MODEL PREDICTIVE CONTROL FOR OPTIMIZING THE OVERALL DREDGING PERFORMANCE OF A TRAILING SUCTION HOPPER DREDGER

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ABSTRACT

Trailing suction hopper dredgers are widely used to excavate sand from the sea bottom. One or two operators control the ship who usually aim to maximize the production of sand. This production depends on the incoming sand mass flow and on the losses during the overflow phase. The incoming flow-rate, the density of the incoming mixture and the grain-size and distribution all influence the sedimentation rate. Currently, the operators' strategy is to maximize the incoming production from the drag head, while little attention is paid to the sedimentation process. This article describes an improved control strategy based on model predictive control to optimize the total process. A predictive control strategy is necessary because the results of the control actions are only observed at the end of the dredging process. The control inputs are the pitch of the screw blades to control the ship's speed, the diesel engine speed to control the mixture flow-rate and the drag head visor angle to control the incoming density in the drag head. The optimization objective is to maximize the sand content in the hopper at the end of the cycle, the tons of dry solids (TDS). As the dredging cycle also includes sailing and discharging, the optimal dredging strategy depends on the total cycle time. Therefore the degrees of freedom to achieve the optimization objective are the control inputs as well as the dredging time. Our simulation results show that the production-oriented strategy, currently used by operators, is suboptimal. The achievable improvement depends on the type of sand and ranges between 5 % and 11 % for coarse and fine sand.

INTRODUCTION

A well known technique for optimizing the dredging cycle is the tangent method (IHC Holland 1991). This method determines, based on the paying load curve and the sailing and discharging time, the optimal dredging time. This method is not suitable for online use, since it can only determine the optimum stopping time afterwards. Under operating conditions, the soil type, the inputs, such as the flow-rate of the pump and the ships speed and disturbances, all influence the paying load curve. Under these conditions it is very difficult to calculate the optimal dredging time, because the disturbances and control inputs are not known in advance. Therefore, optimization of the dredging cycle requires an integral approach that takes all processes into account which influence the performance.

One of the first who recognized the importance of determining the optimal stopping time online was Knust (1973). He installed an analogue computer on the dredger "Ludwig Franzius" that determined the optimal stopping time online. Nowadays digital computers perform this task. Others automated the dredger by using expert knowledge of the operator and capture this in fuzzy rules (Ikeda et al. 1995). Moreover the modern dredger has a lot of sensors, such as a radioactive density measurement, mixture velocity measurement, draught and hopper volume measurement etc. These developments pave the way for advanced optimization and estimation techniques such as particle filtering (Babuška et al. 2006) and model predictive control as described in this article.

Two processes dominate the production of a trailing suction hopper dredger: the incoming production process from the drag head, pump and pipeline and the sedimentation process in the hopper. High incoming production with a large flow-rate can negatively influence the sedimentation which results in large overflow loss. This effect increases when the grain size of the sand is smaller. When optimizing the integral process both processes must be taken into account.

This paper addresses the optimization of the dredging performance by finding the optimal control strategy. Optimal control of a very nonlinear system such as the dredging process is a complicated issue. By defining this as a constraint based optimization, you can solve this by the classic theory of Optimal Control as developed between 1955 and 1970. The solution to the optimization problem is solved by the Hamilton-Jacobi-Bellman equation. Unfortunately, it is virtually impossible to solve the optimal control problem analytically in most cases. Therefore we propose to solve the optimal control problem numerically.

The sedimentation process is a slow process, moreover it is hidden to the naked-eye and measurements. Not until the end of the dredging cycle, it becomes clear how fast the sand has settled. To incorporate the sedimentation process into the optimization strategy it is therefore necessary to predict the sedimentation behavior based on the inputs of the system. A method which is particular suitable for optimization based on future predictions is model predictive control (Maciejowski 2002).

This technique uses an internal model to predict the behavior of the ship and an optimization technique to find the optimal future control sequence. The controller applies the first step in this sequence to the system and the whole process starts again. The controller achieves closed loop behavior in this way that is able to reject disturbances and model uncertainties.

Here we focus on a common configuration of a trailing suction hopper dredger which is the diesel direct configuration. The ship has two diesel engines, each attached to its own propeller and dredge pump via gearboxes. Adjusting the pitch of the screw blades controls the ship's speed. A flow-rate controller, available on most modern dredgers, adjusts the pump speed so that the flow-rate remains constant.

The dredge pumps transport sand through a suction pipe from the sea bottom to the hopper. The drag head, connected to the suction pipe see Fig. 1, excavates the sand from the bottom. Its function is to break the coherence of the sand at the bottom. There are three excavation mechanisms: injecting water under high pressure in the sand with water jets, cutting the sand pack with teeth and eroding sand with sucking up water. In contrast to the stationary dredger, this ship sails during the excavation.

In the hopper, the heavy grains settle at the bottom and form a sand bed. One or two overflow pipes discharge the excess water. Once the height of the hopper content reaches the height of these pipes, water and light weight grains start flowing out. As the sand bed grows, the density of the outgoing mixture increases, which leads to higher overflow losses. Although some of the losses are unavoidable due the natural settling process, the inputs, such as the pump speed and the change in overflow position, influence the rest of the losses.

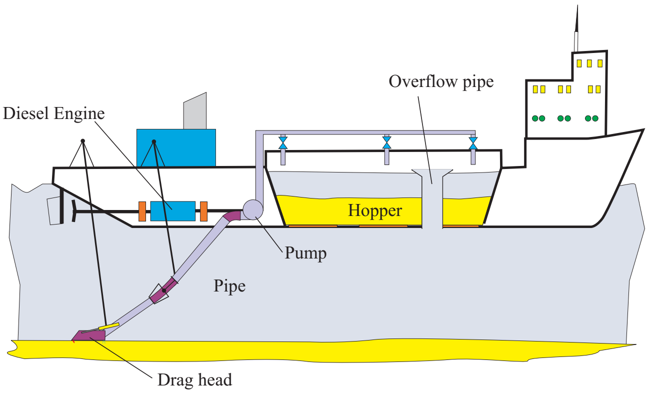


Figure 1. A schematic drawing of a hopper dredger.

OPTIMIZATION OBJECTIVE

In practice the operators focus on the production process of the drag head and pump, and not on the sedimentation process. This leads to the situation where the incoming production is high, but that due to the high flow-rate, the sedimentation rate is poor. It is hard to take this effect explicitly into account, because the sedimentation rate is not measured. Not until the end of the dredging process it becomes clear what the results of the control actions are. This delay between the control action and the performance indication requires a predictive model. Therefore we suggest a model predictive control approach that takes both the production and the sedimentation process into account.

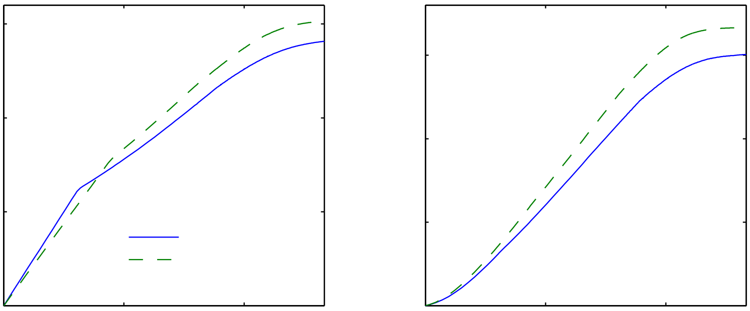
The production of a trailing suction hopper dredger depends on a range of variables. Some of these variables we manipulate, such as the pump speed, the ship's speed or the visor angle, but other variables are disturbances, such as the dredging depth and the the ship's draught. The complexity of the optimization is in the coupling of the important sub-processes. For the predictive controller we choose three manipulated variables: the screw blade pitch ϕ for adjusting the ship's speed, the diesel engine speed ω_d which is connected to the pump to control the pump speed ω_p and the visor angle α_v which determines the excavation depth of the drag head. We base this choice on the inputs that influence the performance the most.

Illustrative Example

To illustrate the above described character of the process we compare two different loading strategies for finer sand material with a grain size of 0.19 mm. The loading strategy is according to a constant tonnage loading system, where a controller reduces the overflow height to maintain the maximum draught at the end of the cycle. We keep the mixture flow-rate constant during the entire dredging phase and compare the following two strategies:

1) the incoming production is maximal (200 ton/min), with a flow-rate of 7 m^3/s,
2) the production is 175 ton/min, with a lower flow-rate of 5 m^3/s.

Fig. 2 shows that until 40 minutes strategy 1 results in more tons of dry solids, however at the end of the dredging cycle, strategy 2 results in 8 % more tons of dry solids in the hopper. This means that strategy 1 leads to higher overflow losses, whereas strategy 2 leads to a faster rising sand bed m_s and less losses, see Fig. 2 (right).



with ϕ the screw pitch, ω_d the diesel engine speed and α_v the visor angle. The state vector $\mathbf{x}$ is:

$$\mathbf{x}(t) = \begin{pmatrix} V_t(t) \\ m_t(t) \\ m_s(t) \\ Q_i(t) \\ v_{sh}(t) \end{pmatrix}$$

where V_t is the hopper volume, m_t is the hopper mass, m_s is the sand bed mass in the hopper, Q_i is the flow-rate and v_{sh} is the ship's speed. The first three states describe the hopper sedimentation dynamics, the flow-rate represents the pump pipeline dynamics and the ship's speed the sailing dynamics.

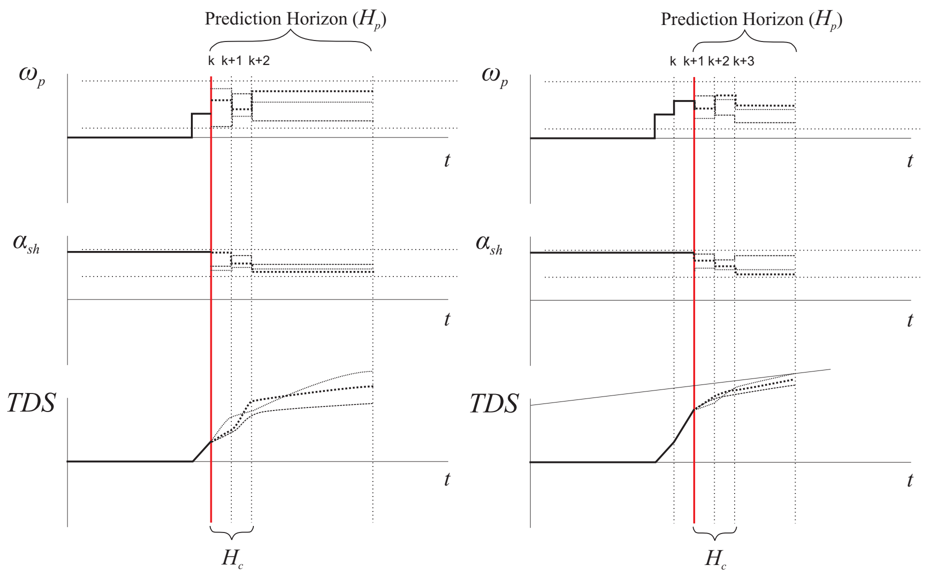


Figure 3. Illustration of the MPC algorithm applied to the optimization of the hopper dredger: left the optimization in the predictive controller at time step k, right the optimization in the predictive controller at time step $k+1$.

MODEL PREDICTIVE CONTROL

Model predictive control is a technique that calculates the control actions based on an internal model of the system (Maciejowski 2002). This internal model makes prediction based on the assumed input trajectory and initial conditions. These predictions are necessary to evaluate the objective function, which is a mathematical representation of the control goal to be achieved. The predictive controller uses an optimization scheme to search for the control actions that give the best predicted behavior. The optimization scheme chooses the best input trajectory and applies only the first element of that trajectory to the plant. This repeats itself every sampling interval. Since the prediction horizon remains the same length, it slides along each sampling interval, the so-called receding horizon.

We demonstrate the model predictive controller with an example. The left part of Fig. 3 at time k gives three possible control sequences for the diesel engine speed and the visor angle. For these sequences, the model predicts a trajectory for the tons of dry solids. The predictive controller applies the first control action of the optimal sequence. Then the process starts over again at time $k+1$ as can be seen in the right panel. The inputs for which the algorithm searches the optimal solution are within the control horizon H_c, but the prediction takes place for a prediction horizon H_p. This reduces the number of decision variables to reduce complexity. For the remainder of the prediction horizon the inputs are constant. The figure also illustrates that the prediction horizon may vary. As the process comes near the end of the cycle, the prediction horizon shrinks, because it is not necessary to predict the process behavior beyond the optimal dredging time. This principle, the shrinking-horizon predictive control, is typical for batch processes (Joseph & Hanratty 1993, Thomas et al. 1994, Liotta et al. 1997).

Fig. 4 illustrates the model predictive controller with a general block scheme. At every time step k, the predictive controller receives measurements of the states of the total system. Given the state vector $\mathbf{x}(k)$, the optimizer simulates the internal model for various input sequences and predicts the future state evolution. The objective function calculates the performance which is returned to the optimizer. The optimizer searches through the

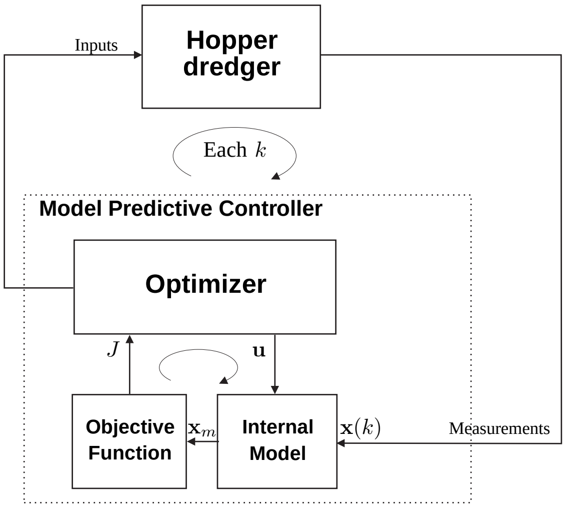


Figure 4. Block diagram of the model predictive controller applied to the hopper dredger.

solution space to find the optimal control strategy. Once a terminal condition is met, the first control action of the optimal sequence is applied to the system and at the next sample time the predictive controller starts over again.

One particular benefit of the model predictive control strategy is the ability to satisfy constraints in the system. Every practical system has constraints, for example input constraints such as the maximum pitch or state constraints such as the maximum allowable hopper mass m_t. Very often, the optimal operation point is at or close to the constraints.

Because we want to exploit the nonlinear behavior of the system, we choose a nonlinear modeling approach for the model predictive control scheme. This, however, has consequences. First of all, the optimization problem is not necessarily convex and therefore it is not guaranteed that the solver finds the global optimum. Moreover the optimization becomes computationally hard which has consequences for the minimal sampling rate which can be achieved. Fortunately the hopper process is a slow process, so the sampling rate can be in the order of minutes. But still we are looking for a computationally fast model which simulates the whole dredging cycle within several seconds. This requirement rules out some modeling approaches such as partial differential equations which are normally solved by finite element techniques.

MODELING

The goal of this model is to predict the tons of dry solids for a future input trajectory. The inputs are the screw pitch ϕ, the diesel engine speed ω_d and the visor angle α_v, so the model must contain all subsystems in between these inputs and the tons of dry solids. We distiguish four parts based on this: a ship model, a drag head model, a pump and pipeline model and a hopper model, see Fig. 5. The figure shows also the interactions of the four individual models.

The screw pitch ϕ determines the forces of the propellers to control the ship motion. These forces accelerate the ship with a total mass that is varying due to the hopper load, therefore the acceleration depends on the mass m_t. The trailing force of the drag head pulls the ship. This trailing force depends on the cutting depth of the drag head and on the friction between the drag head and the bottom.

The are no models available in the literature to predict the drag head production based on the control actions. Therefore we obtain the drag head model via automatic black box modeling (Maertens et al. 2005). This results in a model that predicts the incoming drag head density based on the flow-rate Q_i and the ship's speed v_{sh}. The control inputs available on the drag head manipulate the incoming density. The following inputs are available: the drag head visor angle which determines the cut height, a water valve that dilutes the mixture in the drag head, water-jet-nozzles that loosen and dilute the sand before excavating and drag head force on the bottom. In this paper we consider only one input that controls the incoming density between the minimum and the maximum value.

The pump is controlling the flow-rate in the pipe and drag head. The diesel speed changes the pump speed to adjusts the manometric head which the pump uses to accelerate the mixture in the pump and pipeline. The pressure losses are composed of the resistance forces and the static pressure losses for lifting the mixture from the sea bottom to the pipeline outlet. These static losses are time varying as the pipeline outlet position above the sea level decreased when the mass in the hopper increases. The mass which the pump has to accelerate

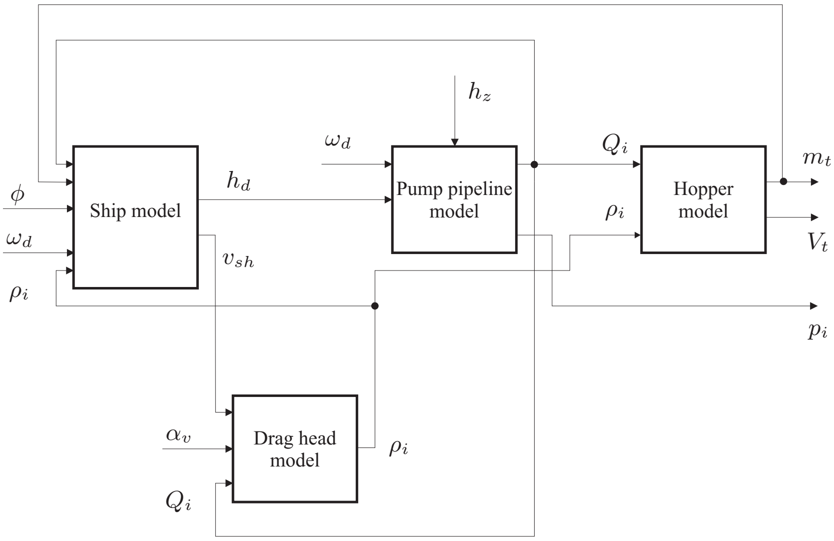


Figure 5. Block diagram of the total process model that is used in the MPC.

depends on the average density ρ_{pi} in the pipeline. This density depends on the incoming drag head density ρ_d. The average density ρ_{pi} in the pipeline has also a large influence on the pipe resistance forces, moreover the density of the pump ρ_{pu} influences the manometric head which the pump delivers. Since the time scale of the pump pipeline process is much smaller than that of the predictive controller, we assume no transport delay:

$$\rho_i = \rho_{pu} = \rho_{pi} = \rho_d$$

In the hopper a flow-rate Q_i enters with an incoming density ρ_i. These two inputs influence the sedimentation process as well as the outgoing density. The mass m_t and the volume V_t of the hopper content determine the tons of dry solids in the hopper, which gives the performance of the total process, see (2).

Ship Model

The drag head production depends only on the forward velocity and not on the sidewards velocity, therefore we choose a 1D approximation of the ship motion. Two screws propel the ship with a variable screw pitch to regulate the thrust force. The hull and lowered pipes encounter a resistance force with water. Moreover, the drag head causes a friction force and a cutting force if it is equipped with teeth. The simplified motion equation, based on the second law of Newton, for the ship's speed v_{sh} is the following:

$$\dot{v}_{sh} = \frac{1}{m_{sh} + m_t}(F_{th} - F_d - F_c) \qquad (5)$$

$$h_d = f(m_t) \approx a_d m_t + b_d \qquad (6)$$

where F_{th} is the thrust force of the screw blades, F_d is the drag resistance force, F_c is the cut force of the drag head, m_{sh} is the mass of the empty ship and h_d is the ships draught, which outputs to the pump pipeline model, see Fig. 5. The coefficients a_d and b_d are calibrated using data. The draught of the ship is a function of the hopper mass. We assume that the empty ship mass is constant. A linear approximation already gives an accurate estimation of the draught h_d. It is of course possible to use a more accurate approximation such as a lookup table. In the derivation of (5) we neglected the time derivative of the mass because this term is very small. Curve fitting on a detailed and accurate model for the thrust force resulted in the following simplified model:

$$F_{th} = 2K_T\,(\omega_d N_s)^2\,\phi^{\frac{3}{2}}$$

where K_T is a constant, ω_d is the diesel engine speed, ϕ is the pitch of screw blades and N_s is the gear ratio from the diesel engine to the screw axis. Here we assume one input that controls the blades on both screws and one input that controls both engines, therefore we multiply the force by two. The combined ship's drag force of the hull, pipe and drag head is the following:

$$F_d = k_d |v_{sh}| v_{sh}$$

where k_d is the drag coefficient. This coefficient is time varying, because of increasing draught and bottom disturbances. Miedema (1987) showed in his research that the relation for the non cavitating cutting is:

$$F_c = k_c h_c^2 v_{sh}$$

where h_c is the cutting depth of the blades and k_c is the cut force coefficient, which depends on soil characteristics, but is considered constant in this paper.

Drag Head Model

This model must predict the incoming density ρ_d into the drag head. There are hardly any models described in literature that predict the drag head process. Therefore we choose a nonlinear data driven black box modeling (Maertens et al. 2005) approach. An algorithm automatically builds polynomial models by analyzing a large data set with relevant measured variables. The algorithm calibrates the models on the data and a genetic algorithm searches through the large number of models to select the best for the prediction. This model depends only on variables which have large correlation with the predicted incoming density. This automatic black box modeling approach results in the following model for the density:

$$\rho_i = -aQ_i^2 + bv_{sh} + c \tag{7}$$

where a, b and c are positive coefficients. This model is obtained from data in the case that the drag head is not controlled. The drag head has a water inlet valve and a controllable visor angle. With these control inputs it is possible to regulated the drag head density. The data set for which the model is valid was recorded with a drag head in the so-called loose mode where the drag head exerts a constant pressure on the bottom. We assume that (7) is an upper bound for the density and that it is possible to decrease the incoming density by decreasing the visor angle or to open a control valve (the water flap) on top of the drag head. The controlled incoming density has the following model:

$$\rho_i = \alpha_v(-aQ_i^2 + bv_{sh} + c) + (1 - \alpha_v)\rho_w \tag{8}$$

where $0 \leq \alpha_v \leq 1$ is the control input for the visor angle. This assumption must still be validated in practice which is a subject for further research.

Pump Pipeline Model

Studies of the pump and pipeline are numerous (Durand & Condolios 1952, Fürböter 1961, Jufin & Lopatin 1966, Wilson 1992, Miedema 1996, Bree 1977, Matoušek 1997). The model of the pump and pipeline must predict the flow-rate Q_i based on the pump speed ω_p for a given density. The system of equations for the pump pipeline model is the following:

$$\dot{Q}_i = \frac{A_p}{\rho_i L_p}(\Delta p_{man} - \Delta p_{loss} - \Delta p_s - \Delta p_d) \tag{9}$$

(10)

where Δp_{man} is the manometric head that the pump uses to accelerate the mixture, Δp_{loss} is the pipe line resistance, Δp_s is the static head loss, Δp_d the pressure loss over the drag head, A_p is the average area of the pipeline, ρ_i is the average density in the pipeline and L_p is the pipe line length.
The diesel engine drives the pump by means of a gear box with gear ratio N_p. Dependent on the diesel engine speed, the pressure head for pumping water is the following:

$$\Delta p_{man,w} = h_{0n}\,(\omega_d N_p)^2 - h_{1n}\omega_d N_p Q_i - h_{2n}Q_i^2$$

where h_{0n}, h_{1n} and h_{2n} are the pump coefficients. During dredging, mixture is flowing through the pump, which influences the pressure head. This influence depends on the particle size and distribution in the mixture together with the concentration. This so-called solids effect influences the pump head as follows:

$$\Delta p_{man} = \Delta p_{man,w}(1 + 1.65\alpha_p C_t)$$

with α_p a coefficient dependent on the grain-size, C_t the transport concentration in the pump:

$$C_t = k_t \frac{\rho_i - \rho_w}{\rho_q - \rho_w}\,.$$

where k_t is the transport coefficient which is unity in case of no slip.
There exist many models for the pipeline resistance (Durand & Condolios 1952, Wilson 1976, Fürböter 1961, Jufin & Lopatin 1966). Here we choose the Führböter model, because it is easy to calibrate on data. The pipeline consists of an inclined part under water and a horizontal part above water:

$$\Delta p_{loss} = \Delta p_{ph} + \Delta p_{pi}$$

where Δp_{ph} is the resistance of the horizontal pipe and Δp_{pi} is the resistance of the inclined pipe. The part of the pipeline which is under water is inclined. This inclination reduces the solids effect. Worster & Denny (1955) were one of the first to incorporate this effect. The pressure drop for a horizontal pipeline and inclined pipeline is:

$$\Delta p_{ph} = a_p Q_i^2 + \frac{b_p C_t}{Q_i} \qquad \Delta p_{pi} = a_p Q_i^2 + \frac{b_p C_t}{Q_i}\cos(\alpha)$$

with

$$a_p = 8\frac{\lambda_f}{D^5}\frac{\rho_w L_p}{\pi^2} \qquad b_p = S_{kt}\pi\left(\frac{D}{2}\right)^2 L_p$$

where λ_f is the friction coefficient of water, ρ_w is the water density, D is the pipe diameter, L_p is the pipe length, C_t is the transport concentration, S_{kt} is the solids effect coefficient and α is the angle of the suction pipe.
The static head loss is:

$$\Delta p_s = (\rho_i - \rho_w)h_z g + \rho_{pi}(h_{hi} - h_d)g$$

where h_{hi} is the distance from the ship's keel to the pipe inlet in the hopper, g is the gravitational acceleration, h_z is the dredging depth and h_d is the draught, see (6).
The vapor pressure of the mixture in front of the pump limits the allowable suction pressure. If this pressure becomes too small, the pump starts cavitating. This is thus an important constraint in the optimization algorithm. The inlet pressure of the pump is:

$$p_i = p_{atm} + \rho_w g h_z - \rho_i g(h_z - (h_d - h_{pd})) - \Delta p_{loss,s} - \Delta p_d$$

where $\Delta p_{loss,s}$ is the resistance pressure of the suction pipe, h_{pd} is the pump height above the keel, p_{atm} the atmospheric pressure and Δp_d the pressure loss over the drag head.

Hopper Model

The excavated sand enters the hopper with the flow-rate Q_i and density ρ_i. At the bottom a sand bed is forming. For the optimization it is necessary to model the bed rise velocity and the overflow density. If the overflow density is too high the dredging process should be stopped. Since we are not interested in any other internal behavior of the hopper process, a 1D approximation over the height is sufficient. In the literature, this process has been modeled with partial differential equations (Dobbins 1944, Camp 1946, Rhee 2002), but because we need a fast model these are not the best and obvious choice. We developed a fast but accurate model that predicts both the overflow density and the bed rise velocity (Braaksma et al. 2007). We validated this model on test rig data as well as on real dredger data.

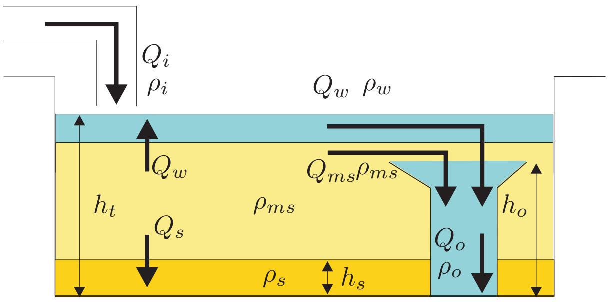


Figure 6. A schematic of the water-layer model.

The model has three state variables: the total mass in the hopper m_t, the total volume V_t of the mixture in the hopper and the mass of the sand bed m_s. A constant tonnage control loading system controls the overflow height h_o. The pump and pipeline model determines the incoming flow-rate and the drag head model the incoming density. The following differential equations describe the sedimentation dynamics:

$$\begin{aligned} \dot{V}_t &= Q_i - Q_o \\ \dot{m}_t &= Q_i\rho_i - Q_o\rho_o \\ \dot{m}_s &= Q_s\rho_s\,. \end{aligned} \tag{11}$$

The first two equations represent the volume and mass balance, respectively. The third equation gives the rate of sand sedimentation, where Q_s is the sand flow-rate from the mixture layer to the sand layer and ρ_s is the sand density. The overflow-rate Q_o is the sum of the water flow Q_w and the mixture soup flow Q_{ms}, see Fig. 6. The ratio of these two flows and the density of the mixture soup ρ_{ms} determine the outgoing density ρ_o. We leave a detailed description out for compactness and refer to (Braaksma et al. 2007) for the details.

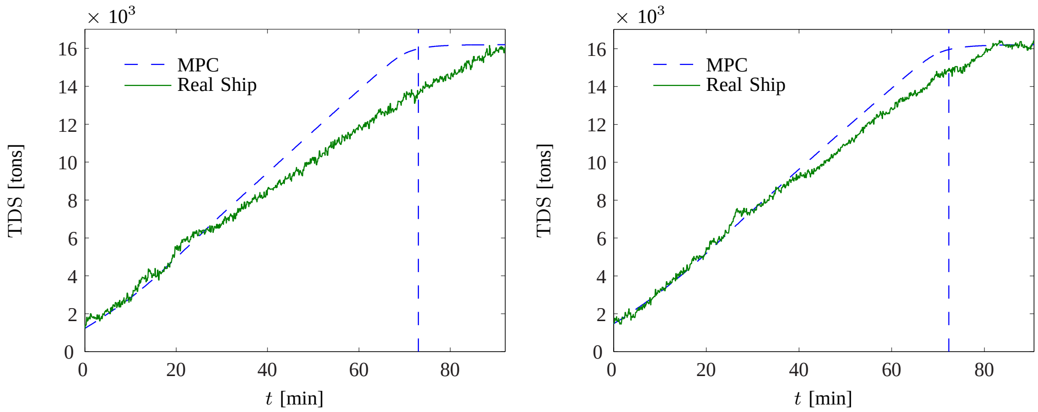


Figure 7. Comparison of the MPC strategy with a poorly performing operator (left) and a well performing operator (right) for coarse sand. The vertical dashed line is the optimal stopping time for the predictive control strategy.

RESULTS

We choose two scenarios to illustrate the performance of the model predictive control strategy: coarse sand and medium sand. Since we have only data available for coarse sand, we only compare this scenario with data from a trailing suction hopper dredger with a hopper volume of 13000 m^3. We use the measured data of the dredging depth h_z as a disturbance. We have estimated the grain-size between 1 and 2 mm. The model is carefully calibrated with the ship data and used in the model predictive controller as well as in the plant model to simulate the performance. We choose for the total sailing and discharge time a value of three and a half hours.

Fig. 7 shows the comparison of an operator (Real Ship) with the simulated model predictive control performance. The left figure shows poor operator performance and the right figure shows good operator performance. These results illustrate that the Model Predictive controller performs slightly better than a good operator, but much better than a poorly performing operator. The optimization leads to a shortening in dredging time by 10 - 18 minutes, when stopping at the predicted optimal dredging time T_d which is given by the vertical dashed line. This is an improvement of 10 % to 18% of the total dredging time.

Fig. 8 shows the inputs computed by the predictive controller. The controller manipulates the pitch α_v such that the ship sails at the maximum allowed speed of 2 m/s. This is a predefined constraint based on examining the data. If this constraint is not present the algorithm would maximize the speed to unrealistic values. In our setting, the faster the ship sails the better the performance. The controller manipulated the visor such that in the first 20 minutes the vacuum limitation of the pump is not violated. If in this period the pump would suck up a higher density, then the pressure drop over the pipeline would cause the pump to cavitate. Thereafter the predictive controller manipulates the visor to maximize the production. The pump speed is maximal in this example except for some deviations in the beginning which are caused by the variable dredging depth. The flow-rate shows an increasing trend, this is caused by the increasing draught of the ship. When the draught increases, the geodetic head loss becomes smaller, so that the flow-rate increases.

The real benefit of the model predictive control is for dredging of finer sand, because then the hopper sedimentation process is more important. In the following scenario we use the same dredging depth disturbance as the previous example, but with an average grain-size diameter of 0.2 mm.

This smaller grain-size reduces the friction losses in the pipeline and increases the effect of solids in the pump. In this scenario, the inlet pressure is no longer decisive and predictive controller manipulates the visor angle such that the incoming density is maximal. However, the increase in the flow-rate would result in an increase of the overflow losses, but also in a reduction of the incoming production. Therefore the controller automatically reduces the pump speed to lower the flow-rate. Fig. 9 illustrates the difference in performance between reducing the pump speed and keeping it at the maximum value. This shows that lowering the pump speed improves the production.

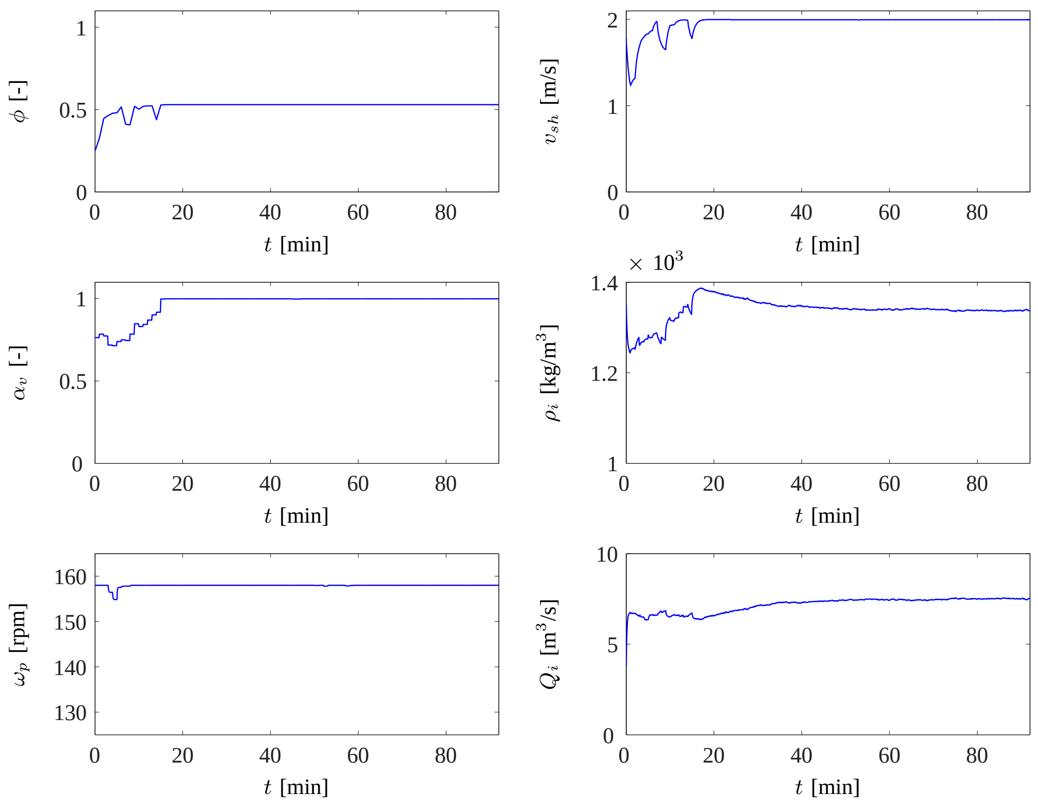


Figure 8. The inputs for coarse sand: in the left column the control inputs to the system of calculated by the predictive controller, in the right column the resulting process behavior.

Fig. 10 shows the inputs for medium grain-size sand. The predictive controller manipulates the screw pitch to sail at the maximum speed and the visor such that the maximum density is flowing into the hopper. But it reduces the pump speed significantly when dredging the medium grain-size sand.

CONCLUSIONS

This paper shows a nonlinear model predictive controller. For this controller we derived a model of the whole trailing suction hopper dredger. It consists of four parts which takes the sailing process, the drag head process, the pump pipeline process and the hopper process into account. Nonlinearities and coupling effects between the four processes characterize the model. To improve the dredging performance and find a trade off between the excavation process (production) and the sedimentation process, a model predictive control strategy is proposed. The results based on simulations lead to the following conclusions.

The excavation process mainly determines the optimal operation when dredging coarse sand, because the sand settles very well in the hopper. By using a model predicive controller, simulations show an decrease in the total dredging time between 8 and 18 minutes. There are two main reasons for the improvement. Firstly, the controller prevents cavitation by adjusting the visor angle and controlling the incoming density ρ_i. Secondly the controller maintains a constant ship's speed of 2 m/s by adjusting the screw pitch. The ship data showed that due to cavitation and the resulting safety measures (opening the water valve) the flow-rate fluctuated largely and that the ship speed varied significantly. The model predictive controller prevents both and therefore results in better performance. The performance improves between 4 % and 6% for the cycle production with a sailing and discharge time of 3.5 hours. This means an increase in week production between 19152 tons and 37296 tons which is approximately 1 to 2 ship loads.

For medium sand, the predictive controller uses a different strategy then for coarse sand. For this type of sand, the sedimentation process is also important for the total performance. In this case the controller lowers the pump speed to improve the settling efficiency and reduces the flow-rate to obtain a higher incoming density. For medium sand the performance improves with 11 % for the cycle production, compared to a strategy with maximum pump speed.

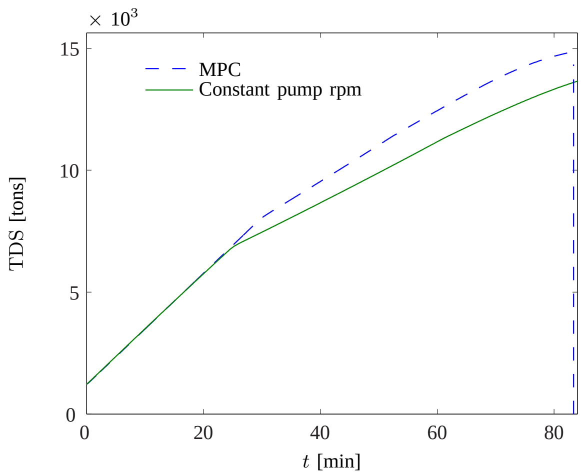


Figure 9. Tons of dry solids calculated by the predictive controller for sand with the diameter of 0.2 mm.

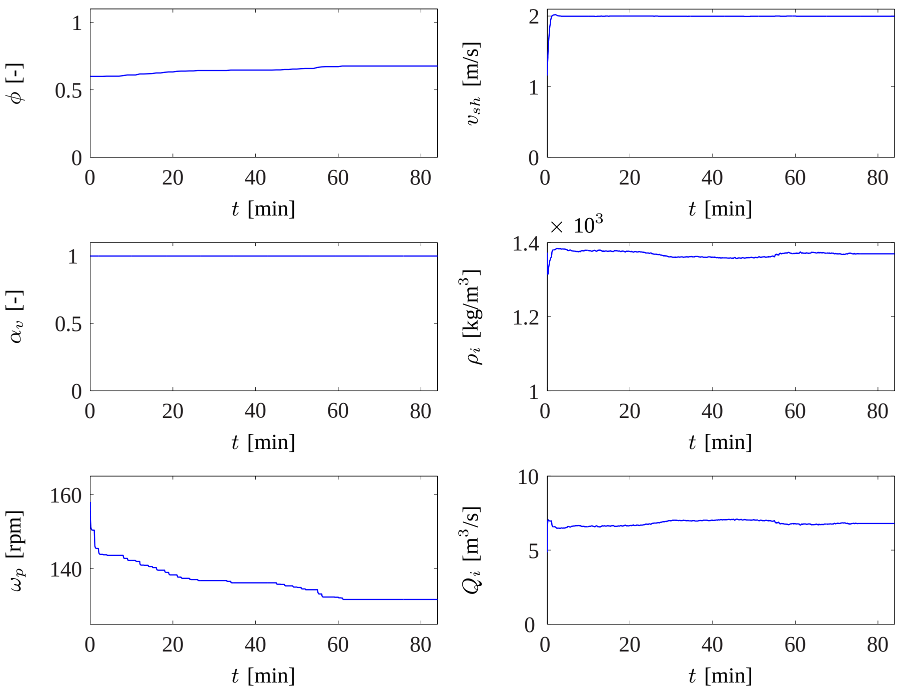


Figure 10. The inputs for medium grain-size sand: in the left column the control inputs to the system calculated by the predictive controller, in the right column the resulting process behavior.

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