Ultrasonic Level Scanning for Monitoring Mass Flow of Complex Fluids in Open Channels - A novel sensor fusion approach using AI techniques

Khim Chhantyal, Håkon Viumdal and Saba Mylvaganam
Faculty of Technology, Natural Sciences, and Maritime Sciences, University College of Southeast Norway
Kjølnes Ring 56, 3918 Porsgrunn, Norway
{khim.chhantyal, hakon.viumdal, saba.mylvaganam}@usn.no

***Abstract*—Open channel flow of complex fluids is found in many offshore applications and is currently monitored using Coriolis meters (good uncertainty with an expensive device) and simple paddle meters (very poor uncertainty). Recent publications in IEEE by the current authors indicate that the flow of complex fluids in open channels can be estimated by level measurements in the open channel by scanning the surface of the fluids in the open channel with an array of ultrasonic sensors. Complex fluids possess rheological properties dependent on flow, density, pipe dimensions etc. As an interesting industrial application of different types of sensors, this paper presents the basic configuration of the sensors used in a pilot scale study with some selected samples of complex fluids. A comparison of the performances of the sensors using coefficient of variations (CV) with respect to the mean values of the measurands is given as a preamble before using them in the final mass flow estimation. The group on multiphase studies in USN recently used various statistical parameters in the identification of flow regimes in multiphase flow studies as reported in the IEEE Sensors Community. In addition, the measurand values are filtered using different algorithms. The flow in the open channel is estimated using a Radial Basis Neural Network (RBNN) with the levels from the ultrasonic scanning array as inputs and the mass flow as output. The paper summarizes the findings with some indications of their implications to the offshore and other industries.**

I. INTRODUCTION

In oil and gas industries, the drilling operation is one of the important phases. During the drilling operation, drilling fluid (so called complex fluid, showing rheological behavior dependent on flow rate, density, dimensions etc.) is continuously circulated to enhance the drilling operation. However, it is challenging to monitor operations of control of flow and density of these complex fluids under high temperature and high-pressure conditions. One of the biggest challenges while drilling is maintaining the wellbore stability. For any kind of reservoir, there exist a certain pressure window or the pressure range within which the drilling operation can be operated safely. In the case of failure to maintain the pressure, either there is a loss of drilling mud or there is an influx of formation fluids into the drilling mud (often termed as 'kick'), [1]. These two problems reduce the safety factor, reliability, and production. In extreme cases, it is highly dangerous, e.g. the Deepwater Horizon explosion, [2].

One way of monitoring the operating pressure is by using delta rule, which exploits the difference between drilling mud inflow rate into the wellbore and drilling mud outflow rate from the wellbore. In literature [3]–[7], different sensors and sensor systems are presented for the inflow and outflow measurements. In this study, the focus is on the outflow measurement using an open channel with Venturi constriction. Specifically, this work focuses more on the sensors measurements.

II. SYSTEM DESCRIPTION

A flow loop available at University College of Southeast Norway (USN), Campus Kjølnes consist of mud tank, pump, different types of sensors, and open channel with Venturi constriction dedicated for flow measurement. The flow loop is constructed in a collaboration with STATOIL to study the possibility of using open Venturi channel for flow measurement in the drilling operations. An extremely simplified P&ID diagram with different sensors used in this work is shown in Figure 1. The 3D view of the open Venturi channel with three ultrasonic sensors over the different locations of the channel is shown in Figure 2. In this study, a model drilling fluid consisting of potassium carbonate (as densifier) and xanthan gum (as viscosifier) is circulated in the flow loop. The fluid has the density of 1153 kg/m^3 and the viscosity of $23 - 100$ cP for corresponding shear rates of $500 - 1$ s^{-1}. In a previous study by the current authors [8], the multivariate data analysis showed that the fluid flow (mass flow measured using Coriolis mass flow meter) depends on the three ultrasonic level measurements positioned over the open Venturi channel. Hence, we will focus on the fusion of the data from these three sensors.

III. METHODS AND RESULTS

In this section, the statistical analysis of the different sensor measurements is performed, two different types of filters are studied, and the implementation of filtered sensor measurements are tested using an empirical model.

A. Statistical Analysis of Sensor Measurements

To investigate the statistical properties of sensor measurements, different experiments are performed with the flow rates changing from 250 - 500 kg/min. For each of the flow rates, the corresponding mean and standard

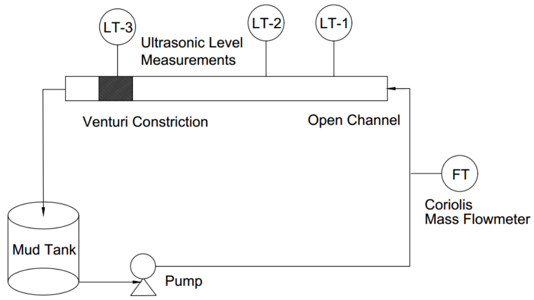

Fig. 1: Extremely simplified P&ID for the flow loop with the measurands used in the study. Schematic shows the hard sensors in the system under study.

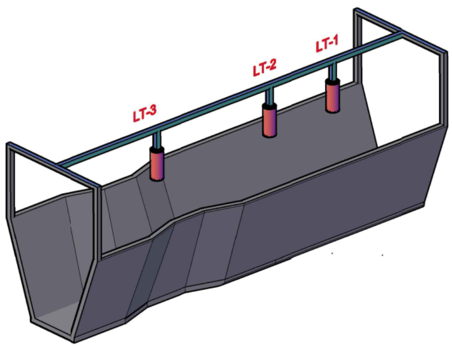

Fig. 2: An open channel with Venturi constriction and three ultrasonic level sensors (LT-1, LT-2, and LT-3) at different locations over the channel. LT-3 is the ultrasonic level sensor placed right above the throat section of the Venturi constriction. [8]

deviations of each sensor measurements are calculated. Finally, the coefficient of variation (CV) is calculated using the relation $CV = (standard\ deviation/mean) * 100\%$. The high value of CV indicates the high variations in the sensor measurements. Hence, for a sensor to have a good accuracy and precision, the CV value should be low or close to 0%. Figure 3 shows the CV plot for all the sensors at different mass flow rates.

In Figure 3, Coriolis mass flow readings have the lowest percentage of CV, whereas ultrasonic level measurement above the throat section of Venturi constriction has the highest CV value. Three different ultrasonic level sensors with the same systematic uncertainty ($\pm 0.25\%$) have different random variations. It is due to the locations of the ultrasonic sensors with respect to the open Venturi channel. The ultrasonic sensor LT-2 has the lowest CV value among the level sensors because the surface of the fluid below the sensor is laminar due to the Venturi effect. The back propagation of hydraulic jump is not fully developed around the position of ultrasonic sensor LT-1. This creates some turbulence on the fluid surface below LT-1 and hence has more random variations compared to LT-2. However, the ultrasonic sensor LT-3 always measures the turbulent fluid surface within the throat section of Venturi constriction and hence has the highest random variations.

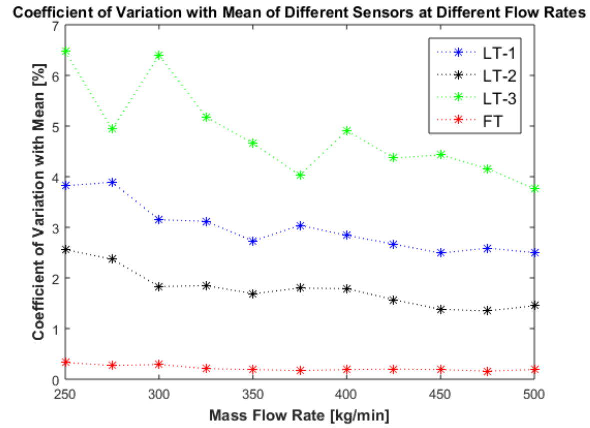

Fig. 3: Coefficient of variation of different sensors at different flow rates. The lowest value is seen in the CV of Coriolis meter (an expensive choice). LT-3 shows the highest CV due to flow related phenomena at the Venturi constriction.

B. *Filtering Sensor Measurements*

The statistical analysis above show that the time series from the sensors have considerable stochastic behavior. As an important step in preprocessing, the three sets of time series from the sensors LT-1, LT-2, and LT-3 are needed to send through some kind of noise filters. In this section, Moving Average Filter (MAF) and first order Low Pass Filter (LPF) are introduced. In MAF, an user-defined fixed number of previous data are used to define the present filtered measurement. MAF filter can reduce noise and restore the dynamics of the sensor measurement. However, with a large number of previous measurements, it suffers from the time-delay response in the dynamics of the signal. In the case of a small number of the previous measurement, it might fail to restore the dynamics of the signal. Hence, there is a trade-off between restoring dynamics and time-delay in using MAF.

Mathematically, the MAF gives equal weight/importance to all the previous measurements. This approach is not applicable for all types of measurements. For fast changing signals, large importance should be given to recent measurements and small weights should be assigned to old measurements. Low Pass Filter is designed with an idea of varying weights to the previous measurements based on the time of measurement. [9]

In our case, both types of filters can be used as the measurement values do not show huge variations. Figure 4 shows a section of the time series before and after sending it through MAF (with 10 previous measurements) and LPF (with filter constant of 0.7) in the LT-3 ultrasonic level measurements. The filtered signals look smoother than the original noisy level measurement after the removal of many spikes not necessarily due to the flow phenomena.

C. *Case Study: Radial Basis Networks for Flow Estimations*

To analyse the significance of the pre-conditioned sensor measurements, we have trained a radial basis neural network

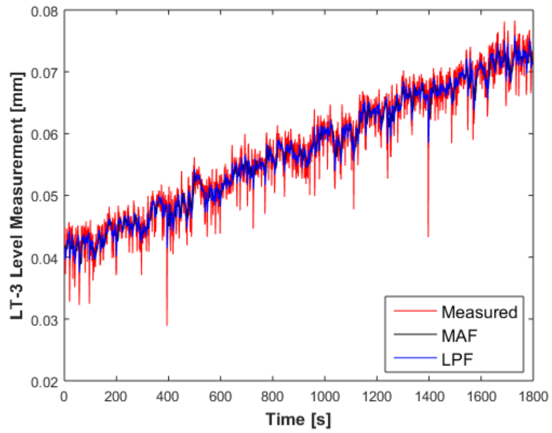

Fig. 4: Moving Average Filter (MAF) and Low Pass Filter (LPF) applied to the ultrasonic level measurement (LT-3) above the throat section of Venturi constriction.

(RBNN) with three neurons and optimal spread based on cross-validation. The network takes three ultrasonic level measurements as inputs and mass flow rate as an output. Figure 5 shows the comparison of flow rates estimated by the unfiltered and filtered RBNN with the reference Coriolis mass flow meter readings. RBNN with unfiltered inputs has noisy flow rate estimations with root mean squared error (RMSE) of 8.43 kg/min. Whereas, RBNN with filtered inputs has comparatively smoother flow rate estimations with RMSE of 7.10 kg/min, which are preferable for further usage (for example: controlling the pump, valve, etc.). Using RBNN, the data from the array of ultrasonic sensors are fused successfully to give reliable and accurate enough estimates of mass flow, thus making the expensive Coriolis meter redundant and leading to considerable reduction in maintenance costs.

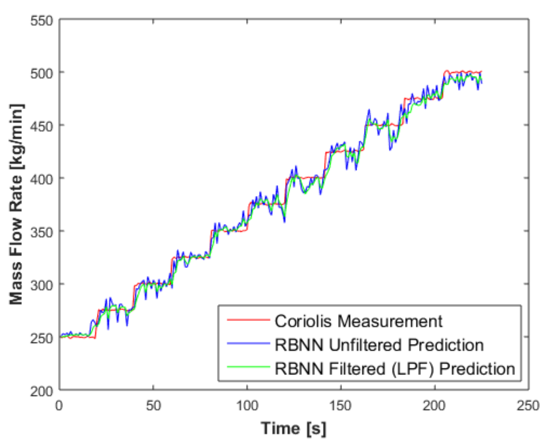

Fig. 5: The comparison of Coriolis mass flow readings with the estimated flow rates using radial basis neural network (RBNN) with unfiltered and filtered ultrasonic level measurements.

IV. Conclusion

Using multilevel scanning by an array of ultrasonic sensors of the level of fluids in an open Venturi channel, good estimate of the mass flow is obtained using a RBNN with three ultrasonic level measurements as inputs and mass flow as the only output. The time series of the levels from the array of ultrasonic sensors are treated using moving average and low pass filters before feeding the data to the RBNN. Due to flow related phenomena in around the Venturi constriction, the level observed right above the constriction by the sensor LT-3 shows greater variations in CV values and in its unprocessed (raw) time series. The three different ultrasonic level time series from the sensors LT-1, LT-2, and LT-3 after low pass filtering fed into the RBNN delivers good and reliable estimate of the mass flow in the open Venturi channel. This result may lead to simple open channel flow monitoring in offshore industries as well as other industries having such channels for facilitating the flow of complex fluids. A normal Coriolis meter for such applications may cost many folds of the total cost of the ultrasonic sensor arrays deployed in this feasibility study. With special intrinsically safe measurement system, the price of using and maintaining a Coriolis meter for this application will be prohibitively high, hence the interest of the industrial actors involved in this feasibility study launched to investigate techniques leading to a simpler and cheaper solution.

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