Mass Flow Measurement of Slurry Using Coriolis Flowmeters

Wasif Shafaet Chowdhury
School of Engineering
University of Kent
Canterbury, United Kingdom
wc247@kent.ac.uk

Yong Yan
School of Engineering
University of Kent
Canterbury, United Kingdom
y.yan@kent.ac.uk

Jingqiong Zhang
Dept of Automatic Control and Sys Eng
University of Sheffield
United Kingdom
jingqiong.zhang@sheffield.ac.uk

Marc-Antony Coster-Chevalier
Research and Development Department
KROHNE Ltd
Wellingborough, United Kingdom
m.coster@krohne.com

Jinyu Liu
Research and Development Department
KROHNE Ltd
Wellingborough, United Kingdom
j.liu4@krohne.com

***Abstract*—Coriolis flowmeters have been proven to be effective while measuring single phase flows, however, the measurement accuracy degrades in case of multiphase flows. In this paper a Gaussian Process Regression (GPR) based soft-computing correction model is proposed for two-phase (sand-water) slurry mass flow measurement using Coriolis flowmeters. Experimental tests were conducted on a purpose-built slurry flow test rig for two different orientations of Coriolis measuring tubes i.e. upward and downward. Five different mass flowrates, 8200, 12000, 14300, 17000 and 20000 kg/h, were tested with Solid Volume Fraction (SVF) ranging between 0 – 1.6%. A number of features, including apparent mass flowrate, density, SVF, and solid weight concentration are used as inputs to GPR models. Two GPR models are trained and tested to estimate the measurement errors of slurry mass flow measurement for the upward and downward orientations of Coriolis flowmeters, respectively. The performances of the GPR models are assessed in comparison with the reference readings. The experimental results suggest that the proposed correction models have successfully limited the relative errors within ±0.2% for all the five mass flowrates and SVFs from 0-1.6% for both upward and downward orientations of Coriolis flowmeters.**

Keywords*—*slurry flow, mass flow measurement, Coriolis flowmeter, solid volume fraction, Gaussian process regression.

I. Introduction

Solids conveyance through pipes are encountered in many industries around the world, mostly for the economic advantages of this model of transportation [1]. A typical example of such a system is slurry transportation. Slurry is a mixture of solid particles suspended in a liquid medium. It is typically used to convey solids by carrier liquid, such as coal-water slurry, paper pulp, drilling mud and clays [2]. In the broad variety of environments in which solids hydro transport is applied, different solid–liquid mixtures are produced and conveyed primarily through pressurized pipes. Water is typically the carrying liquid but the carried solid particles can vary greatly, from very fine to very coarse and from very heavy to very light [3]. Hydraulic transport of solids is of great importance in many industries for various processes, for instance, mining process, manufacturing process (e.g. production of cement, brick, mortar, concrete or glass), including dredging, oil and gas, chemistry, agriculture or waste treatment [4]. Slurries are important in oil-sand industries as well for the transportation of oil-sand from mine to the extraction facility [4]. Depending on the operating conditions, material type and shape of solids the slurry flow regimes can vary. Example flow regimes are: homogeneous, heterogeneous, heterogeneous with moving bed and stationary bed [3, 5]. Slurry is a very complex flow and has attracted considerable attention of many investigators across the world.

In a slurry flow the two phases (liquid and solid) interact with each other while flowing through conduit which significantly affects the behaviour of the mixture flow and results in measurement errors [3]. In highly demanding industrial processes, accurate measurement of solid-liquid two-phase flow is of great importance to realize flow quantification, operation monitoring, process optimization and product quality control [6]. Therefore, significant efforts have been devoted to address the challenges of slurry flow metering over the past few decades [6-9]. As conventional flow measurement techniques, acoustic sensors [6], differential pressure devices incorporating pressure transducers [7] or venturi meters [8] have been used for slurry flow measurements. However, these methods have some limitations such as: the typical shortcomings of acoustic methods i.e. the external noises negatively affecting the measurement performance or blockage at the constricted area of a venturi meter. A combination of an Electromagnetic Flowmeter (EMF) with Electrical Resistance Tomography (ERT) for slurry flow measurement is discussed in [9]. Where the authors developed an in-situ technique based on the measurements of EMF and ERT to study the flow rates of individual phases in a vertical flow. However, the EMF results must be treated with reservation when the flow pattern at the EMF mounting position is a non-homogenous flow and the flowrates obtained by the EMF should be corrected by considering the slip velocity [9]. Moreover, the working principle of EMF is based on Faraday's law of electromagnetic induction, hence, EMF is only able to sense electrically conductive fluid medium. On the other hand, for electrical tomography methods the measured electrical properties are always sensitive to the changes in fluid dielectric properties as well as flow regimes. Frequent online calibrations are required in order to offer accurate flow measurement results, which would limit the application of electrical tomography techniques into real-world industrial processes.

Coriolis flowmeters have been in use for mass flow measurement of single phase flows for decades. It is the most accurate single-phase mass flowmeter, with the benefit of offering multiple outputs, including direct measurement of mass flowrate, density, temperature and even viscosity in some cases [10]. Since volumetric flowrate can be sensitive to process conditions, mass flowrate measurement has become more favourable, particularly in the highly demanding applications [10]. The potential extension of Coriolis flow metering technology from single-phase flows to multiphase flows has received considerable attention over the past few years. However, the primary limitation of this flow measurement technique is the degradation of accuracy while measuring multiphase flows. Phase decoupling [11], compressibility [12], asymmetric damping [13] and velocity profile [14] are identified as the sources of measurement errors. Among them phase decoupling effect is one of the most common and significant source that leads to measurement inaccuracies [11]. It is a negative error and theoretical treatments of this error for different types of mixtures (including slurry) flowing through Coriolis tubes are discussed in [11, 13]. Although, these studies provide theoretical treatment of the error they lack practical implementation in case of slurry flow measurements. With the rapid development of artificial intelligence and machine learning tools, soft computing techniques have shown the potential to assist Coriolis flowmeters for satisfactory multiphase flow metering [15].

This study aims to extend the Coriolis flow metering technology for two-phase slurry mass flow measurement by incorporating soft-computing techniques. The behaviours of two 50 mm bore Coriolis flowmeters while measuring sand-water slurry mass flow were practically examined through a series of experimental tests. The tests were conducted on a purpose-built slurry test rig under a range of mass flowrates (8200-20000 kg/h) and Solid Volume Fractions (SVFs) 0-1.6%. The effects of Coriolis measuring tubes' geometry and orientation conditions are also examined by installing the two Coriolis flowmeters on horizontal pipe sections, however, with their measuring tubes in upward and downward orientations. A number of parameters of interest, i.e. mixture mass flowrate, density, SVF etc. were extracted and examined for all the test conditions from both the flowmeters. The original errors of Coriolis flowmeters for measuring tubes upward and downwards orientations are presented. The effects of flowmeters tube geometry and orientation conditions that leads to measurement inaccuracies are also discussed. Later, a Gaussian Process Regression (GPR) based soft-computing correction model is proposed to estimate and compensate the errors in slurry mass flow measurement.

II. Methodology

A. Overall Measurement Strategy:

Fig. 1 illustrates the basic principle and structure of the proposed slurry mass flow measurement system using a Coriolis flowmeter. From Fig. 1 it can be seen that Coriolis flowmeters are mounted on a pipeline with their measuring tubes in upward and downward orientations. The flowmeters provide the mass flow and density readings of the mixture flowing through the tubes [10]. Even though these parameters are erroneous under two-phase conditions, they still reflect the true mixture mass flow and SVF to some extent. The GPR based correction model is to be incorporated in the flowmeters to correct the apparent slurry mass flow readings.

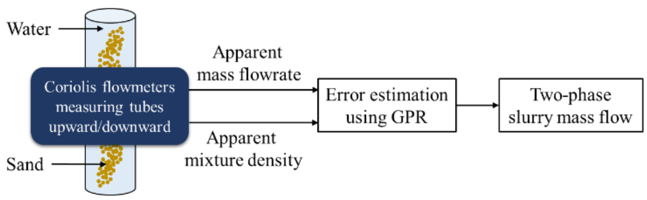


Fig. 1. Principle and structure of the proposed slurry mass flow measurement system.

The GPR [16] is used since the flow measurement error trends of upward and downward orientations of Coriolis flowmeters are observed to be fairly linear and repeatable. The observed error trends are discussed in detail in Section III.

B. Gaussian Process Regression (GPR):

GPR is used to estimate the errors since it does not require a fitting function to be declared in exact form. It uses a covariance matrix that reflects the correlation between the features of the sample in Gaussian Process (GP). As a result GPR shows a great fitting ability. The GPR model is discussed in detail in [16].

A GP is a collection of limited number of random variables which have (consistent) joint Gaussian distributions. That is, for any input feature x from the feature matrix $x = \{x_1, x_2, x_3, \dots \dots, x_n\}$, its probability distribution function $f(x)$ follows the Gaussian distribution. Hence, the GP is specified as:

$$f(x) \sim GP(\mu(x), k(x_n, x_n)) \tag{1}$$

where $\mu(x)$ is the mean function and $k(x_n, x_n)$ is the kernel function created by the covariance matrix.

In GPR the Bayesian principle is used to construct a predictive model. Where the undermined parameters of kernel function are iteratively achieved to determine the optimal parameters. Based on that a prior distribution is established for the n dimensional training samples. Then the joint posterior distribution of training samples y and estimated output $\hat{y}$ for the test samples $(\hat{x})$ are established:

$$\begin{bmatrix} y \\ \hat{y} \end{bmatrix} \sim N\left(0, \begin{bmatrix} K(X,X) & K(X,\hat{X})^T \\ K(X,\hat{X}) & K(\hat{X},\hat{X}) \end{bmatrix}\right) \tag{2}$$

Where $N()$ indicates a normal distribution, T denotes the transpose matrix. $K(X,X)$, $K(\hat{X},\hat{X})$ and $K(X,\hat{X})$ represents the covariance matrices among inputs from training set, test set as well as training and test sets, respectively. The following equations give the covariance matrices:

$$K(X,X) = \begin{bmatrix} k(x_1,x_1) & k(x_1,x_2) & \cdots & k(x_1,x_n) \\ k(x_2,x_1) & k(x_2,x_2) & \cdots & k(x_2,x_n) \\ \vdots & \vdots & \ddots & \vdots \\ k(x_n,x_1) & k(x_n,x_2) & \cdots & k(x_n,x_n) \end{bmatrix} \tag{3}$$

$$K(X,\hat{X}) = [k(x_1,\hat{x}) \quad k(x_2,\hat{x}) \quad \cdots \quad k(x_n,\hat{x})] \tag{4}$$

$$K(\hat{X},\hat{X}) = k(\hat{x},\hat{x}) \tag{5}$$

The joint posterior distribution of estimated value $\hat{y}$ can be given as:

$$P(\hat{y} | \, x, y, \hat{X}) \sim N(f | 0, K(X,X)) \tag{6}$$

Finally, the mean distribution is used as the estimated output.

$$\hat{y} = K(X,X)K(X,X)^{-1}y \tag{7}$$

As the key to GPR, the kernel function determines the property of GP, and used to obtain covariance matrix. Common kernel functions includes Rational Quadratic Kernel (RQK), Exponential Kernel (ExK), Squared Exponential Kernel (SEK) and Matern 5/2 Kernel (M5/2K), which are defined as follows:

$$k_{RQK}(x_i, x_j) = \sigma^2 (1 + \frac{r^2}{2\alpha l^2})^{-\alpha} \quad (8)$$

$$k_{ExK}(x_i, x_j) = \sigma^2 exp\left(-\frac{r}{2l^2}\right) \quad (9)$$

$$k_{SEK}(x_i, x_j) = \sigma^2 exp\left[-\frac{r^2}{2l^2}\right] \quad (10)$$

$$k_{M5/2K}(x_i, x_j) = \sigma^2 \left(1 + \frac{\sqrt{5}r^2}{\sigma} + \frac{5r^2}{3\sigma^2}\right) exp\left(-\frac{\sqrt{5}r}{\sigma}\right) \quad (11)$$

r is defined as:

$$r = \|x_i - x_j\| \quad (12)$$

α is a scale-mixture parameter (α > 0), σ and l are height and length scale parameters, respectively, x_i and x_j represents two points in space, respectively.

In order to determine the optimal kernel function a comparative analysis is carried out in Section III based on the Root Mean Square Error (RMSE).

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2} \quad (13)$$

Where m is the number of test data, y_i and $\hat{y}_i$ are the reference and predicted values of i-th test, respectively.

III. Experimental Results and Discussion

A. Test Facility and Conditions

A laboratory-scale 50 mm bore dilute sand-water slurry flow test rig was designed and constructed to acquire the experimental data of this study. Figs. 2 and 3 illustrate the schematic and physical implementation of the test rig, respectively. The rig consists of two deeper V-shaped Coriolis flowmeters (KROHNE OPTIMASS 6400 S50) with their measuring tubes upward and downward orientations; three tanks: slurry tank (1500 litres), weighing tank (300 litres) and buffer tank; and three pumps: main pump (centrifugal, rated 5.5 kw), secondary pump and agitator (0.37 kw). The slurry tank is used to store sand-water and the agitator is placed over the tank to create dilute sand-water slurry. A weighing system with uncertainly lower than the meters under test is used to acquire the reference mixture mass readings. The buffer tank is used for sand-water separation and a secondary pump is there to feed the separated water back into slurry tank. All of these pumps, flowmeters and tanks are connected through a main circulation loop pipeline. The main pump is used to allow the dilute slurry flow throughout the pipeline homogenously. A number of valves are also there to regulate the direction of slurry flow. Two motor control inverters are in place to control the frequencies of main pump and agitator to achieve the desired mass flowrates and SVFs, respectively.

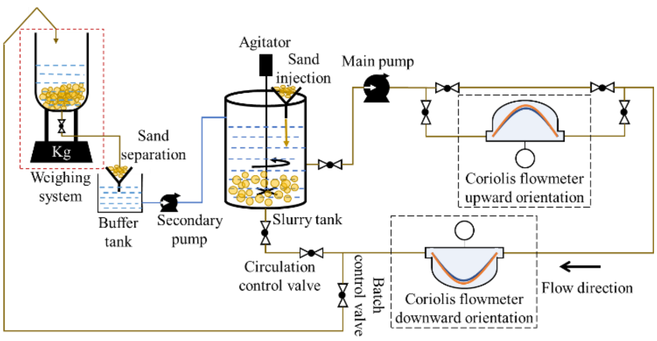


Fig. 2. Schematic of the (sand-water) two-phase slurry test facility.

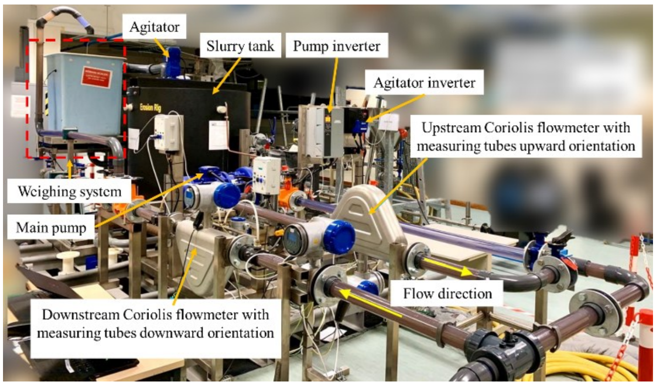


Fig. 3. Two-phase slurry test facility.

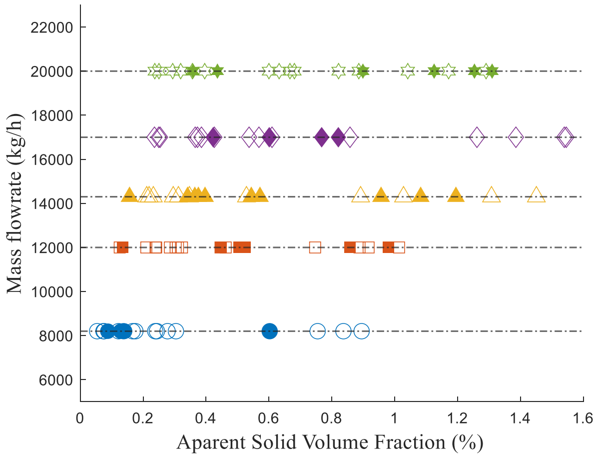


Fig. 4. Experimental test matrix of (sand-water) two-phase slurry mass flow measurement (unfilled markers-training and filled markers-test).

Fig. 4 illustrates the experimental test matrix from upward and downward orientations of Coriolis flowmeters, each having 100 samples in total, for five different mass flowrates (8200, 12000, 14300, 17000 and 20000 kg/h) and SVFs 0-1.6%. In this research 70% of data from the test matrix are used to train the two GPR models whereas the remaining 30% are used to test the models. The training and test data are shown in Fig. 4 as unfilled and filled markers, respectively.

B. Sensor Features:

Several features, including apparent SVF, apparent mass flowrate, apparent mixture density, apparent Solid Weight Concentration (SWC), apparent mixture mass and reference mixture mass, are analysed to quantify the behaviour of slurry mass flow.

All of the apparent features, except for SVF ($\alpha_{s,app}$) and SWC ($\beta_{x,app}$), are directly obtained from the Coriolis flowmeters. The following two equations are used to determine the apparent SVF and SWC respectively:

$$\alpha_{s,app} = \frac{\rho_{app} - \rho_w}{\rho_s - \rho_w} \times 100\% \quad (14)$$

$$\beta_{x,app} = \frac{\rho_s(\rho_w - \rho_{app})}{\rho_{app}(\rho_w - \rho_s)} \times 100\% \quad (15)$$

Where ρ_s, ρ_w and ρ_{app} are sand (2680 kg/m^3), water (998 kg/m^3) and apparent mixture densities, respectively.

The reference mixture mass is obtained from the weighing tank and it is used to calculate the relative error (%),

$$E_{\dot{m}} = \frac{m_{app} - m_{ref}}{m_{ref}} \times 100\% \quad (16)$$

Where m_{app} and m_{ref} are the apparent and reference mixture mass, respectively.

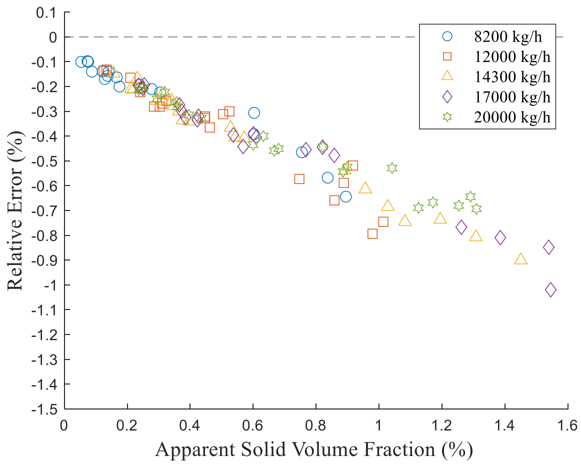
Table I demonstrates the list of features used to train and test the models. It also includes corresponding physical definition of each feature.

TABLE I. INPUT FEATURES AND THEIR CORRESPONDING PHYSICAL DEFINITIONS

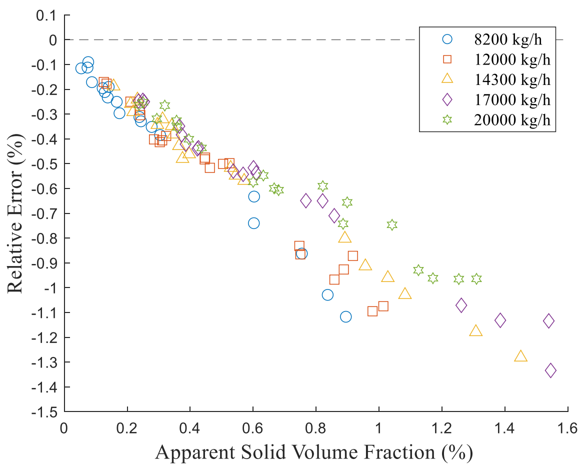
ID	Features	Physical definition
x_1	Apparent mixture density (kg/m^3)	Sand-water mixture denstiy reading from the Coriolis flowmeters.
x_2	Apparent mass flowrate (kg/h)	The mass flowrate reading from Coriolis flowmeters based on the calibration cahracteristics for single-phase flows.
x_3	Apparent SVF ($\alpha_{s,app}$) (%)	Volume fraction of solid (sand) obtained through Eq. (14).
x_4	Apparent SWC ($\beta_{x,app}$) (%)	Solid weight concentration obtained through Eq. (15).
y	Desired RE (%)	Relative error (RE) in mixture mass reading (Eq. (16)) of Coriolis flowmeters.
$\hat{y}$	Estimated RE (%)	Estimated relative error.

C. *Analysis of the Original Errors:*

Fig. 5 illustrates the original errors obtained from the upward and downward Coriolis flowmeters, respectively, under all test conditions.



(a) Measuring tubes in upward orientation



(b) Measuring tubes in downward orientation

Fig. 5. Relative errors in slurry mass flow measurement from Coriolis flowmeters without the correction model.

It is noticeable that for both flowmeters the errors are negative, which in turns proves that phase decoupling error is the most significant source of errors that a Coriolis flowmeter experiences while measuring slurry mass flow. The figures also reveal a strong correlation between SVF (%) and relative error (%). Moreover, the errors of downward meter (-1.4%) are higher in terms of absolute value than those of upward meter (-1.1%). It is because sand particles get accumulated at the bottom of deeper V-shaped tubes of the downward meter due to gravitational effect. Whereas, for the upward flowmeter this accumulation happens at the inlet side of the tubes. As a result, at the initial state the downward flowmeter's density readings are higher than that of upward flowmeter. This results in additional negative errors for the downward meter. This phenomenon is also known as asymmetric damping [13]. Another possible source of errors is imbalance; this error arises if the mixture flow is not equally split into each of the two measuring tubes. Therefore, it can be observed that, other than density differences between multiple phases, tube geometry and installation orientations of Coriolis flowmeters measuring tubes' can also affect the flowmeters behaviour. In addition to that, the upward orientation of Coriolis measuring tubes' is more favourable for slurry mass flow measurement compared to downward orientation.

D. *Kernel function selection:*

Since, kernel functions in a GPR model play a vital role, it is crucial to determine the most suitable one prior to model training. As discussed in Section II four types of kernel functions (RQK, ExK, SEK and M5/2K) are typically used in GPR. In this study four GPR models are implemented with all the four kernel functions. Fig. 6 shows the performances of the four kernel functions. It is evident that Matern 5/2 exhibits lowest RMSE compared to others and is thus used in this study for the correction model.

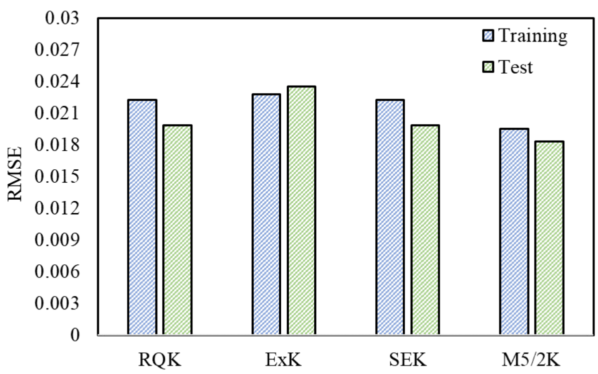
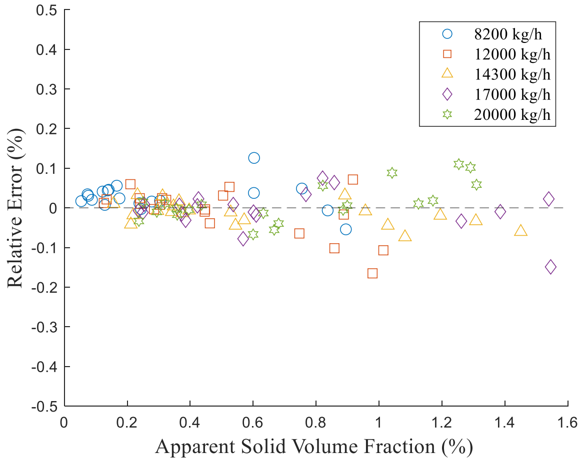


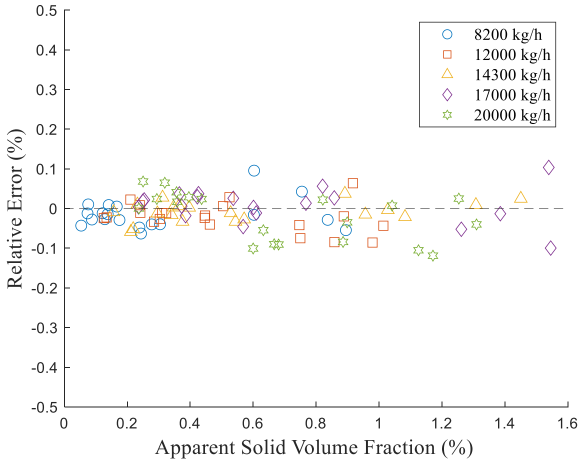
Fig. 6. Performance analysis of GPR model for different kernel functions.

E. *Mixture mass correction:*

In order to estimate the errors illustrated in Fig. 5 and later compensate them two GPR models are trained and tested with the features extracted from upward and downward flowmeters. The estimated errors are later incorporated with the apparent mixture mass flow readings of corresponding Coriolis flowmeters to achieve the desired mass flow of slurry. Fig. 7 presents the relative error (%) of the proposed correction model for upward and downward orientations of flowmeters, respectively. It is evident that the proposed model can effectively estimate and compensate the errors in slurry mass flow measurement. The errors are within $\pm 0.2\%$ for both upward and downward orientations of Coriolis measuring tubes under all test conditions.



(a) Measuring tubes in upward orientation



(b) Measuring tubes in downward orientation

Fig. 7. Relative error in slurry mass flow measurement from Coriolis flowmeters with the correction model.

IV. Conclusion

In this paper two Gaussian Process Regression based correction models have been applied under two different orientations of Coriolis flowmeters to estimate the errors of the flowmeters while measuring sand-water slurry mass flow. The estimated errors were later incorporated with the apparent mass flow readings to determine the desired slurry mass flow. The effectiveness of the proposed model is verified through a range of experimental tests. The results have shown that the relative errors of corrected slurry mass flows are no greater than ±0.2% for both upward and downward orientations of flowmeters under all test conditions. In comparison with the original errors, the proposed models have provided significant improvements in measurement accuracy under all sand-water slurry flow conditions. This outcome has effectively extended the applicability of Coriolis flowmeters to two-phase slurry mass flow measurement. Efforts will be made in future to estimate and compensate the density errors as well as to determine sand weight fraction.

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