ESTIMATING THE IMMEASURABLE: SOIL PROPERTIES

J. Braaksma[1], J. Osnabrugge[2] and C. de Keizer[3]

Abstract: The dredging process is characterized by the strong influence of soil properties, which vary with changing excavation locations. For optimizing the dredging production and energy consumption, it is necessary to know these properties. The problem is that a lot of these soil properties are not measured or very difficult to measure. By taking soil samples, it is possible to give a raw indication, but this does not cover the total dredging area.

Equipment for measuring the properties on-line are complex and, if available at all, too expensive to use. As an alternative, we use estimation methods. These estimation methods are based on knowledge obtained with the development of training simulators in the last decade. 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, it is possible to forecast the dredging dynamics accurately.

In this paper we present a, for the dredging industry, novel approach which uses the models in an inversed 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. In this paper four estimation examples will be described and the advantage for controlling the process control such as:

- estimating the mean grain size of the dredged soil
- estimating the overflow losses
- estimating the dredging forces
- estimating the anchor positions

The use in practice of the immeasurable will be described as well as future developments.

Keywords: Extended Kalman Filter, Particle Filter, Overflow Losses, Anchor Position, Dynamic Positioning and Dynamic Tracking, Trail Speed Control

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1 INTRODUCTION

The dredging process is characterized 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 parameterized 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 complete different manner. Instead of predicting the system behaviour based on complete knowledge of the soil properties, the soil properties are predicted/estimated by measuring the system behaviour, see figure 1.

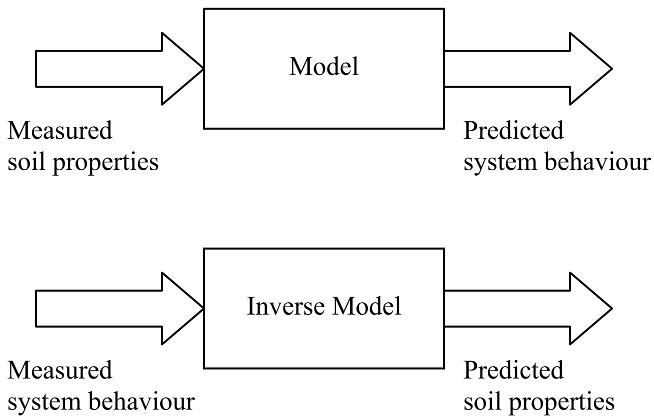

Figure 1. Two different applications of the same model. Top: predicting the system behaviour based on measured soil properties. Bottom: the model is uses inversely for predicting the soil properties based on the measured system behaviour.

Model-Based Control Design and Model-Based Control
Our goal is optimizing the dredging performance with the use of control and automation systems onboard of dredgers. During the operation of the ship, it is unknown which soil type is being dredged. This makes the use of the models impossible since the soil type parameters are unknown.
Why do we need models for controlling the dredgers?

- **Nonlinear system behaviour.** Due 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 rely 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 of-the-shelf sensors must be ruggedized which make them expensive. Also some physical properties are very hard to measure reliably. Therefore when possible it is desirable to estimate the variable instead of measuring it. This requires an accurate model of the process.
- **Process optimization.** The ultimate goal for a dredger is maximizing the profit while respecting the constraints of the equipment and environment. The system behaviour can be predicted with the use of models. This enables us to find the optimal control strategy by calculating the effect of many possible strategies. This so-called Model Predictive Control (MPC) technique maximizes the performance of the dredger, see Braaksma (2008).
- **Decision support.** A decision support system can help the operator maximizing 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 life time prediction in 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 we need to estimate these parameters online. This paper presents a selection of estimation techniques that are implemented in our automation systems or techniques that will be implemented in the future dredging automation equipment.

2 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 if the losses do not become 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, we developed an estimator for the overflow losses 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 ρ_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 ρ_o and flow-rate Q_o. This is described with the following balance equations:

$$\begin{aligned} \dot{V}_t &= Q_i - Q_o \\ \dot{m}_t &= \rho_i Q_i - \rho_o Q_o \,, \end{aligned} \tag{1}$$

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 m_t and level sensors in the hopper to calculate V_t. Furthermore, a sensor is available for measuring the incoming density ρ_i and a sensor for measuring the flow-rate Q_i. This means that in equation 1 only ρ_o and flow-rate Q_o are unknown.

2.1 The Estimation Problem

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

$$\begin{aligned} V_{t,k+1} &= V_{t,k} + T_s(Q_{i,k} - Q_{o,k}) \\ m_{t,k+1} &= m_{t,k} + T_s(\rho_{i,k} Q_{i,k} - \rho_{o,k} Q_{o,k}) \,, \end{aligned} \tag{2}$$

where T_s is the sampling period. These state equations are augmented with a random walk model for ρ_o and Q_o. We assume the most general state-space model:

$$\begin{aligned} x_{k+1} &= f(x_k, u_k, \varepsilon_k) \\ y_k &= h(x_k, \varepsilon_{yk}) \end{aligned}$$

and define the augmented state, input and output vector:

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

The complete nonlinear state-space representation becomes:

$$\begin{pmatrix} x_{1,k+1} \\ x_{2,k+1} \\ x_{3,k+1} \\ x_{4,k+1} \end{pmatrix} = \begin{pmatrix} x_{1,k} + T_s(u_{1,k} - x_{3,k}) + \varepsilon_{x1,k} \\ x_{2,k} + T_s(u_{1,k}u_{2,k} - x_{3,k}x_{4,k}) + \varepsilon_{x2,k} \\ x_{3,k} + \varepsilon_{x3,k} \\ x_{4,k} + \varepsilon_{x4,k} \end{pmatrix}, \quad u = \begin{pmatrix} Q_i \\ \rho_i \end{pmatrix}, \quad y = \begin{pmatrix} V_t \\ m_t \end{pmatrix}.$$

This estimation problem is nonlinear, therefore we need to apply nonlinear estimation techniques such as the Extended Kalman Filter (EKF), Uncented Kalman Filter (UKF) or a Particle Filter (PF), see Welch, G. & 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 ρ_o and Q_o see Babuška et al. (2006) and Lendek et al. (2008). Therefore a PF is used to solve the estimation problem, see Babuška et al. (2006). This algorithm is implemented in our Draught and Loading Monitor (DLM) software for online estimation of the overflow losses.
With the two estimations, the so-called `load efficiency' is calculated as follows:

$$Loadeff = \left(1 - \frac{m_0}{m_i}\right) \cdot 100 \quad [\%]$$

with

$$m_0 = \frac{\rho_0 - \rho_w}{\rho_q - \rho_w} Q_o \rho_q \text{ and } m_i = \frac{\rho_i - \rho_w}{\rho_q - \rho_w} Q_i \rho_q ,$$

where ρ_w is the density of water and ρ_q is the density of sand (quartz). This load efficiency indicates to the operator which percentage of incoming sand flows overboard. This enables the operator to monitor the instantaneous hopper load efficiency.

2.2 Measurement Results

The algorithm is firstly 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 of the medium sized hopper dredger during its first sea-trials.
The dredging cycle which is 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. Then, 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 you can see 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.

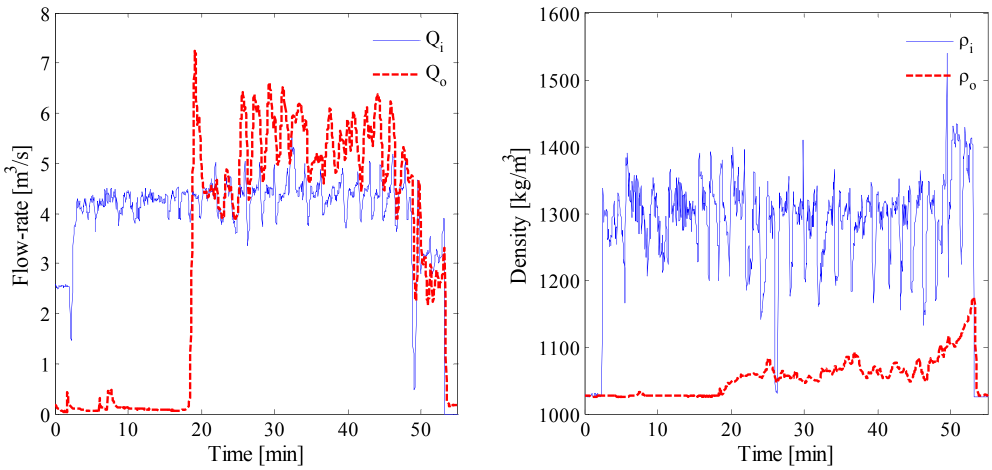

Figure 2. Results of the overflow loss estimator during the sea-trials of a recently built hopper dredger. Left: the incoming and the estimated outgoing flow-rate. Right: the incoming and the estimated outgoing density.

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/m^3. The sand bed reaches the overflow height at the end of the dredging 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.

3 TRAIL FORCE ESTIMATION IN DP/DT AND THE TRAIL SPEED CONTROLLER

The dredging forces during the trailing of TSHD are mainly caused by the cutting force of the drag head. 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 it is of vital importance to know the dredging forces, therefore we use estimation techniques to accomplish this.

3.1 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 drag head 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 drag head. 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.

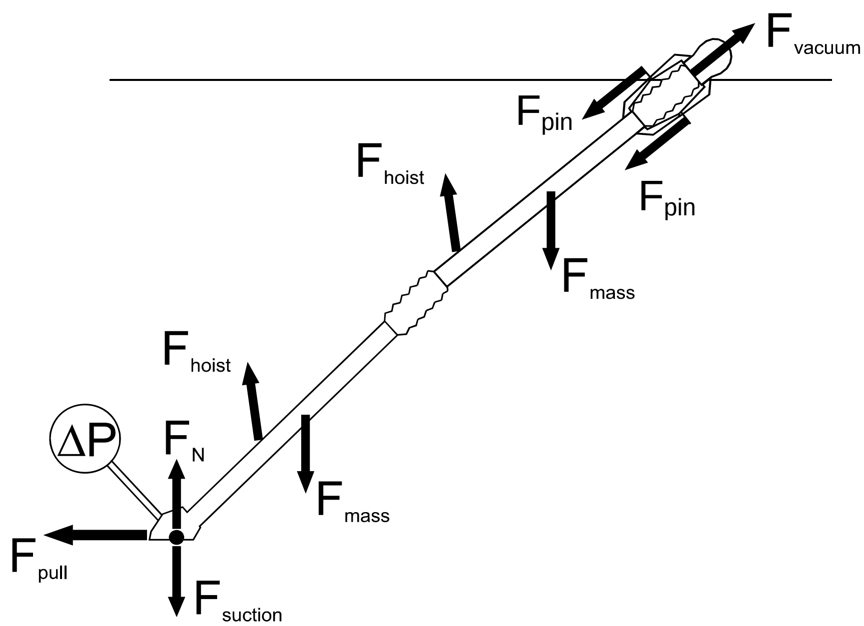

Figure 3. Forces acting on suction tube.

Unfortunately, the dredging forces are difficult to measure. Usually these are measured in the two pins of the upper hinge of the suction tube, see 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 etc.
These compensations make the calculation prone to sensor errors and sensor inaccuracy. Calibrating the sensors regularly helps preventing 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.

3.1.1 Current and Drag Head Force Estimation

We solved the reliability issue by combining advanced techniques such as model based estimation, filtering and adaptation to the changing dredging forces. An extended Kalman filter 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. The distinction can be made because we use the prior knowledge that dredging forces vary rapidly and current forces vary slowly. High accuracy is guaranteed as is shown in (IHC Systems, 1996).

3.1.2 New Measurement Principle

Although the previous section described how we solved the reliability issue, 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 drag head (IHC Systems, 1997). Figure 4 shows a comparison between the differential pressure over the drag head (thin solid line) and the dredge force (dotted line).

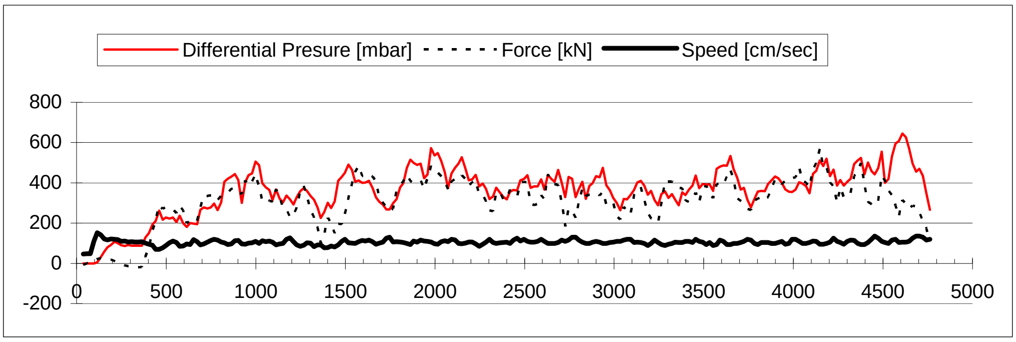

Figure 4. Relation between differential pressure and dredge head pull (time-scale = 5000 sec.).

At first glance the signals look similar, however, careful investigation shows that the relationship varies due to a varying soil type, the use of jet water, pumping speed and sharpness of the drag head teeth etc.
Fortunately the EKF of section 3.1.1 is robust enough to cope with the inaccuracy of using the pressure difference. Sea trials didn't show any noticeable performance degradation. And even if there were any differences, the increase in reliability, due to the absence of the measurement pins, favours the new approach.

3.2 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 of ships with a one-man-bridge. The second advantage is that the excavation height will be constant for a constant production-rate.

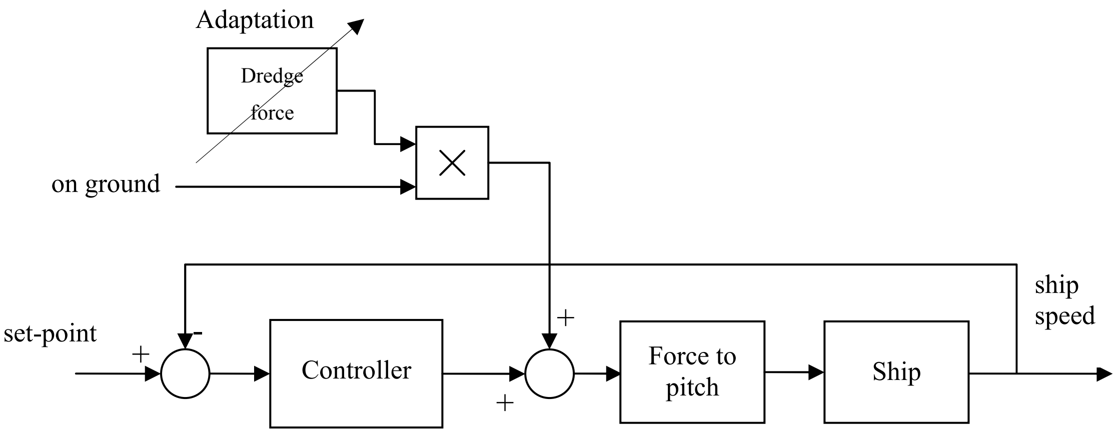

Figure 5. Schematic overview of the Trail Speed Controller.

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 feed-forward. The estimation of the "Dredge force" is comparable with the method of section 3.1.

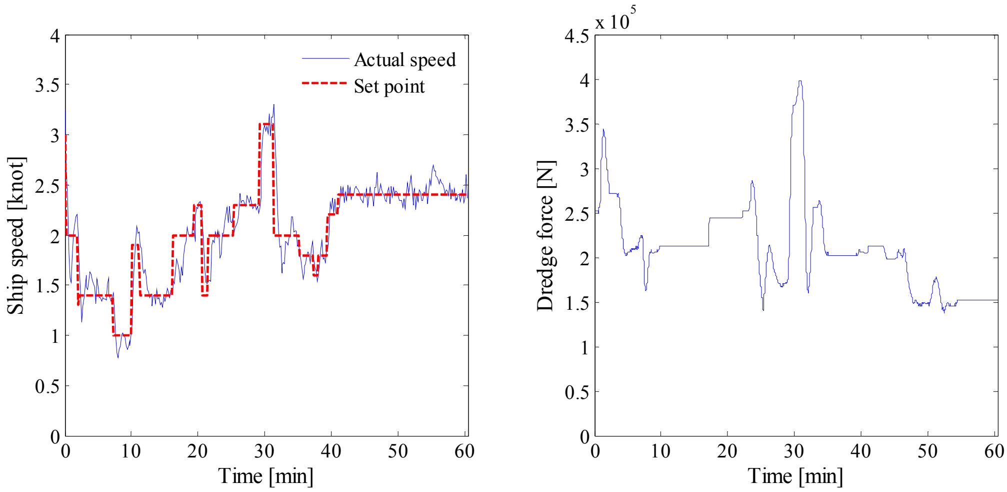

Figure 6.Measurement results of the Trail Speed Controller. Left: tracking performance, right: dredge force estimation.

Figure 6 shows the measurement results of a TSHD during sea trials. The left figure shows the tracking performance of the TSC and the right figure shows the dredge force estimation. When the drag head is lifted from the bottom, the estimation freezes which can be seen in the figure.

4 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 we know the grain diameter we can for example optimise the production of the discharge process see 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 life time prediction in behalf of preventive/scheduled maintenance and also for improving the design of pumps and pipes.
In this section, we describe 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 α. In the model we have introduced, there are only two parameters to be estimated: the factor α and the grain diameter d_m. For the estimation of such unknown parameters, an Extended Kalman filter (EKF) has been designed. The EKF has been chosen, since it has a recursive formulation, which makes it an efficient implementation, and it naturally handles the uncertainties in the process itself and in the measured signals. The only measurements needed for the EKF are mixture flow, mixture density and the discharge pressure. The tests, carried out onboard several cutter suction dredgers (CSD), have proven the effectiveness of the proposed estimation scheme.

4.1 The Estimation Problem

A simplified model of the discharge process in the pipeline is given by the following equations:
The evolution in time of the flow in the discharge-pipeline can be described by the second-law of dynamics as

$$\dot{Q} = \frac{S}{\rho L} \cdot \left(H_{disc} - \Delta H_l - p_0 \right)$$

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

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

Both homogeneous and heterogeneous losses can be conveniently expressed as a function of the losses due to pure water flowing into the pipeline

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

by using a proper correction factor. For homogeneous losses, such a factor depends on the mixture density

$$\Delta H_{\hom} = \frac{\rho}{\rho_w} \Delta H_w$$

whereas, for heterogeneous losses, it depends on the critical speed v_{kr} according to the formula of Jufin-Lopatin (Jufin, A. P. & Lopatin, N. A., 1966)

$$\Delta H_{het} = \left[1 + 2 \left(\frac{v_{kr}}{v} \right)^3 \right] \Delta H_w$$

The *critical speed* is given by

$$v_{kr} = \sqrt[3]{\frac{1}{2} \cdot C_T \cdot 33000 \cdot \left(g \cdot d \right)^{\frac{3}{2}} \cdot \frac{d_m}{d}}$$

where C_T is the *transportation coefficient* and is defined as

$$C_T = \frac{\rho - \rho_w}{\rho_g - \rho_w}$$

From the previous equations, a continuous-time state-space representation of the discharge process can be determined, if we make the following positions

$$x_1 = Q \qquad\qquad u_1 = H_{disc} - p_0$$
$$x_2 = d_m \qquad z = x_1 = Q$$
$$x_3 = \alpha \qquad\qquad u_2 = \rho - \rho_w$$

It can be noticed, that the state vector of the system (first-order dynamics in our case), has been extended, by including the unknown parameters in the system model.
The continuous-time state-space representation must be discretized, in order to design a proper estimation scheme. The discrete-time state-space model can be written in the general form

$$x_1(k+1) = f_1\left(x(k), u(k), w_1(k)\right)$$
$$x_2(k+1) = f_2\left(x(k), u(k), w_2(k)\right)$$
$$x_3(k+1) = f_3\left(x(k), u(k), w_3(k)\right)$$
$$z(k) = h\left(x(k), v(k)\right)$$

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 minimizes 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 linearize such a model around the most recent state estimate. Then, the filter can be designed with respect to the linearized system. This design procedure is known as *Extended Kalman Filter (EKF)*. Compared to other estimation schemes, the Kalman filter has several advantages: (i) it is computationally efficient due to its recursive formulation; (ii) it has a simple and intuitive structure in the form of a predictor-corrector; (iii) it directly takes into account model uncertainties and noise.

In the model of the discharge-pipeline we have been using, the mean density in the discharge pipeline has been considered as input. However, we cannot directly measure the mean density in the pipeline, 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 certainly extent, independent from the model used for the density propagation.

4.2 Experimental Results

The experimental data have been recorded during a dredging session on the CSD *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): $L_1 = 100\text{m}$ $\quad d_1 = 850mm$
- Segment II (driver): $L_2 = 660\text{m}$ $\quad d_2 = 850mm$
- Segment III (pipeline on land): $L_3 = 7060\text{m}$ $\quad d_3 = 900mm$

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

In figure 7, we have reported the recorded tracks of the discharge pressure H_{disc} , the flow Q , and the density injected into the pipeline ρ_m . These quantities represent the measured signals used by the Kalman filter for the estimation of the mean-grain-diameter.

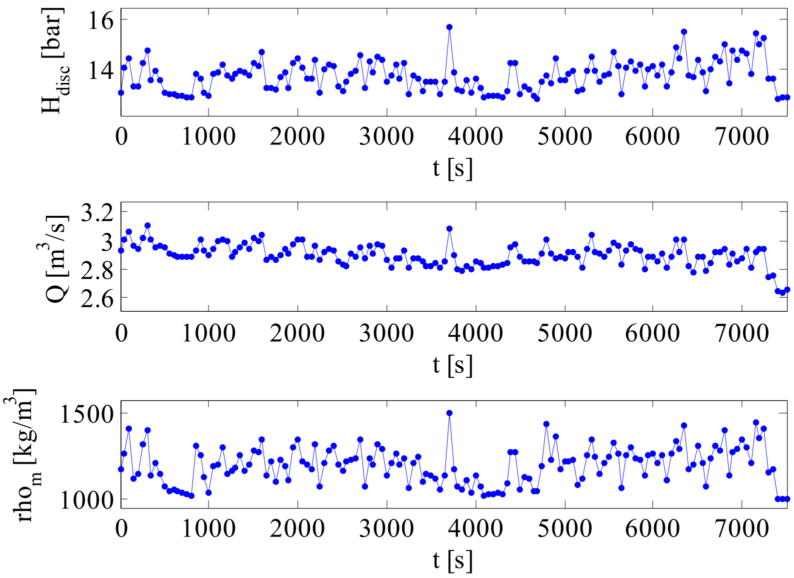

Figure 7. Measured signals used by the Kalman filter.

Here we have reported the evolution in time of the estimate of the mean-grain-diameter (and the corresponding estimation error), as provided by the extended Kalman filter. From figure 8, we can see that the estimate nicely converges to a boundary region around the measured value of the grain diameter. We can also notice that the convergence is quite slow, but this is something we cannot go around, since it is due 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), we can affect the convergence properties of the filter, but not change them dramatically.

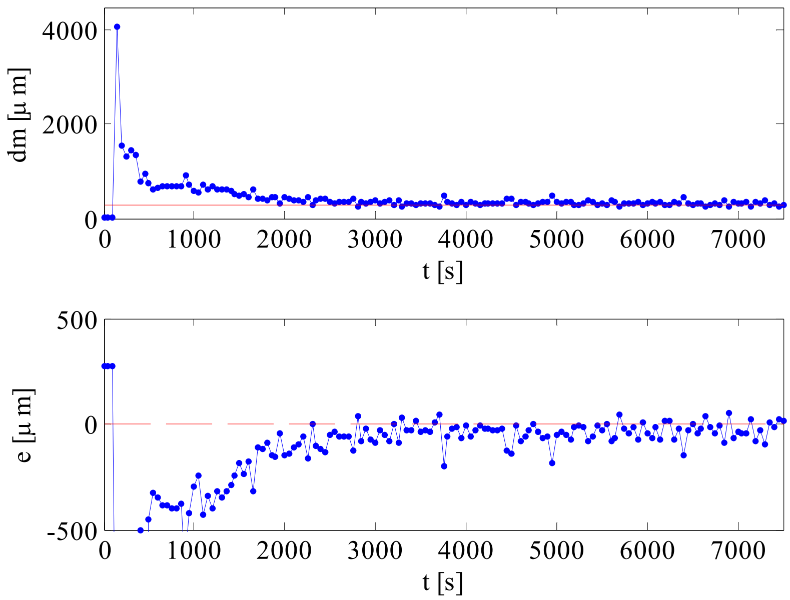

Figure 8. Measured value of the mean grain diameter (continuous constant value) and the estimated mean diameter (continuous lines with dots), and the corresponding estimation error for Ts = 50 s.

We can better see from table 1, 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).

Table 1. The table presents the real mean diameter [µm], the estimated mean diameter [µm] and the relative percentile error [%] averaged over the last 10 samples (=500s).

Real mean diameter $[\mu m]$	Estimated mean diameter $[\mu m]$	Relative error $[\%]$
285	312	9.4

Subsequently, we have also run the Kalman filter without down-sampling the data (T_s = 5s), 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 2. The table presents the real mean diameter [µm], the estimated mean diameter [µm] and the relative percentile error [%] averaged over the last 100 samples (=500s).

Real mean diameter $[\mu m]$	Estimated mean diameter $[\mu m]$	Relative error $[\%]$
285	309	8.4

Comparing figure 8 and figure 9, we can notice 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 α is very small (as we have also 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.

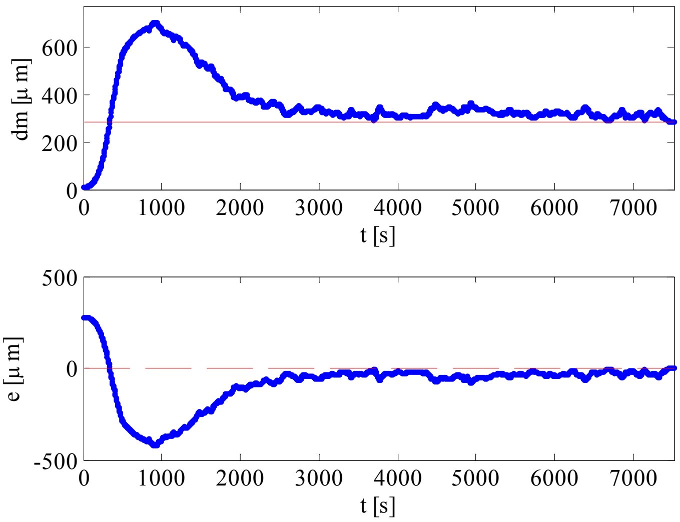

Figure 9. Measured value of the mean grain diameter (continuous constant value) and the estimated mean diameter (continuous lines with dots), and the corresponding estimation error for T_s = 5 s.

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 a 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.

5 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. Furthermore, when the local ground condition at the bottom 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.

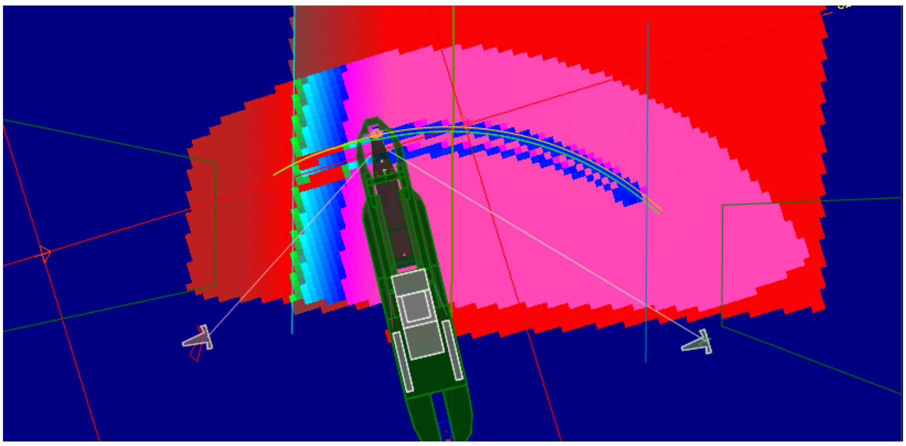

Figure 10. Top view of the dredger with the estimated anchor positions as presented to the dredge master.

In this section the online estimation of the anchor positions is discussed. The anchor position estimator is implemented and in use onboard several CSD. 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, see 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.

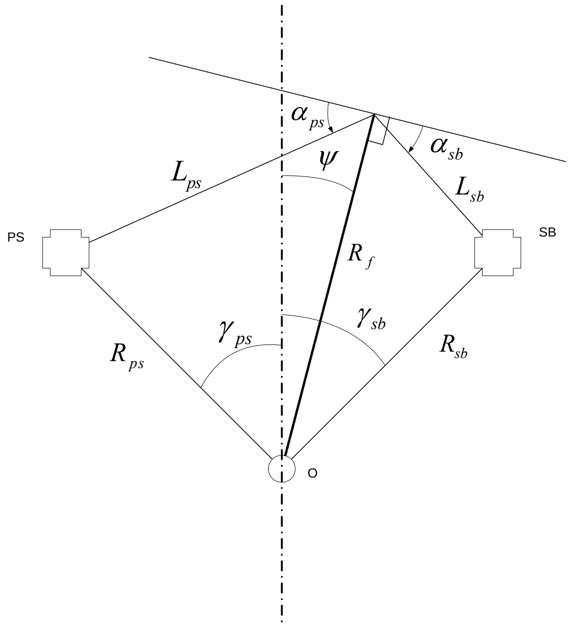

Figure 11. Reference system Anchor position estimator.

The computations are based on a batch algorithm which tries to minimize 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.

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

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

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

where i = *sb, ps* and R_i, γ_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 ψ is the swing angle.

The minimization 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, see figure 12.

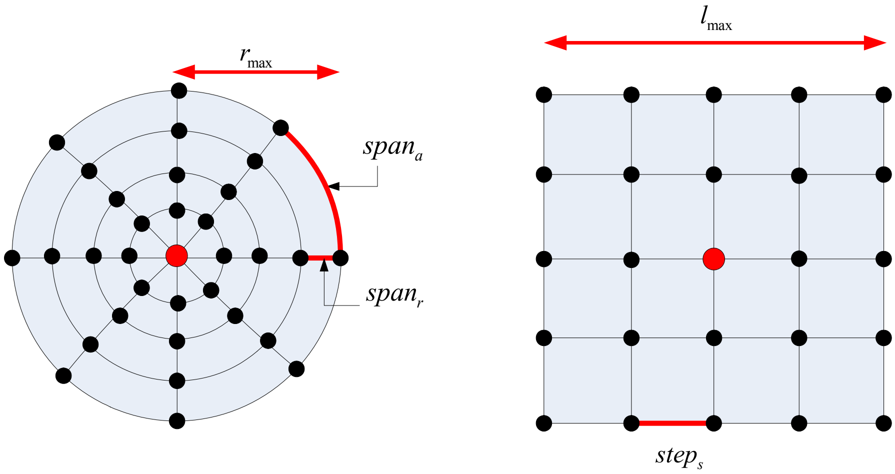

Figure 12. A circular and square grid of points for the approximated minimum search.

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 α_{sb} and α_{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.

6 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 drag head and jet penetration depth to optimize 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 faster updated.
- Estimating the settling velocity of particles in the hopper and sand bed height.

7 CONCLUSIONS

Modelling the dredging process has enabled us to develop advanced control algorithms that optimize 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 estimation techniques described in this paper. We described an overview of estimation techniques which are developed during the last years and presented briefly the future developments.

An overflow loss estimator based on a particle filter has been developed and implemented in the latest releases of the DLM software. This estimator can support the operators in the decision making when to stop dredging and warn 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. 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 drag head. This has also been implemented in our newly developed trail speed controller.

For the discharge process, we have described a simple nonlinear dynamical model in the pipeline of a cutter suction dredger. 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 d_m. The experimental results prove the feasibility and the effectiveness of the proposed estimation scheme.

Finally this paper presented an anchor position estimator which has been succesfully implemented on board of several cutter suction dredgers. This system can give an early warning to the operators when the anchor is dragged over the bottom.

8 NOMENCLATURE

C_T	transportation coefficient	v	speed in the discharge-pipeline
d	discharge-pipeline diameter.	v_{kr}	critical speed in the discharge-pipeline
d_m	mean-grain diameter.	V_t	total volume of sand and water in hopper
e	error	x	state
f	state transition function	X	number of segments
g	gravity acceleration	y	output
h	measurement function	α	weighting factor
H_{disc}	discharge pressure	α_{ps}	angle of port side winch
k	discrete time step k	α_{sb}	angle of starboard side winch
L	discharge-pipeline length.	ΔH_{het}	heterogeneous pressure losses
L	discharge-pipeline length.	ΔH_{hom}	homogeneous pressure losses
L_{ps}	measured length port side winch	ΔH_l	pressure-losses in the discharge-pipeline
L_{sb}	measured length starboard side winch	ΔH_w	losses in the discharge-pipeline for water
m_t	total mass of sand and water in hopper	ε_k	Process noise
p_0	atmospheric pressure	ε_{yk}	Measurement noise
Q	flow in the discharge-pipeline	λ	friction coefficient
Q_i	incoming flow in hopper	ρ	mean-density in the discharge-pipeline.
Q_o	outgoing flow through overflow weir	ρ_g	mean-grain density.
R_f	swing radius	ρ_i	incoming density of mixture in hopper
S	discharge-pipeline section.	ρ_o	outgoing density through overflow weir
T_s	Sample time	ρ_w	water density.
u	input	ψ	swing angle

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