ABSTRACT

The dredging process is characterised by the strong influence of soil properties, which vary with changing excavation locations. For optimising the dredging production and energy consumption, knowledge of these properties is necessary. The problem is that many of these soil properties are not measured or are very difficult to measure. By taking soil samples, a raw indication can be reached, but this does not cover the total dredging area.

Equipment for measuring the properties online are complex and, if available at all, too expensive to use. As a less expensive alternative, estimation methods based on knowledge obtained with the development of training simulators in the last decade were used here. For these training simulators, sophisticated soil models, together with the dredging equipment, are modelled to simulate the dredging process dynamically. By using specific soil parameters, the dredging dynamics can be forecasted accurately.

In this article a novel approach for the dredging industry is presented, one which uses the models in an inverted way: Using the models and the measurement data to estimate the soil type dependent parameters. To obtain this objective, several advanced filters have been successfully implemented and tested in practice. Examples are recursive least squares filtering, linear Kalman filters and more complex techniques such as the extended Kalman filter and the Particle filter. Four estimation examples are described and the advantages of controlling the process control for estimating: 1) the mean grain size of the dredged soil; 2) the overflow losses; 3) the dredging forces; and 4) the anchor positions. The use in practice of the immeasurable will be described as well as future developments.

The author wishes to thank J. Osnabrugge, Engineer R&D and C. de Keizer, Manager R&D, both of IHC Systems for their collaboration on this work. This article appeared in the CEDA Dredging Days Proceedings 2009 and is reprinted here with permission in a slightly adapted version.

INTRODUCTION

The dredging process is characterised by strong nonlinear system behaviour. This behaviour has been extensively studied and modelled (Jufin, 1966; Miedema, 1987; Matoušek, 1997; van Rhee, 2002) mostly with static models and lately also with dynamic models. In general, these models describe the physical behaviour and are parameterised in terms of the geometric properties and the physical properties. Usually, these models are used for predicting the system behaviour assuming that all the necessary soil characteristics are known or measured. Several laboratory or field experiments are available to obtain the parameters such as sieving a sample of sand or performing a penetration test.

For the purpose of control, these models can be used in a completely different manner. Instead of predicting the system behaviour based on complete knowledge of the soil properties, the soil properties are predicted or estimated by measuring the system behaviour (Figure 1).

MODEL-BASED CONTROL DESIGN AND MODEL-BASED CONTROL

The goal here is optimising the dredging performance with the use of control and automation systems onboard dredgers. During the operation of the ship, the type of soil type being dredged is unknown, which makes the use of the models impossible since the soil type parameters are unknown.

Above: Side winches of a CSD. Anchor position estimators were placed on several cutters. The anchor position effects the angles of the side winches which then effects the swing speed and production of the dredger.
After obtaining his M.Sc. degree in Electrical Engineering from Delft University of Technology, the Netherlands in 2003 at the control laboratory, he received his Ph.D. from the same university in 2008. His Ph.D. research was focussed on the model-based optimisation of hopper dredgers. Since September 2007, he has been employed at IHC Systems, where he continues the research on the model-based optimisation of hopper dredgers within the research project called “Smart Dredgers”.

Each year at selected conferences, the International Association of Dredging Companies grants awards for the best papers written by younger authors. In each case the Conference Paper Committee is asked to recommend a prizewinner whose paper makes a significant contribution to understanding important theoretical or practical aspects of dredging and related fields. The purpose of the IADC Award is “to stimulate the promotion of new ideas and encourage younger men and women in the dredging industry”. The winner of an IADC Award receives € 1000 and a certificate of recognition and the paper may then be published in Terra et Aqua.

IADC AWARD 2009 PRESENTED AT CEDA DREDGING DAYS, ROTTERDAM, THE NETHERLANDS NOVEMBER 4-6 2009

An IADC Best Paper Award was presented at CEDA Dredging Days 2009 in Rotterdam to Jelmer Braaksma. After obtaining his M.Sc. degree in Electrical Engineering from the Delft University of Technology, the Netherlands in 2003 at the control laboratory, he received his Ph.D. from the same university in 2008. His Ph.D. research was focussed on the model-based optimisation of hopper dredgers. Since September 2007, he has been employed at IHC Systems, where he continues the research on the model-based optimisation of hopper dredgers within the research project called “Smart Dredgers”.

Why are models needed for controlling the dredgers?

• Nonlinear system behaviour. Owing to the strong nonlinear system behaviour of the dredging process, the standard linear controllers such as a PID-controller do not give the desired performance. The design of advanced control techniques often relies on dynamic models. A common approach is model-based control design where the model is used for deriving the controller. Models can also be part of the controller (model-based control), which is the case in adaptive control.

• Virtual sensors. The dredging process is a hostile environment for sensitive equipment such as sensors. The normal off-the-shelf sensors must be “ruggedised” which makes them expensive. Also some physical properties are very hard to measure reliably. Therefore whenever possible estimating the variable instead of measuring it is desirable. This requires an accurate model of the process.

• Process optimisation. The ultimate goal for a dredger is maximising the profit while respecting the constraints of the equipment and environment. The system behaviour can be predicted with the use of models. In this way the optimal control strategy can be found by calculating the effect of many possible strategies. This so-called Model Predictive Control (MPC) technique maximises the performance of the dredger (Braaksma, 2008).

• Decision support. A decision support system can help the operator maximising the performance by using models (see previous bullet). Furthermore, estimation of the soil parameters such as the grain diameter can be used for the development of advanced wear models of the pumps, pipes and valves. These wear models may be used for lifetime prediction on behalf of preventive/scheduled maintenance.

Most of these models need soil parameters for accurate prediction of the process. Therefore in order to use them online, these parameters must be estimated online. This article presents a selection of estimation techniques that are implemented in IHC automation systems or techniques that will be implemented in the future dredging automation equipment.

OVERFLOW LOSS ESTIMATOR

Overflow losses play an important role in the dredging process of a trailing suction hopper dredger (TSHD). The losses have a negative influence on the dredging performance, therefore an operator must constantly monitor whether the losses are not becoming too large. Stricter environmental legislations require that the overflow losses must be limited especially in areas of fragile ecosystems. On the other end of the spectrum is agitation dredging where the overflow losses are kept intentionally high to discharge the fine-grained fraction which can then be transported and permanently deposited outside the channel by tidal, river or littoral currents.

Measuring the density and the mixture velocity in or near the overflow weir is a technical challenge. The turbulent mixture flow encapsulates air bubbles that distort the measurement. Moreover, placing sensors in the hostile environment near the overflow requires much maintenance and a rugged housing. Since the density is usually measured with a radioactive measurements device, this requires qualified and skilled personnel and sufficient precautions to avoid accidents.

To overcome these difficulties, an estimator for the overflow losses was developed which only requires sensors already available on every modern hopper dredger. The method is a model-based approach based on only the balance equations. In the hopper a mixture
with density $\rho_i$ and flow-rate $Q_i$ is discharged. This fills the hopper until the mixture level reaches the height of the overflow weir. Then, a mixture of sand and water flows out of the hopper through the overflow weir with density $\rho_o$ and flow-rate $Q_o$. This is described with the following balance equations:

$$V_t = Q_t - Q_o$$

$$m_t = \rho_o Q_t - \rho_s Q_o$$

where $V_t$ is the mixture volume and $m_t$ is the total mass of sand and water in the hopper. Modern TSHD are equipped with draught sensors which are used to calculate the incoming density $\rho_i$ and level sensors in the hopper to calculate $V_t$. Furthermore, a sensor is available for measuring the flow-rate $Q_i$ and $Q_o$.

### The Estimation Problem

The estimation problem is to estimate the outgoing density and the outgoing flow-rate. For that equation 1 was discretised by using the Euler method:

$$V_{t,k+1} = V_{t,k} + Ts\left(Q_{i,k} - Q_{o,k}\right)$$

$$m_{t,k+1} = m_{t,k} + Ts\left(\rho_i Q_{i,k} - \rho_s Q_{o,k}\right),$$

where $Ts$ is the sampling period. These state equations are augmented with a random walk model for $\rho_o$ and $Q_o$. Assuming the most general state-space model:

$$x_{t,k+1} = f(x_{t,k}, u_{t,k}, \xi_{t,k})$$

$$y_{t,k} = h(x_{t,k})$$

and defining the augmented state, input and output vector:

$$x = \begin{pmatrix} V_t \\ m_t \\ Q_o \\ \rho_o \end{pmatrix}, \quad u = \begin{pmatrix} Q_t \\ \rho_i \end{pmatrix}, \quad y = \begin{pmatrix} V_t \\ m_t \end{pmatrix}$$

the complete nonlinear state-space representation becomes:

$$\begin{pmatrix} x_{t,k+1} \\ x_{t,k+1} \\ x_{t,k+1} \\ x_{t,k+1} \end{pmatrix} = \begin{pmatrix} \cdot \\ \cdot \\ \cdot \end{pmatrix} + \begin{pmatrix} \cdot \\ \cdot \\ \cdot \end{pmatrix} + \begin{pmatrix} \cdot \\ \cdot \\ \cdot \end{pmatrix}$$

This estimation problem is nonlinear, therefore nonlinear estimation techniques such as the Extended Kalman Filter (EKF), Uncented Kalman Filter (UKF) or a Particle Filter (PF) must be applied (see Welch, G. and Bishop, G., 2002 for a general introduction into Kalman Filters and Arulampalam et al., 2002 for a tutorial on the PF). It was found that an EKF or an UKF cannot simultaneously estimate $\rho_o$ and $Q_o$, while an EKF for the incoming density $\rho_i$ can be used (see Babuška et al., 2006). Therefore a PF is used to solve the estimation problem (see Babuška et al., 2006).

This algorithm is implemented in the Draught and Loading Monitor (DLM) software for online estimation of the overflow losses used here.

With the two estimations, the so-called “load efficiency” is calculated as follows:

$$\text{Load eff} = \left(1 - \frac{m_o}{m_i}\right) \cdot 100 \text{ [%]}$$

where $m_o = \frac{\rho_o - \rho_w}{\rho_s - \rho_w} Q_o \rho_q$ and $m_i = \frac{\rho_i - \rho_w}{\rho_s - \rho_w} Q_i \rho_q$.

### Measurement Results

The algorithm is first tested on a simulation model and tested with measured data. These results can be found in Babuška et al. (2006) and Lendek et al. (2008). This section shows the results of the filter working online on board a medium-sized hopper dredger during her first sea trials.

The dregging cycle shown in these figures consists of three phases: no overflow phase, constant volume phase and constant tonnage phase. In the first phase, nothing is flowing overboard and thus the outgoing flow-rate is zero. In the second phase material starts flowing overboard. During this phase the mixture volume in the hopper remains constant and thus on average the outgoing flow-rate equals the incoming as can be seen in Figure 2. Finally, in the third (constant tonnage) phase the overflow is lowered to maintain the maximum draught. In this phase the outgoing flow-rate becomes larger than the incoming flow-rate as the total mixture volume in the hopper decreases.

The soil type in the dredging area is medium/ coarse sand, therefore the overflow losses are small. Figure 2 shows that in the beginning the outgoing density is approximately 1080 kg/m³. The sand bed reaches the overflow height at the end of the dregging cycle. As a consequence the overflow density increases. When these losses become too large it is not economical to continue and the dredger should sail to the discharge area.

### NOMENCLATURE

- $C$ transportation coefficient
- $d$ discharge-pipeline diameter
- $d_s$ mean-grain diameter
- $e$ error
- $f$ state transition function
- $g$ gravity acceleration
- $h$ measurement function
- $H_{sp}$ discharge pressure
- $k$ discrete time step
- $L$ discharge-pipeline length
- $l_{ps}$ measured length port side winch
- $L_s$ measured length starboard side winch
- $m$ total mass of sand and water in hopper
- $m_t$ total mass of sand and water in hopper
- $p$ atmospheric pressure
- $Q$ flow in the discharge-pipeline
- $Q_i$ incoming flow in hopper
- $Q_f$ outgoing flow through overflow weir
- $R_{ps}$ starboard side winch radius
- $R_{ps}$ starboard side winch radius
- $S$ discharge-pipeline section
- $T$ sample time
- $v$ speed in the discharge-pipeline
- $v_f$ critical speed in the discharge-pipeline
- $V$ total volume of sand and water in hopper
- $V_t$ state
- $X$ number of segments
- $x$ output
- $\alpha$ weighting factor
- $\alpha_{ps}$ angle of port side winch
- $\alpha_{sb}$ angle of starboard side winch
- $\Delta H_{het}$ heterogeneous pressure losses
- $\Delta H_{hom}$ homogeneous pressure losses
- $\Delta H_{losses}$ losses in the discharge-pipeline for water
- $\epsilon$ process noise
- $\epsilon_v$ measurement noise
- $\lambda$ friction coefficient
- $\rho$ mean-density in the discharge-pipeline
- $\rho_s$ mean-grain density
- $\rho_i$ incoming density of mixture in hopper
- $\rho_o$ outgoing density through overflow weir
- $\rho_{w}$ water density
- $\psi$ swing angle
- $\psi_{sw}$ swing angle
TRAIL FORCE ESTIMATION IN DP/DT AND THE TRAIL SPEED CONTROLLER

The dredging forces during the trailing of TSHD are caused mainly by the cutting force of the draghead. This cutting theory has been studied by Miedema (1987). The cutting force depends on the soil type, permeability and dredging depth. These parameters are not exactly known during the dredging process. Moreover, these properties vary from place to place. For a dynamic positioning and dynamic track controlling system knowing the dredging forces is of vital importance, therefore estimation techniques were utilised to accomplish this.

Smart Draghead-Pull-Sensor in Dynamic Positioning and Dynamic Tracking

During dredging, it is of major importance to keep your track and maintain the optimal dredging speed. The force caused by the draghead such as the cutting force pulls on the side of the ship. This dredging force may become so large that 100% of the available propulsion power is necessary whereas only 5 to 10% is required for maintaining a ship speed of 2 to 3 knots without dredging. Dredging can lead to an increase of power up to 10 times.

An accurate Dynamic Positioning and Dynamic Tracking (DpDt) system requires measuring the dredging forces that act upon the dredging pipe and draghead. This measurement is then used in the DpDt system to immediately compensate these forces by adjusting the actuating propellers, rudders and bow-thrusters, before the track deviation or speed deviation is even measured. This improves the tracking performance significantly.

Unfortunately, the dredging forces are difficult to measure. Usually these are measured in the two pins of the upper hinge of the suction tube (Figure 3). This is not the actual pulling force as the figure shows. Calculating this involves many compensations, e.g., for the weight of the suction pipe, the mass of the dredged mixture, tension in the hoisting wires and so on. These compensations make the calculation prone to sensor errors and sensor inaccuracy. Calibrating the sensors regularly helps prevent inaccuracy, but reliability is still an issue. As a consequence of dredging in a hostile environment, the expensive force sensors need to be replaced regularly.

Current and Draghead Force Estimation

The reliability issue was solved by combining advanced techniques such as model-based estimation, filtering and adaptation to the changing dredging forces. An extended Kalman filter (EKF) is used, which uses an accurate model of the dynamics of ship and the disturbances such as wind and current. Internally the estimates of the position, speed and heading are compared with the measurements. The error is used to adapt the estimates for the current and the dredging forces. The patented adaptation algorithm makes a distinction between calibration errors and the disturbance forces such as the current and dredging forces. This distinction can be made because of the prior knowledge that dredging forces vary rapidly and current forces vary slowly. High accuracy is guaranteed as is shown in (IHC Systems, 1996).

New Measurement Principle

Although the previous section described how the reliability issue was solved, the force estimation still relies on the measurement pins that are vulnerable and need to be changed regularly. This has been solved by a measurement principle that uses the differential pressure over the draghead (IHC Systems, 1997). Figure 4 shows a comparison between the differential pressure over the draghead (thin solid line) and the dredge force (dotted line).
At first glance the signals look similar, however, careful investigation shows that the relationship varies as a result of varying soil type, the use of jet water, pumping speed and sharpness of the draghead teeth and so on. Fortunately the EKF described in the section above on “Current and Draghead Force Estimation” is robust enough to cope with the inaccuracy of using the pressure difference. Sea trials did not show any noticeable performance degradation. And even if there were any differences, the increase in reliability, because of the absence of the measurement pins, favours the new approach.

**Force Estimation in the Trail Speed Controller**

The trail speed controller (TSC) is used to maintain a constant trail speed during dredging. Therefore, the ship navigator only needs to focus on navigating and monitoring the dredging process. This is especially the case on board ships with a one-person bridge. The second advantage is that the excavation height will be constant for a constant production-rate.

The control problem for the TSC is much simpler than that of DpDt, because the TSC controls only the longitudinal speed. Therefore only the propeller pitches are actuated. Figure 5 shows a schematic overview of the control implementation. The controller structure is a classical combination of feedback and feedforward. The estimation of the “Dredge force” is comparable with the method of the section “Smart Draghead-Pull-Sensor in Dynamic Positioning and Dynamic Tracking”.

Figure 6 shows the measurement results of a TSHD during sea trials. The lefthand figure shows the tracking performance of the TSC and the righthand figure shows the dredge force estimation. When the draghead is lifted from the seabed, the estimation freezes which can be seen in the figure.

**GRAIN SIZE ESTIMATOR**

An important soil property for the dredging process, and in particular for the hydraulic transport process, is the mean grain diameter $d_m$ of the dredged material. The behaviour of the dredge pumps and pipes are significantly influenced by the grain diameter. If the grain diameter is known, the production of the discharge process can for example be optimised (Braaksma, 2007, part 2). Furthermore the grain diameter can be used for the development of advanced wear models of the pumps, pipes and valves. These wear models may be used for lifetime prediction on behalf of preventive/scheduled maintenance and also for improving the design of pumps and pipes.

This section describes how to estimate the mean grain diameter online by means of a simple model of the discharge process. In this model, a nonlinear behaviour is introduced by the pressure-losses in the pipelines. Such losses can be thought as a linear combination of homogeneous and heterogeneous losses, by means of a weighting factor $\alpha$, which takes values in the range $[0,1]$.

Both homogeneous and heterogeneous losses can be conveniently expressed as a function of the losses due to pure water flowing into the pipeline by using a proper correction factor. For homogeneous losses, such a factor depends on the mixture density $\rho$ whereas, for heterogeneous losses, it depends on the critical speed $v_c$ according to the formula of Jufin-Lopatin (Jufin, A. P. and Lopatin, N. A., 1966)

$$\Delta H_w = 0.5 \frac{L}{X_D} \rho_w v^2$$

The evolution in time of the flow in the discharge-pipeline can be described by the second-law of dynamics as

$$\dot{Q} = \frac{S}{\rho L} (H_{exc} - \Delta H_t - P_c)$$

The pressure-losses in the discharge-pipeline can be reasonably expressed as a weighted average of homogeneous losses $\Delta H_{hom}$ and heterogeneous losses $\Delta H_{het}$, by means of a weighting factor $\alpha$, which takes values in the range $[0,1]$.

$$\Delta H_t = \alpha \Delta H_{hom} + (1-\alpha) \Delta H_{het}$$

The tests, carried out onboard several cutter suction dredgers (CSD), have proven the effectiveness of the proposed estimation scheme.

**The Estimation Problem**

A simplified model of the discharge process in the pipeline is given by the following equations:

The pressure-losses in the discharge-pipeline can be reasonably expressed as a weighted average of $\Delta H_{hom}$ and $\Delta H_{het}$, by means of a weighting factor $\alpha$, which takes values in the range $[0,1]$.

$$\Delta H_t = \alpha \Delta H_{hom} + (1-\alpha) \Delta H_{het}$$

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$$\Delta H_{het} = \left[1 + 2 \left(\frac{\rho}{\rho_w} \right)^2 \right] \Delta H_w$$

Figure 5. Schematic overview of the Trail Speed Controller.

Figure 6. Measurement results of the Trail Speed Controller. Left: tracking performance, right: dredge force estimation.
The \textit{critical speed} is given by
\[ v_c = \sqrt{\frac{1}{Z} \cdot C_t \cdot 33000 \cdot (g \cdot d)^2 \cdot \frac{d_m}{d}} \]
where \( C_t \) is the \textit{transportation coefficient} and is defined as
\[ C_t = \frac{\rho - \rho_w}{\rho - \rho_m} \]

From the previous equations, a continuous-time state-space representation of the discharge process can be determined, if the following positions are made:
\[ x_1 = Q \]
\[ x_2 = d_m \]
\[ z = x_1 = Q \]
\[ u_1 = H_{\text{dis}} - \rho_m \]
\[ u_2 = \rho - \rho_m \]
\[ x_3 = \alpha \]

It can be noticed that the state vector of the system (first-order dynamics in this case) has been extended, by including the unknown parameters in the system model. The continuous-time state-space representation must be discretised, in order to design a proper estimation scheme. The discrete-time state-space model can be written in the general form:
\[ x_i(k+1) = f_i(x(k), u(k), w_i(k)) \]
\[ x_2(k+1) = f_2(x(k), u(k), w_2(k)) \]
\[ x_3(k+1) = f_3(x(k), u(k), w_3(k)) \]
\[ z(k) = h(x(k), v(k)) \]

Given a process that can be described by a linear stochastic discrete-time model, the Kalman filter represents the optimal recursive solution to the discrete-data linear filtering problem. In other words, the Kalman filter provides an optimal estimate of the state of the system, given the measurements of the input and output signals. The filter estimate is optimal in the sense that it minimises the estimate error covariance.

Since the model of the process is nonlinear in the state and input variables, the design of a Kalman filter, for the estimation of the state, cannot be directly accomplished. As a preliminary step, it is necessary to linearise such a model around the most recent state estimate. Then, the filter can be designed with respect to the linearised system. This design procedure is known as “Extended Kalman Filter”. Compared to other estimation schemes, the Kalman filter has several advantages: (1) it is computationally efficient because of its recursive formulation; (2) it has a simple and intuitive structure in the form of a predictor-corrector; and (3) it directly takes into account model uncertainties and noise.

In the model of the discharge-pipeline being used here, the mean density in the discharge pipeline has been considered as input. However, the mean density in the pipeline cannot be directly measured, but only the density injected at the beginning of the discharge pipeline. The problem is, then, how to determine the mean density in the pipeline, given the density of the mixture which enters the discharge pipeline. In such a calculation, the phenomenon of density propagation along the discharge-pipeline must be taken into account, because, for the typical lengths of the pipelines (several km) and the typical speeds of the flow (4-7 m/s), the corresponding time-constants are not negligible.

The propagation can be taken into account in different ways (first-order filter, second-order delay-model with three time-constants, “finite-element-like” approach). The simulations and experimental results suggest that the effectiveness of the proposed approach based on Kalman filtering is, to a certain extent, independent from the model used for the density propagation.

**Experimental Results**

The experimental data have been recorded during a dredging session on the CSD \textit{Rubens}, while working in the Deurganckdok (nearby Doel, Belgium). The pipeline is made up of three segments with the following lengths and diameters:

- Segment I (SB pump to driver):
  \[ L_1 = 100 \text{ m} \quad d_1 = 850 \text{ mm} \]
- Segment II (driver):
  \[ L_2 = 660 \text{ m} \quad d_2 = 850 \text{ mm} \]
- Segment III (pipeline on land):
  \[ L_3 = 7060 \text{ m} \quad d_3 = 900 \text{ mm} \]

For the dredged soil a mean diameter of about 285 \( \mu \text{m} \) has been measured. Since for this data-set, the measurements of the losses were not provided, when pumping only water into the pipeline, the value \( \lambda = 0.01045 \) was assumed for the friction coefficient.

In Figure 7, the recorded tracks of the discharge pressure \( H_{\text{dis}} \), the flow \( Q \), and the density injected into the pipeline \( \rho_m \) are reported. These quantities represent the measured signals used by the Kalman filter for the estimation of the mean-grain-diameter.

Here the evolution in time of the estimate of the mean-grain-diameter (and the corresponding estimation error), as provided by the extended Kalman filter, are reported. From Figure 8, one can see that the estimate nicely converges to a boundary region around the measured value of the grain diameter. Also note that the convergence is quite slow, but this is something that cannot be avoided, since it is owing to the slow dynamics of the discharge pipeline itself (this was also evident from the simulation results). Of course, with a different tuning of
the user-defined parameters of the Kalman filter (covariance matrices), the convergence properties of the filter can be affected, but they cannot be changed dramatically.

One can better see from Table I, what is also suggested by Figure 8: the extended Kalman filter is able to achieve a good accuracy (the results are comparable to those achieved in simulations).

Subsequently, the Kalman filter was also run without down-sampling the data (Ts = 5 s), and with a different tuning for the covariance matrix of the measurements (a higher value has been used, in order to have a smooth estimate). It can be seen from Figure 9, that the estimate converges very close to the real mean grain diameter, also with this different setting. This is also confirmed by the relative error (Table II).

Comparing Figure 8 and Figure 9, it is clear that the overshoot is definitely less pronounced in the second case.

For the available experimental data, it has been found that the estimated value of the weighting factor \( \alpha \) is very small (as also was found in simulation). As a consequence, a simplified model, considering only the heterogeneous losses can be conveniently used. However, it is likely that, under different experimental conditions (different grain diameters), the model based on both homogeneous and heterogeneous losses will outperform the simplified model based only on heterogeneous losses.

For the considered experimental data the performance of the extended Kalman filter was satisfactorily. Regarding the performance the following remarks are important:

- The pipeline layout (pipe lengths and diameters, geometric height difference) should be well known.
- The accuracy of the estimated friction coefficient is a critical factor, since it deeply influences the outcome of the mean grain diameter estimation. Moreover, during dredging generally it is not common to pump water into the discharge-pipeline, if not at the end of the dredging session, when it is needed for cleaning the pipeline. This obviously limits the availability of data for the estimation of the friction coefficient.
- The used equations are only valid for sand with a maximum grain size of 2 or 3 mm. For other soil types or grain sizes the estimated grain diameter will not be reliable anymore.
- Furthermore, the used equations are only valid if no or less sedimentation is present in de pipeline. A significant amount of sedimentation in the pipeline will result in a higher estimated grain diameter.

**ANCHOR POSITION ESTIMATOR**

Regarding the dredge process of a CSD the anchor positions are of great importance. If the anchors lie too far backwards of the dredger the angles of the side winches will be unfavourable and the effective side winch force will be limiting the swing speed (i.e., the production). Especially at the end of the swing the CSD can get stuck due to the worse angle of the hauling side winch.

<table>
<thead>
<tr>
<th>Table I. The real mean diameter [( \mu m )], the estimated mean diameter [( \mu m )] and the relative percentile error [%] averaged over the last 10 samples (=500s).</th>
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<tbody>
<tr>
<td>Real mean diameter [( \mu m )]</td>
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<td>285</td>
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</table>

<table>
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<tr>
<th>Table II. The real mean diameter [( \mu m )], the estimated mean diameter [( \mu m )] and the relative percentile error [%] averaged over the last 100 samples (=500s).</th>
</tr>
</thead>
<tbody>
<tr>
<td>Real mean diameter [( \mu m )]</td>
</tr>
<tr>
<td>285</td>
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</table>

Figure 8. Measured value of the mean grain diameter (continuous constant value) and the estimated mean diameter (continuous lines with dots), and the corresponding estimation error for Ts = 5 s.

Figure 9. Measured value of the mean grain diameter (continuous constant value) and the estimated mean diameter (continuous lines with dots), and the corresponding estimation error for Ts = 5 s.
Furthermore, when the local ground condition at the seabed around the anchor is poor, the anchor can not get enough grip and will move during the swing movement of the dredger (i.e. dragging of the anchor). It is important the dredge master quickly notices this dragging.

In this section the online estimation of the anchor positions is discussed. The anchor position estimator is implemented and in use onboard several CSDs. The estimator gives an advice to the dredge master when to reposition the anchors and also detects dragging of the anchors. Figure 10 shows a top view of a CSD with the estimated anchor positions as presented to the dredge master.

The anchor position estimator computes the position of the anchors in a polar coordinates system, with the main spud as origin, and the angular position evaluated with respect to the centre line (Figure 11). The choice of such a reference system can be convenient, since the swinging motion can be naturally described with the same polar coordinates.

The computations are based on a batch algorithm which tries to minimise the mean square error (MSE) between the measured $L_i$ and estimated $\hat{L}_i$, length of the side winches, over a prescribed number of samples $N_s$ as defined by the size of the batch.

$$MSE = \frac{1}{N_s} \sum_{i=1}^{N_s} (L_i - \hat{L}_i)^2$$

The estimated wire length calculation is based on the following geometric relations:

$$\hat{L}_i = \sqrt{R_i^2 + R_f^2 - 2R_iR_f \cos(\gamma_i + \psi)}$$

where $i = sb, ps$ and $R_i$, $\gamma_i$ are the polar coordinates of the considered anchor, $R_f$ is the swing radius (distance between the main spud and the wire sheaves on the ladder) and $\psi$ is the swing angle.

The minimisation algorithm has been implemented in an approximated form. At each time step, first, a regular grid of points around the current estimate of the anchor position is determined. The grid shape may be circular or square. Next, the mean square error is evaluated for each point of the grid, and the point with the lowest error provides the new estimate for the anchor position (Figure 12).

The knowledge of the anchor positions can be used not only for detecting possible dragging of the anchors, but also for the calculation of the side winch angles $\alpha_{sb}$ and $\alpha_{ps}$. The side winch angles are used for the calculation of the effective side winch forces and for the calculation of the forces acting on the main spud due to the side winches.
FUTURE DEVELOPMENTS

In order to make dredging even more efficient there is still the need for more advanced estimators and accompanying process models. Some of these estimators will only be a small part of an advanced control strategy. Others will be used as decision support to the dredge master. Some examples of ongoing research topics in this area are:

- Estimating the pressure drop over the draghead and jet penetration depth to optimise excavation process.
- Estimating pump wear and predicting the moment for replacement of the impellor.
- Estimating the grain size based on the pump behaviour. The present grain size estimator is based on the discharge pipeline and as a result the estimated grain size is an average of the total pipeline. By also using the pump behaviour the grain size estimate will be updated faster.
- Estimating the settling velocity of particles in the hopper and sand bed height.

REFERENCES


CONCLUSIONS

Modelling the dredging process made it possible to develop advanced control algorithms that optimise the dredging efficiency. Most of these models contain parameters that depend on the soil properties. None of the advanced control algorithms would have been implemented without the use of the estimation techniques described here.

An overflow loss estimator based on a particle filter has been developed and implemented in the latest releases of the Draught and Loading Monitor (DLM) software. This estimator can support the operators in decision-making as to when to stop dredging and can give warning in case of excessive losses. It can also be used for agitation dredging where the goal is to increase the overflow losses.

The tracking and positioning performance for the DpDt system has been improved by an extended Kalman filter (EKF). Moreover the reliability is increased by exchanging the force sensor pins in the upper hinge by a virtual dredge force sensor based on the pressure difference over the draghead. This has also been implemented in the newly developed trail speed controller.

For the discharge process, a simple nonlinear dynamical model in the pipeline of a cutter suction dredger has been described. Based on this model, a recursive estimator (extended Kalman filter) has been designed for the estimation of the unknown parameters in the models, namely, the weighting factor α and the grain diameter dm. The experimental results prove the feasibility and the effectiveness of the proposed estimation scheme.

Finally this article presents an anchor position estimator which has been successfully implemented onboard several cutter suction dredgers. This system can give an early warning to the operators when the anchor is dragging over the seabed.


