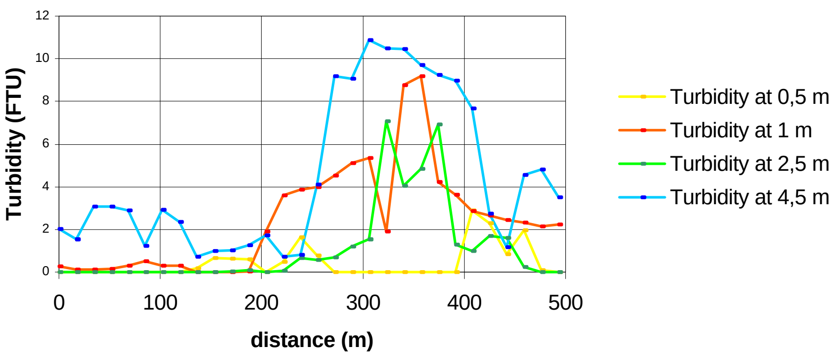


Figure 7 Simplification of the data of ship crossing 1; only the part between the vertical lines was used and the depth was assumed to be at a constant 6 metres

3 Statistical Data Analysis

3.1 Approach

First the inherent uncertainty of the turbidity data is explained in Section 3.2. In Section 3.3 a distribution function is determined for the inherent uncertainty of turbidity. A statistical analysis on the turbidity data determines how often a given turbidity value is expected. This can be modelled by the probability density function (PDF) of a distribution function.

The statistical or parameter uncertainty of the probability calculated for the likelihood of a given turbidity depends on the amount of available data (the number of measurements). Section 3.4 shows how the uncertainty as function of the number of measurements can be quantified. Section 3.5 describes how the statistical uncertainty of turbidity can be derived and determines the maximum allowable turbidity in a probabilistic framework. The optimisation of the number of measurements can be determined from the optimisation of costs. This is described in Section 4. The basic probabilistic theories used for these sections are derived from CUR (1997), Van Gelder (1999) and Vrijling (1990).

3.2 Inherent Uncertainty

The approach of the statistical data analysis depends on the correlation of the data. If the data are correlated less measurements are needed, because one measurement value can be based on the previously measured value. Turbidity is assumed to be a random variable. Currents, dispersion, turbulence, and the amount of suspended sediment released by dredging influence the process of turbidity and make it inherently uncertain. Figure 8 shows an example of turbidity as function of the distance.

By means of auto correlation functions the inherent uncertainty can be shown. In Nieuwaal (2001) autocorrelation is explained and examples of auto correlation of the ship crossing, location and depth are shown. The auto correlation functions show low correlation values (< 0,5). This means that the turbidity values can not be interpreted from each other and are inherently uncertain as expected. Higher correlation values imply that less measurements are needed. With a correlation of 100% only one measurement is required. For the further approach of this study the correlation will be assumed to be zero. When the actual correlation is assumed, a more advanced statistical analysis has to be used.

3.3 Distribution Function for the Inherent Uncertainty of Turbidity

The previous section concluded that the turbidity data are not correlated, which means that the turbidity is inherently uncertain. In this section the inherent uncertainty will be modelled by a distribution function.

A statistical analysis on the turbidity data determines how often a given turbidity value is expected. The turbidity T at location (x,d) can be modelled by a probability density function $f(T)$. First the distribution function has to be determined. The turbidity data contain a large number of very low values, or zeros. These are the natural, or background values that are measured by the measuring vessel at the edges of the plume, or when no clear plume can be observed. A way to separate the back ground values from the extra turbidity is to use a Binomial-Exponential distribution.

To check whether data fit well in the distribution function a computer program called 'Bestfit' was used. 'Bestfit' used a χ-square method (Van Gelder 1999). The program fitted the 58 measurements of T at location (x,d) in several distribution functions and determined the best fit. Because the distribution functions of 'Bestfit' do not include the BE-distribution, the background, or zero values were left out and for 20 tested locations the exponential distribution function came out as a good fit. For all 120 locations the turbidity data are fitted in a Binomial-Exponential distribution. Nieuwaal (2001) shows that at most locations the turbidity measurements fit well in the distribution. Figure 8 shows an example of a good fit.

In this figure the data seem to be grouped. No explanation is found for this than that

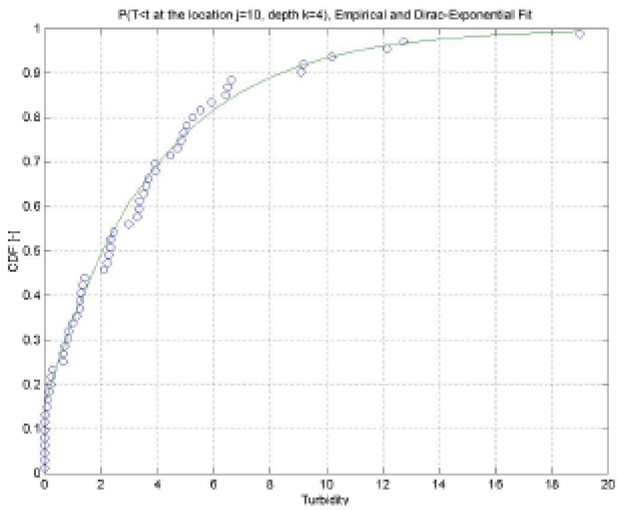


Figure8 An example of a fit of turbidity data in a Binomial-Exponential distribution function

it may be caused by the measurement equipment. Since the effect is only small and does not affect further conclusions this is not investigated in more detail.

For all locations the same distribution is used because the same process, i.e. turbidity is described. The cumulative distribution function (CDF) and the probability density function (PDF) for the BE-distribution function are described as (see Figure 9):

$$F_t(t) = 1-(1- p)\cdot e^{\frac{-t}{m}} \qquad\qquad f_t(t) = \frac{(1-p)}{m}\cdot e^{\frac{-t}{m}}$$

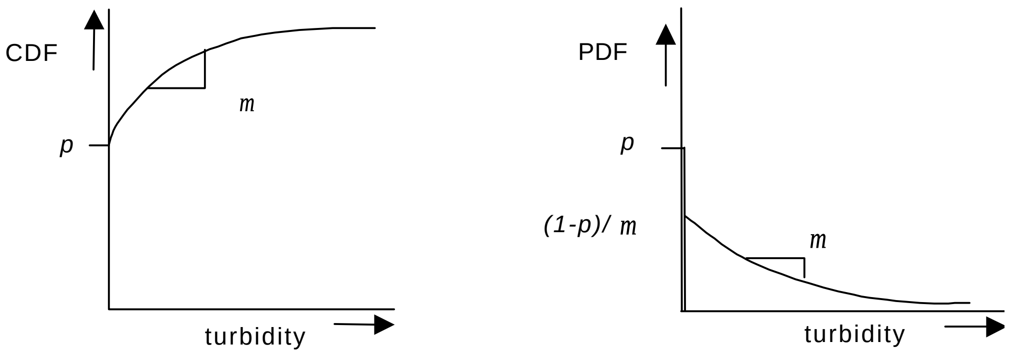


Figure 9 The cumulative distribution function (CDF) and the probability density function (PDF) for the BE-distribution function

The BE distribution has two distribution parameters; p and m. p is the percentage of zero's of the turbidity measurements (background values) and m is the mean value of the non-zero's of the turbidity. For all locations the two parameters of this distribution are calculated for the 58 values.

3.4 Statistical Uncertainty

For further analysis the BE-distribution function will be used. The parameters of the distribution are now determined with a limited number of data. In this situation statistical or parameter uncertainty (or inaccuracy) occurs. The smaller the number of data, the larger the parameter uncertainty. The inherent uncertainty, described by a distribution function (see Section 3.2) can not be changed. An example to illustrate this is the weather forecast; we don't know the temperature at a specific day next year (inherent uncertainty). It can only be modelled by a probability density function probably normally distributed. With a larger number of measurements this probability density function with its mean and standard deviation does not change. But accuracy of the prediction gets larger (statistical uncertainty). The probability density function can be described more accurately.

Statistical uncertainty of parameter p shows itself in the point where the curved line starts and uncertainty of m in the curvature of this line. This is illustrated in Figure 10. The smaller the number of data, the larger the parameter uncertainty.

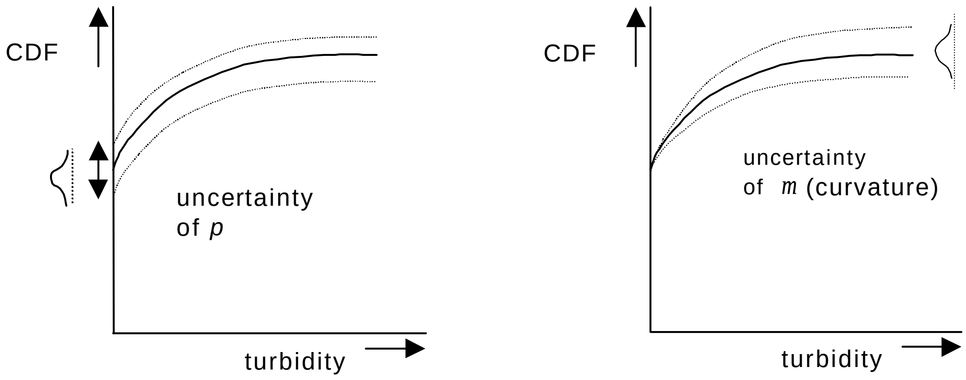


Figure 10 The uncertainty of the parameters visualised in the Cumulative Distribution Function.

Quantification of Parameter Uncertainty

A parameter of a distribution function is estimated from the data and thus is a random variable. The parameter uncertainty can be described by a distribution function, which can generally be modelled by a normal distribution function.

The uncertainty can be quantified by the coefficient of variation value (CV). The coefficient is defined by the standard deviation divided by the mean:
m = mean, s = standard deviation

$$\mathrm{CV} = \frac{s}{m}$$

The derivation of parameter uncertainties can be done *analytical* and *numerical*.

Analytical method
For an overview of analytical expressions is referred to Van Gelder (1999). The Binomial-Exponential function consists of a continuous (exponential) and a discrete (binomial) part. To calculate the coefficient of variance for the estimator *m* expressions for the exponential distribution function can be used. The following calculations are described in more detail in Nieuwaal (2001). As these calculations can be applied in general, the expressions *X* defined as a random value and *x* defined as a realisation of *X* are used.

For the exponential distribution function:

If $F_x(x) = 1 - e^{-\frac{x}{m}}$, and $f_x(x) = \frac{1}{m} \cdot e^{-\frac{x}{m}}$

then $E(X) = \int_0^\infty f(x)x\,dx = m$, and $s(X) = m$

If $X_1, X_2, \ldots, X_n \in \exp(m)$,

then $m^* = \frac{\sum_{i=1}^{n} X_i}{n}$, with m^* is the estimator for the unknown m.

m^* is a function of *n* random variables, and thus is a random variable itself.

$$E(m^*) = \frac{\mathrm{E}\sum X_i}{n} = \frac{1}{n} \cdot \sum \mathrm{E}X_i = \frac{1}{n} \cdot n \cdot m = m$$

and $s(m^*) = \frac{1}{n} \cdot \sqrt{\sum s^2(X_i)} = \frac{1}{n}\sqrt{n \cdot m^2} = \frac{m}{\sqrt{n}}$

For the Binomial-Exponential function the average of the non zero values (in total $n(1\text{-}p)$) is needed

and $\mathrm{E}(m^*) = m$, and $s(m^*) = \frac{m}{\sqrt{(1-p) \cdot n}}$, thus $CV(m^*) = \frac{1}{\sqrt{(1-p)n}}$

Following the same reasoning for the coefficient of variance of the estimator of parameter *p* the binomial distribution function can be used with:

$E(X) = n \cdot p$, and $var(X) = n \cdot p(1-p)$

The binomial distribution function is a model for an experiment with two possible outcomes; one with chance *p* and the other with a chance (1-*p*). If *X* is the random variable for the total number of positive outcomes, then for the Binomial-Exponential function the chance of a zero value is estimated by p^* = #zero's/n= X/n. This results in: $E(p^*) = p$

and $var\left(\frac{X}{n}\right) = \frac{1}{n^2} \cdot var(X)$, thus $var(p^*) = \frac{p(1-p)}{n}$

$var(p^*) = (std(p^*))^2$, thus $std(p^*) = \sqrt{\frac{(1\text{-}p)p}{n}}$, and $CV(p^*) = \sqrt{\frac{1-p}{p \cdot n}}$

Numerical method
The analytical derived values were tested by a numerical parametric statistical estimation method.
The following steps describe this numerical method:

1. The turbidity data can be simulated as follows: generate a random sample from a uniform distribution function, use this as the CDF-value of the BE-distribution and determine the corresponding turbidity.
   Repeat this a hundred times.
2. Determine the amount of zero values and the mean value.

Repeat step 1 and 2 a hundred times and the distribution function of these 100 values for both the parameters can be derived. In practice, this distribution can be satisfactory modelled by a normal distribution function. The mean and standard deviation, and thus the CV of this distribution function can be calculated. From now on this will be described by:

$m \sim N(a,b)$ with mean value a and standard deviation b, $CV(m) = b/a$
$p \sim N(g,d)$ with mean value g and standard deviation d, $CV(p) = d/g$

Parameter Uncertainty as Function of the Number of Ship Crossings

For 20 locations the parameter uncertainty was calculated. Figure 11 shows how the uncertainty of the parameter p and µ depends on the number of measurements for p=0.4 and m=4, which is the average for all locations.

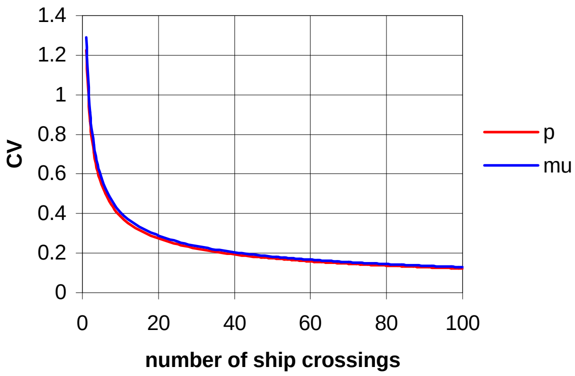


Figure 11 The uncertainty of the parameters as function of the number of ship crossings.

The CV is defined by the standard deviation divided by the mean as described earlier in this section. When the number of measurements increases the CV decreases (and the accuracy increases).

The uncertainty can be larger than 100%; this happens when the standard deviation is larger than the mean value ($b > a$ or $d > g$).

3.5 Determination of the Maximum Allowable Turbidity in a Probabilistic Framework

To determine the maximum allowable turbidity a method of failure chances is used. This theory is also applied to probabilistically determine dike heights (CUR 1997). The Limit State is the state when the resistance (*R*) is equal to the load (*S*) on the dike. When the load is larger than the resistance (*S* >*R*) the construction will fail. The state of the construction can be described by a reliability function *Z*=*R*-*S*. In this

application failure occurs when the turbidity gets larger than a specific *t* (*T* >*t*) and the reliability function can be described by *Z* =*t*-*T*.

The maximum allowable turbidity in the field of investigation is described in a probabilistic way, for instance P(*T*<*t*)=98% (this is the chance of non failure). This means that in average 2 out of 100 measurements may exceed the maximum allowable turbidity *t*. Or similarly, out of 100 locations (*j*,*k*), there may be 2 locations where the turbidity exceeds the maximum allowable turbidity.

The cumulative distribution function (CDF) (shown by Figure 12) is described by:

$$F_t(t) = 1-(1-p)\cdot e^{\frac{-t}{m}}$$

With a required reliability of 98%

$$P\,(T<t) = 0.98, \qquad \text{thus} \quad (1-p)\cdot e^{\frac{-t}{m}} = 0.02, \qquad \text{and} \qquad t = -m \times \ln\left(\frac{0.02}{1-p}\right)$$

Because the distributions of *m* and *p* are modelled by a normal distribution function, *t* may be assumed also a normal distribution by first order reliability theory.

$t \sim N\,(e,z)$ with mean value *e* and standard deviation *z*,

e and *z* (as well as *a*,*b*,*g*,*d*) are dependent on the number of ship crossings *n*. If $n \rightarrow \infty$, $z \rightarrow 0$. Figure 12 shows how uncertainties of *m* and *p* (as described in Section 3.4) determine the uncertainty of *t*.

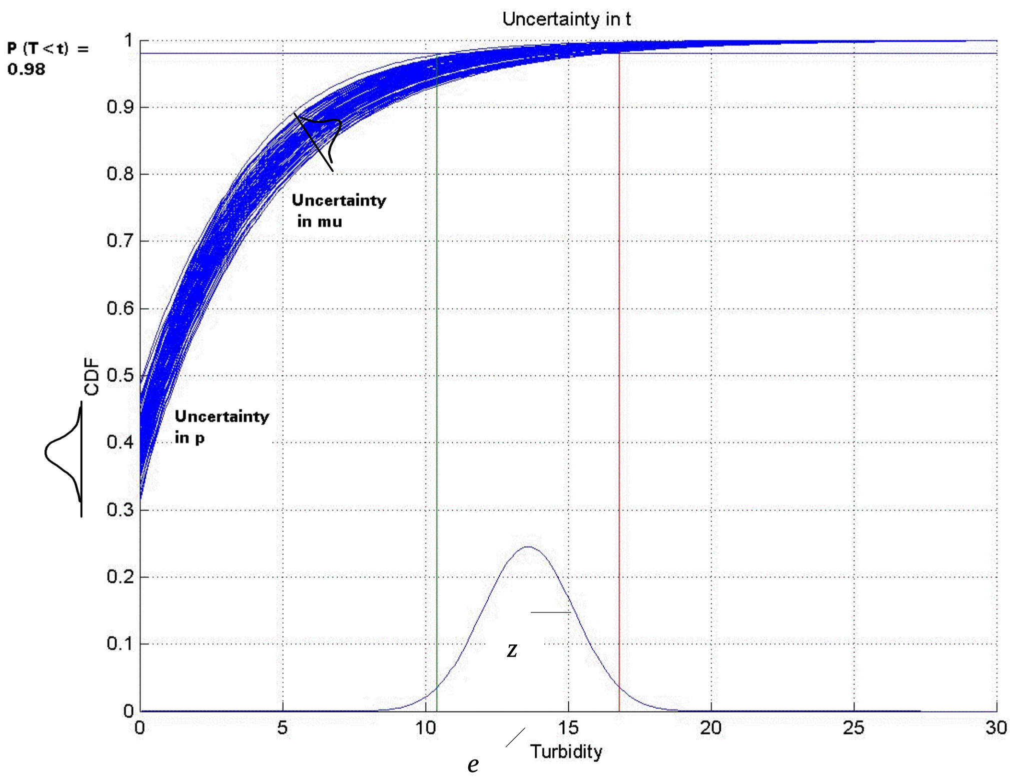


Figure 12 Cumulative Distribution Function of a B-E distribution with parameters p=0.4 and m=4. The parameter uncertainties and the required reliability of 98% determine the allowable turbidity. In this figure 100 measurements were included.

By a linear approximation of the relationship between *t* and its parameters *m* and *p* with Taylor series expressions for *e* and *z* can be determined (see CUR 1997). The outcomes are described below:

$$e = -a \times \ln\left(\frac{0.02}{1-g}\right) \quad \text{and} \quad z = -b \times \ln\left|\ln\left(\frac{0.02}{1-g}\right)\right| + d \times \left|\frac{a}{g-1}\right|$$

Figure 24 shows these parameters as well. Assuming *t* has to be specified with 95% accuracy, then the interval of turbidity values is derived with:
$t = (e - 1.965 \times z \, , \; e + 1.965 \times z)$

In general, assumed that t has to be specified with $(1 - p)$% accuracy, then
$t = (e - F^{-1}(p/2) \times z \, , \; e + F^{-1}(p/2) \times z)$

The chance *p* in this formula differs from the parameter *p* of the BE-distribution. The minimal number of ship crossings can be determined when the interval of turbidity values for an accuracy of 95% is specified. This interval is the probabilistic allowable level of turbidity.

Figure 13 shows the interval as function of the number of measurements at a location with distribution parameters p=0.4 and m=4.

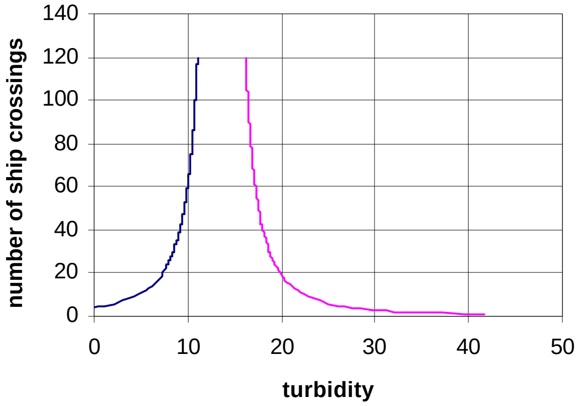


Figure 13 The interval of the allowable level of turbidity decreases with increasing number of ship crossings. p=0.4, m=4

For 58 ship crossings, for a reliability of 98%, the 95% accurate interval of turbidity values is [9.9 , 17.3] FTU. Figure 13 shows the outcomes for 100 shipcrossings. When P(T<t) is smaller the allowable turbidity interval decreases (98% may be a very strict requirement).

To be able to minimise the number of measurements with this method the following requirements have to be specified:

- the required reliability (chance that the turbidity at location (j,k) is smaller than t)
- the required percentage of accuracy of t
- the reliability interval

4. Optimisation of Costs

The number of ship crossings can be optimised as follows:
Assume the costs of one ship crossing is A.
Assume the costs (disadvantages) of having a larger CV-value is B.
Then the total costs can be described by:

$$TC(n) = A \times n + B \times CV(p^*) + B \times CV(m^*)$$

with n = the number of measurements in 24 hours,

$$TC(n) = A \times n + B\sqrt{\frac{1-p}{p \cdot n}} + B \times \frac{1}{\sqrt{(1-p)n}} \qquad (1)$$

The used data of the Øresund project are measurements of one day. Thus the process of turbidity of 24 hours is described and the cost optimisation is for 24 hours as well.

When TC'(n) is the derivative of the function TC(n), the optimal number of ship crossings follows from TC'(n) = 0, with

Giving $n_{opt} = \sqrt[3]{\left(\frac{B\cdot\left((1-p)+\sqrt{p}\right)}{2A\cdot\sqrt{p\cdot(1-p)}}\right)^2}$ (2)

Quantification of Costs

The costs of ship crossings can be assumed. A measuring vessel for 12 hrs/day approximately costs EUR 5000 per week and a vessel for 24 hrs/day costs approximately EUR 7000 per week. The gains of having a smaller CV-value are more difficult to determine. With a smaller accuracy the chance that limits are exceeded without registration by measuring is larger. For example when the measured mean value is smaller than the actual mean value, the chances that the ecosystem will be affected raise. But when the measured mean value is higher than the actual mean value, unnecessary problems between contractor and employer will rise. With larger uncertainties it is more difficult to prove whether effects on the environment are caused by dredging or not. The quantification of the costs will make the optimisation of number of ship crossings workable in practice but it is outside the scope of this report. To show how the optimisation of costs can be used global calculations are made for the Øresund case and a sensitivity analysis is done.

Results Øresund Case and a Sensitivity Analysis

At the Øresund Fixed Link dredging project the environmental protection played a central role. Turbidity measurements were taken 24 hr/day and the costs imposed by the environmental requirements are assumed to be relatively high.

For the following example it is assumed that the optimal number of measurements for the Øresund case is 58. With assumptions for *p* and *A*, a value for *B* can be calculated by equation 2:
n_{opt}= 58 ship crossings
p= 0.4 , this is the average of the *p*-values for all locations
A= 1 , to show the relation between *A* and *B*
Gives:
B=352
These are the assumed relative costs of having a lower accuracy. Because the environment had a high priority at the Øresund projects this value of 352 is assumed to be high.

The quantified accuracy for the assumed number of measurements is: CV(p^*)=0.16 and CV(m^*)= 0.17 (see Figure 13). Figure 14 shows the total costs for the optimal number of ship crossings of 58.

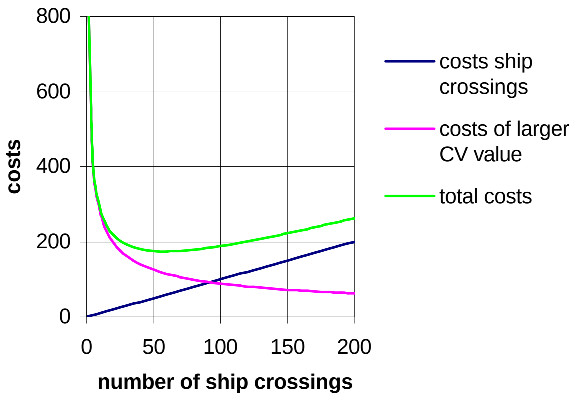


Figure 14 The optimal number of ship crossings

When less measurements can be performed while the rest of the parameters stays the same, the accuracy will decrease, and the total costs will increase. Table 1 shows examples with less measurements for p=0.4, A=1 and B=352. Equations 1 and 2 were used for the calculations.

n	**CV(*p**)**	**CV(*m**)**	**TC(*n*)**	**% related to TC(58)**	**Compensation of *A***
58	0.161	0.170	79.1	100%	1
50	0.173	0.183	79.5	100.5%	0.98
40	0.194	0.201	81.7	103.3%	0.86
30	0.224	0.236	87.0	110%	0.42
20	0.274	0.289	98.9	125%	-1.19

Table 1 The influence of performing less measurements on the uncertainty and the total costs (EUR) with A=1, B=352, p=0.4

Thus when for example only 30 measurements are performed, the total costs of the ship crossings and of the disadvantages of having a larger CV value will raise with 10%.

This may be compensated by using cheaper methods of measurements. When the total costs and B stay the same, A has to decrease (see the last column of Table 1). For 30 measurements the costs of one ship crossing has to be reduced with approximately 60%, and for 20 measurements it is not possible to fully compensate the increase of total costs by reduce the costs of the ship crossings.

In the described example the optimal number of ship crossings was assumed (to be 58) and B was determined. When it is possible to quantify B then the optimal number of ship crossings follows just from B and then the uncertainties can be calculated. Figure 15 shows a sensitivity analysis of the cost parameters. A is kept at a constant value of 1 to determine the influence of B on the optimal number of ship crossings. When accuracy is not important (B=0), no ship crossings are necessary. When accuracy gets more important, the optimal number of ship crossings increases almost linear.

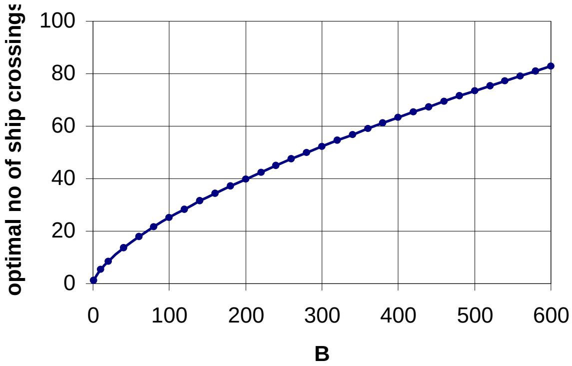


Figure 15 The influence of B on the optimal number of ship crossings. A is kept at a constant value1

When the factor *B* can be assessed in relation to the Øresund case, assuming the same sediment plume behaviour, the number of ship crossings can be optimised for other cases.

CONCLUSIONS

The following conclusions concerning the simplified data of the Øresund Fixed Link project can be made:

1. The inherent uncertainty of turbidity can be described by a Binomial- Exponential distribution function.
2. The exceeding of a certain turbidity level can be tackled with models that are also used in the safety and reliability issues of water defence design.
3. The maximum allowable turbidity can be probabilistically determined as function of the number of ship crossings. For a required reliability and accuracy the number of ship crossings can be determined.
4. The number of ship crossings can be optimised on the basis of the total costs. The total costs consist of the costs of ship crossings and the costs (disadvantages) of having a smaller accuracy of the turbidity probabilistic distribution function. This last factor is assessed in relation to the Øresund case.

Furthermore it is recommended to perform a more detailed data analysis. The data used for the statistical analysis come from turbidity measurements of the Øresund project of one day. To be able to perform the analysis the data were simplified. To investigate if turbidity can be described by a Binomial- Exponential distribution function in general, more analyses with other data have to be performed. The following sorts of data are proposed:

- the raw data of the Øresund project;
- data of another day at the Øresund project of the same dredge
- data of the Øresund project of a different dredge
- data of other projects with different natural conditions, dredges, and soil characteristics.

Finally, to be able to use the results of this study in practice, a quantification of the costs has to be made. An indication for the costs of ship crossings was given in this report but the gains of having a higher accuracy of turbidity distribution functions are more difficult to quantify. In the report this is assumed in relation to the Øresund case. Further investigations into this would be interesting.

Acknowledgements: The authors acknowledge P. van de Kliss of Ballast Nedam Dredging, B. H. Mogensen of Øresundsbrokonsortiet and the Øresundskonsortiet for providing the data of the case study. Further the authors would like to thank prof.ir. H. Ligteringen, prof. M. Donze, ir. M. Geense and ir. G.L.M. van der Schrieck of the University of Technology and ir. G.H. van Raalte of Hydronamic/ Boskalis Westminster for their support.

REFERENCES

Nieuwaal, M., (2001). Requirements for sediment plumes caused by dredging, Master's thesis, TU Delft, December 2001.

Cicero AM, Mecozzi M, Morlino R, Pellegrini D, Veschetti (2001).
Distribution of chlorinated organic pollutants in harbor sediments of livorno (Italy): A multivariate approach to evaluate dredging sediments,
E Environmental Monitoring and Assesment (3): 297-316.

CUR, Civieltechnisch Uitvoerend Centrum Uitvoering Research en Regelgeving (1997), 190 Probabilistics in Civil Engineering, Part 1: Probabilistic Design in theory.

Gotz R, Steiner B, Sievers S, Friesel P, Roch K, Schworer R, Haag F (1998).
Dioxin, dioxin-like PCBs and organotin compounds in the river Elbe and the Hamburg harbour: Identification of sources,
Water Science and Technology 37 (6-7): 207-215.

Øresundskonsortiet (1997). The environment and the Fixed Link across Øresund Øresundskonsortiet, September 1997.

Vrijling, J.K.(1999). Probabilistic design in Hydraulic Engineering, lecture notes wa5310, Delft University of Technology.

Van Gelder, P.H.A.J.M. (1999). Statistical Methods for the Risk-based Design of Civil Structures, Delft University of Technology, 249pp., ISBN 90-9013452-3.