Online Paramter Estimation for a
Centrifugal Decanter System

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Abstract: In many processing plants decanter systems are used for separation of heterogeneous
mixtures, and even though they account for a large fraction of the energy consumption, most
decanters just runs at a fixed set-point. Here, multi model estimation is applied to a waste
water treatment plant, and it is shown using real production data, that it is possible online to
distinguish between different operating modes, which can be used in the control strategy for
energy optimization.

Keywords: Decanter control, Kalman Filtering, Multi Model Estimation

1. INTRODUCTION

In many industrial processes where a fluid/solid mixture
is to be separated a decanter system is an obvious choice,
since it allows for continuous and rapid separation between
solids and liquids. An illustration of a typical centrifugal
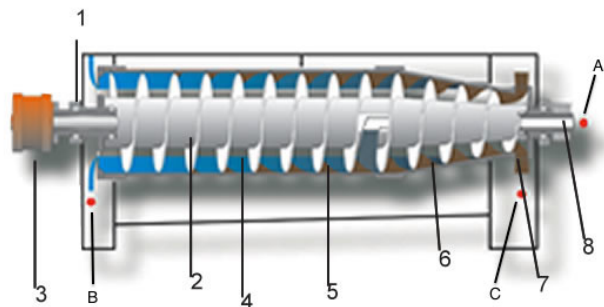decanter is shown in figure 1.

Fig. 1. Sketch of typical centrifugal decanter. Image cour-
tesy of Alfa Laval.

In the above figure the mixture is fed into the decanter
from the right side at A, through the hollow shaft at 8,
and the outlet streams are the clarified fluid phase at B
and the dewatered solids phase at C. The decanter itself
consists of an outer cone, which is driven by a motor at
3. The second motor, which drives the screw conveyer 2 is
also located at 3. The screw conveyer is mounted with a
set of vanes, 5, which pushes the solids towards the right
side as indicated by 4 and 6 into the solids discharge port,
which is located at 7.

As shown in figure 1, then the mixture to be separated is
feed into the decanter from the right side and ejected into

the decanter around the center of the main shaft. At the
left side two motors are located at 3. The main drive is
the one which rotates the bowl of the decanter at a very
high angular velocity thus accelerating the sedimentation
process, were as the other drives the screw conveyer to
extract the solids. The screw conveyer rotates at a low
relative velocity inside the bowl of the decanter. In order to
get a good dewatering of the solids, i.e. a good separation,
the solids layer should be as long as possible within the
bowl of the decanter. This translates to, that the region
within the bowl occupied by the solid fraction (5) should
be as large as possible, without letting solids exit with
the liquid phase. The only way to measure the extend of
the solid phase within the bowl is indirectly through a
torque measurement on the screw motor, since the amount
of solids being moved by the screw and the torque exerted
on the screw are related through a monotone function.
Therefore it is clear, that for a given feed composition and
flow rate, and a given desired filling of the decanter bowl
only one value for the torque will fulfill this, which will be
the control objective for the decanter control.

One of the main difficulties experienced when trying to
control a decanter system is, that the system parameters
are varying quite a lot as a function of the medium
being processed as well as the flow rate of the medium.
This is especially true for decanter systems used for
processing waste water and slaughter house waste, where
the heterogene mixture might vary a lot during a single
run. Thus in order to make a sufficiently good controller for
the system, an online parameter estimation scheme needs
to be in place.

Furthermore, as most decanter systems are operating in-
dependently of the other equipment in the production line,
e.g. feed pumps, then it is not possible to get information
from theses about the current expected operating condi-
tions. Thus it will be valuable to get an indication of up-
line equipments performance as well.

In several industrial plants, the use of online parameter estimation has been proven beneficial in improving the operating performance of the process, either for improving the control in terms of convergence rates and energy consumption, or for fault detection purposes, e.g. Isermann (2011); Kano and Ogawa (2010) and the reference therein. It is therefore envisioned, that such an improvement will also reveal itself in the control of decanter systems.

The data used in the presented study has been obtained during a two day test run at the Aalborg Sewage Treatment Plant West (ASTPW). The data from the first day will be used to extract the model from, along with testing of the parameter prediction algorithms. The algorithm is then run on the data from the second day in order to validate that the proposed procedure is feasible.

To the best of the authors knowledge online parameter estimation on a decanter system has not been published before, therefore no prior results exists for comparison.

In section 2, the proposed model structure is presented and the Kalman Filter structure is recalled in section 3. Online parameter estimation where the parameter is estimated directly is first presented in section 4 followed by the development of the multi model approach for the estimation in section 5. In section 6 the developed estimator is evaluated with the test data set. Finally the conclusions are drawn up in section 7.

2. SYSTEM MODEL

Through previous internal studies of the decanting process, a first order non-minimum phase affine model has been established empirically. As most simple decanter systems only measure on the differential drive motor, where the measurement is the produced torque by the motor, τ, needed for maintaining a specified differential velocity and $\Delta\omega$, of the internal conveyer screws angular velocity relative to the outer cones velocity, this is going to be the output and input to the model used in the following.

The mathematical model for this setup is:

$$\tau(s) = \frac{\tau_0(F)}{s} + \frac{(a(F))\,s + c(F)}{s + b(F)}\Delta\omega(s) + G(s) \quad (1)$$

Where the parameters a, b, c, τ_0 are all process parameters, which are dependent on the current flow, as well as dependent on the current composition of the material being processed. Initial values for these parameters are presented in table 1.

Variable	Value	Unit
a	12	kNm/Hz
b	0.01	Hz
c	-660	Nm
τ_0	8	kNm

Table 1. Coefficients for the decanter

The $G(s)$ term is a noise term. Even though (1) looks benign, then the non-minimum phase along with a high level of process noise makes the estimation process rather difficult. The physical interpretation behind the model and the non-minimum phase is, that when the system is at a steady state operating condition and an increase in the differential velocity is applied, then the conveyer will

initially experience a larger torque due to the increased velocity of the solids which needs to be transported. However, as the solids is pushed out faster the amount of solids within the decanter becomes smaller and thereby the required torque to maintain the differential velocity drops.

It turns out, that one of the most influential parameters of the models performance is the affine parameter τ_0, thus a Kalman filter is introduced to estimate this part of the process. In order to do so, the system will be put on state space form, which for the continuous dynamics gives the following parameters:

$$A = [-b], \quad B = 1, \quad C = [c - ba] \text{ and } D = a,$$

when the system is written as:

$$\dot{x} = Ax + Bu$$
$$y = Cx + Du.$$

Since the system is sampled at 0.1 Hz, the system is discretized to this sampling frequency and augmented with the constant term τ_0, which is to be estimated. This results in the system described by:

$$\Phi = \begin{bmatrix} 0.5335 & 0 \\ 0 & 1 \end{bmatrix} \quad \Gamma = \begin{bmatrix} 7.4248 \\ 0 \end{bmatrix} \quad H = [380\ 1] \quad D = 1909,$$
$$(2)$$

for the discrete system on the form

$$x_{k+1} = \Phi x_k + \Gamma u_k$$
$$y_k = H x_k + D u_k,$$

and the associated state vector as $x_k = [\tau_d\ \tau_0]^T$, where τ_d is proportional to the dynamic contribution to the torque, τ.

3. LINEAR KALMAN FILTER SETUP

The Kalman Filter structure used in this setup is the standard linear formulation, and the prediction step is generated as Grewal and Andrews (2008):

$$x_{k+1}^p = \Phi x_k + \Gamma u_k$$
$$z_k^p = H x_k + D u_k$$
$$P_k^p = \Phi P_{k-1}^p \Phi^T + Q$$

where superscript p denotes prediction values. The update step is likewise generated as:

$$K = P_k^p H^T (H P_k^p H^T + R)^{-1}$$
$$\hat{x}_k = x_k^p + K(z_k - z_k^p)$$
$$P_k = (I - KH)P_k^p.$$

The filter will be run on two different data sets - both obtained from Aalborg Sewage Treatment Plant West (ASTPW). The data sets are obtained during two days of steady state operation of the plant, which means, that most dynamics of the process is being suppressed by the used controller. However, the flow into the decanter is being changed at certain points, which leads to a new steady state operating area for the decanter, which is to be estimated. The first data set ASTPW1, which was recorded during May 8th 2012 will be used as the training set, whereas the second data set ASTPW2, recorded

during May 9th 2012 will be used as the proof set. Both data sets have been obtained using a 10 sec. sampling interval

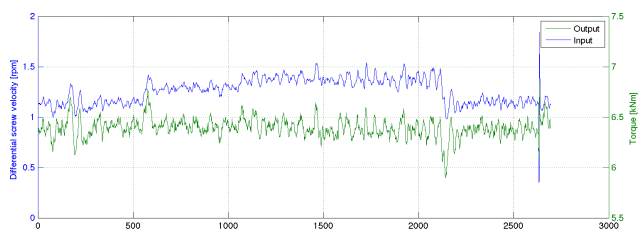The ASTPW1 data set is depicted in figure 2.

Fig. 2. Differential velocity and resulting torque for the ASTPW1 data set.

As a first step, the model described in section 3 is used to check, that it is possible to estimate the constant parameter in the model. By running the LKF as detailed in 3 with R = 1 and Q = $\begin{bmatrix} 0.01 & 0 \\ 0 & 100 \end{bmatrix}$ the result depicted in figure 3 is obtained. The initial guess of the constant has in this case been set to 5450 Nm.
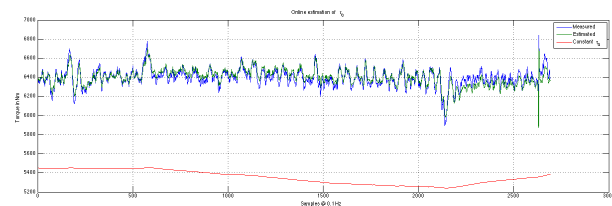
Fig. 3. KF estimation of the constant term with the transfer function.

As it is clearly seen from figure 3, then the filter is able to estimate the affine parameter, however, due to the high amount of noise on the actual measured signals, it converges to the value rather slowly. Hence it will not be optimal for online usage. There are two different approaches to cope with this problem: Either increase the sampling rate to 1 Hz as opposed to the current 0.1 Hz. This should decrease the convergence time by a similar factor, thus getting a good estimate within a quarter of an hour. The second possibility is to estimate a number of models off-line, and then do an online estimation of which model is the most probable. This is the approach, which will be utilized in the following, since it has not been possible to obtain measurements with a higher sampling rate, and the 0.1 Hz sampling interval is a standard interval for many older decanter systems.

The procedure followed in the remainder of this section is thus first to isolate the two different operating conditions, which is present in the ASTPW1 data set and identify models for the two different operating modes. Following this the multi model estimation procedure will be applied to the entire data set to see if the developed estimator is capable of identifying the different operating modes correctly.

4. DUAL MODEL IDENTIFICATION

In order to estimate the models off-line the useful data sets has to be identified first. That is, that on the basis of prior knowledge about the flow set-points, the data set will be divided into static sets, in which only one process model applies.

The plant has been running with a steady inflow of 19 $\frac{m^3}{h}$ from sample 0 - 551 and again from sample 2119 - 2694. In the intermediate interval from sample 552 - 2118 the flow was raised to 23 $\frac{m^3}{h}$.

The model used for identification purposes is (2), where τ_0 is adapted to fit the model at hand.

In the case of the first model, the result of the model identification is seen in figure 4. The identification resulted in a τ_0 value of 5450 Nm.
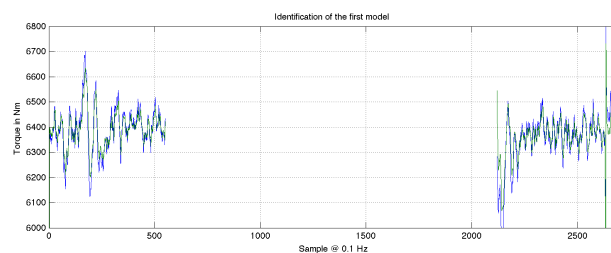

Fig. 4. Estimation of τ_0 for the first model. Green is output estimate and blue is measurement.

Likewise the τ_0 term for the second model was estimated to be 5450 Nm, and the model fit is depicted in figure 5.
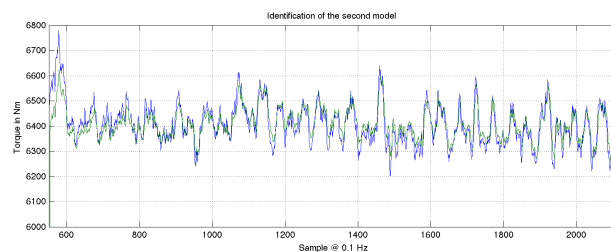

Fig. 5. Estimation of τ_0 for the second model. Green is output estimate and blue is measurements.

As seen from both figure 4 and 5, then there is a quite good agreement between the estimated outputs of the model and the actual process output.

5. MULTI MODEL ESTIMATION

In this step the two identified models from the previous section will be run in parallel, fed with the same input, and a binary discriminator is used to determine, if the underlying process is best described by the first or the second process model.

Ordinarily, a good metric for the model agreement is the covariance matrix, however, since there is no noticeable change in the system dynamics, but only within the τ_0 term, this method can not be used. The place where the influence of τ_0 is most noticeable is within the error between the output and the estimated output, hence this

will be used as a metric for determining which model the process measurements most likely belongs to. The setup is depicted in figure 6.
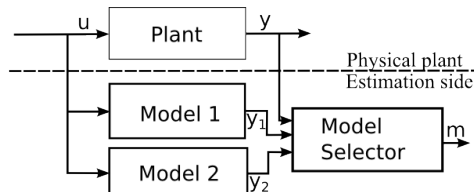

Fig. 6. Structure of the estimation setup.

As it is seen then the output from the controller, i.e. the input the plant, which is know, is fed to the two possible models. From these, two estimated outputs, y_1 and y_2 are generated and fed into the model selector along with the actual output of the plant. As described earlier, the decision process here is a binary decision process, that is, by defining the two error signals $e_1 = |y - y_1|$ and $e_2 = |y - y_2|$ then the model selector output becomes

$$m(k) = \begin{cases} 1 \text{ if } e_1 \leq e_2 \\ 2 \text{ if } e_1 > e_2 \end{cases} \qquad (3)$$

For the ASTPW1 data set, and the above identified models the two error signals e_1 and e_2 are depicted in figure 7.
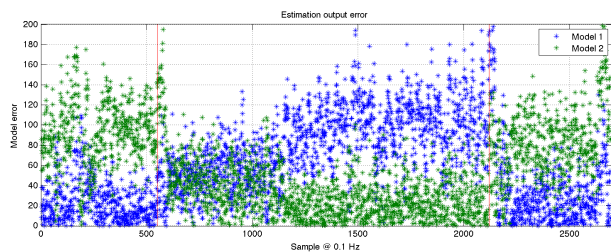

Fig. 7. Output estimation error of the two model estimations.

And using the discriminator directly, as described in (3), figure 8 is produced. Each dot represents one data sample, and throughout the experiment, only two different models are available for selection. The two vertical lines indicates when the inflow was changed. As it is seen, then the estimator is quite good in estimating the correct model when the process is stationary. However, when the process changes parameters, e.g. changes the inflow, the transition from one model to the other is, first of all highly affected by the slow change in the dynamics, which in combination with a quite high noise/disturbance level gives rise to a considerable amount of jitter in the transition phase. For the ASTPW1 data set it should also be mentioned, that just after the first flow change, around 600 samples into the set there was an error with the flocculent addition, which is part of the explanation of the murky results just after the first model transition.

The same result, but where the model output estimates have been first order low pass filtered with a 5 min. time constant, can be seen in figure 9. Here it is seen, that through an appropriate filtering, and a hysteresis decision rule, it would be possible to use the method online without introducing controller jitter. For this run, hysteresis levels of 1.7 for going to model 2 and 1.3 for going to model 1 would produce a control with only two switches.
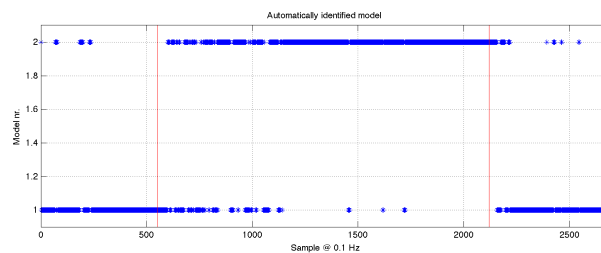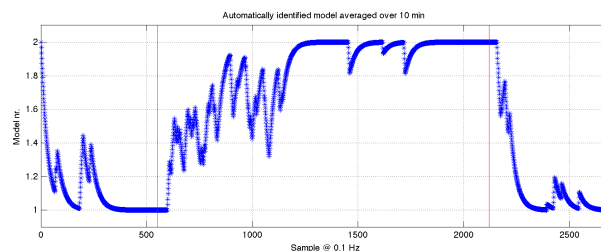

Fig. 8. Estimation of which model is the most probable.

Fig. 9. Estimation of which model is the most probable after a low pass filtering has been applied.

6. RESULTS

The final step in this analysis is to use the designed estimator on an unknown data set, which in this case will be the ASTPW2 data set.

The output of the estimator is shown in figure 10, and a 5 min. first order low pass filtered version, as for the training data set is shown in figure 11. As with the previous plot the two vertical lines indicate the times when the inflow pumps set-point was changed.
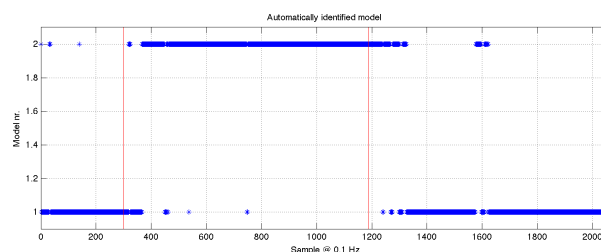

Fig. 10. Estimation of which model is the most probable for the ASTPW2 data set.
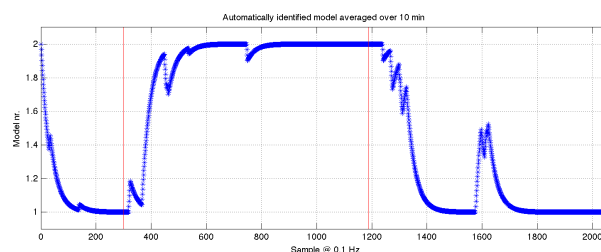

Fig. 11. Estimation of which model is the most probable for the ASTPW2 data set after a 5 min. first order low pass filtering.

Compared with the results of the training set in figure 8, then the results depicted in figure 10 shows a much more clean result, meaning, that there are a lot fewer incorrect model identifications. The same is true, if the

filtered version is studied. Here it is even seen, that a hysteresis decision function is no longer needed because the estimation output is very well behaving. The peak appearing around sample 1600 is actually the polymer pump, which was turned off at this point, which introduced a large disturbance to the system.

7. CONCLUSION

In this paper it has been shown how it is possible to perform model estimation on a decanter system running in steady state. As mentioned initially, it is quite difficult to get a good identification of a dynamic model solely based on measurements during static operation. However, as seen from figure 10 and 11, then it is indeed possible to distinguish between different apriori estimated models online. From change in process set-points and until the estimation has converged to the new model a delay of around 10 min. has been observed in the available data set. However, it should be taken into account, that the process itself has very slow dynamics towards input variations with a rise time of 20 to 30 min. Being able to estimate the current operating conditions of the decanter now opens the possibility of utilizing this information in the overall control strategy for the decanter.

ACKNOWLEDGEMENT

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