Co-operative sensor fusion using time warping in multimodal tomometry for process control

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Abstract- **Recent studies in process tomography have mostly focused on image processing and enhancement of images obtained from Electrical Capacitance, Electrical Resistance, Electrical Impedance, Gamma- and X-ray- tomographic modalities. In the process industries, there is a growing need for fast acting measurement and control procedures, architectures and their implementation within existing sensor and control suites. With this industrial relevance, a multimodal tomometric sensor fusion is studied involving pressure and capacitance measurements in a two phase flow rig. Pressure is measured using standard pressure sensors, whereas the capacitance are measured using arrays of capacitance electrodes placed on the periphery of a section of the pipe in the multiphase flow rig. These capacitance measurements are performed by using ECT-modules. In this paper, the focus is on early slug detection and timely characterization of these slugs formed in the two phase flow. To associate simultaneous occurrence of slug based phenomena in the time series of the pressure and ECT-signals, dynamic time warping (DTW) algorithms are used. The usage of DTW and the multimodal tomometric sensor suite with pressure and ECT-modules leads to a co-operative sensor data fusion, which can help to identify characteristic features of slugs in two phase flows, which can be significant inputs to the process control unit in the assessment/implementation of necessary actions, such as activating choke valves, reducing pump outputs of one or more of the phases flowing in the rig. Time series of pressure and ECT-signal are studied using DTW and results are compared and fused with some discussions on how these could be used in process control.**

Keywords- ***Multimodal tomometry, ECT (Electrical capacitance Tomography), sensor fusion, soft sensor, two phase flow, Dynamic Time Warping (DTW)***

NOMENCLATURE

ECT	Electrical Capacitance Tomography
DTW	Dynamic Time Warping
TB	Taylor Bubble

LIST OF SYMBOLS

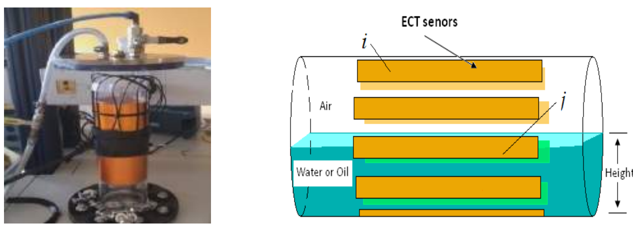
N	Number of capacitance Electrodes
α_w	Water volume ratio
C_{ij}	Capacitance measurement between electrodes *i* and *j*.
P_w	Warping path
X ,Y	Time series signals
δ	Squared distance between two time series elements
Co_{δ}	Cost matrix
Dp	Differential pressure (mbar)
t_s	Time window of the slug (s)
V_s	Slug Velocity (m/s)
d	Distance between two ECT sensor planes
τ	Time lag (s)
L_s	Liquid slug length (m)
h_{Dp}	Pressure peak (normalized)
$\bar{h}_{Dp}$	Mean of the Pressure peak
$\sigma_{h_{Dp}}$	Standard deviation of the Pressure peak

I. INTRODUCTION

Electrical capacitance tomography (ECT) is gaining increased acceptance in multiphase flow measurements. Most of the research facilities of leading industries have included ECT in their measurement systems. Pressure signals coming from well-established sensors in the study of flow in pipes, have vast amount of information on multiphase flows. The information from pressure signals has been used to characterize some flow parameters. In this paper, ECT measurements and differential pressure (Dp) measurements are fused and the results from the fusion are used to identify and characterize the liquid slug.

Dynamic time warping (DTW) technique has been used mainly in speech recognition applications [1]. DTW techniques are used here to fuse the Dp and ECT signals.

II. TEST FACILITY WITH THE MEASUREMENT SYSTEM



(a) (b)

Figure 1. (a) The actual sensor head used in experiments (b) Schematic diagram. Cij is the capacitance measured between the elctrodes i and j covering all the combinations excluding i=j. i, j= 1, 2, …,12.

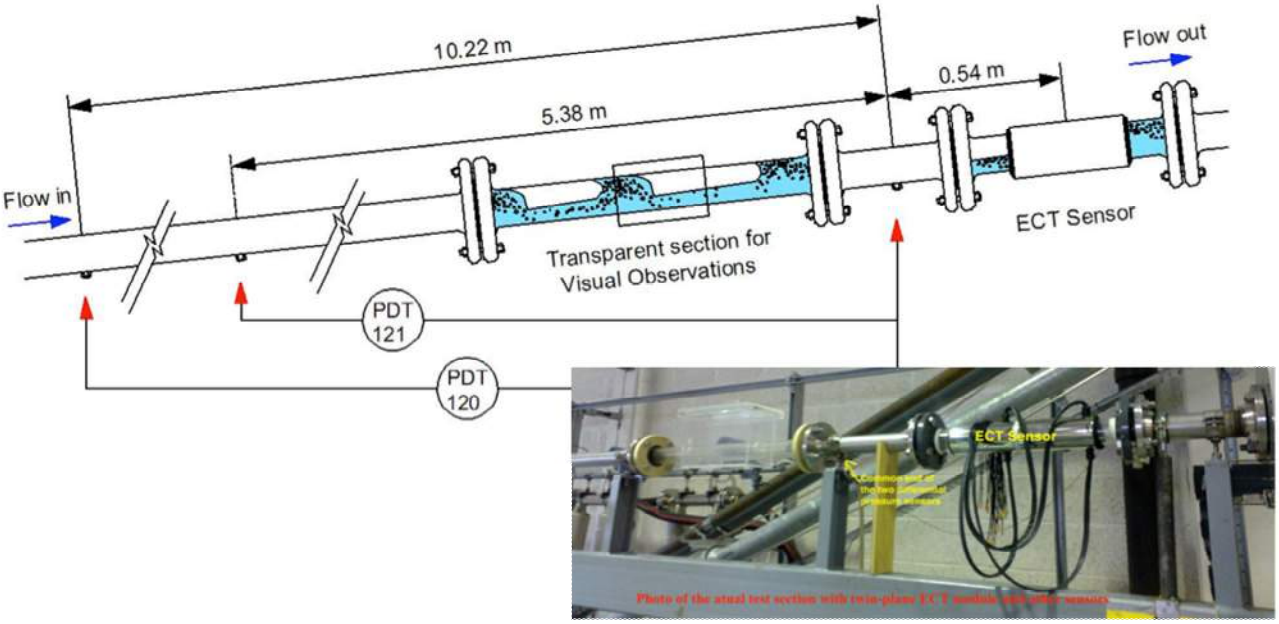


Figure 2. Test section in the multiphase flow rig containing pressure and ECT-modules with details of relevant dimensions. Inset: Photo of the actual test section with twin-plane ECTm module and other sensors

A. Electrical Capacitance Tomography

Electrical capacitance tomography (ECT) is a non-invasive method of imaging the cross sectional permittivity distribution of a mixture of materials with different permittivities inside vessels, based on inter-electrode capacitance measurements, [2]. In generating images needed for estimating the distribution of materials, the capacitances between all possible combinations of the electrode pairs are measured, using an array of electrodes placed externally around the periphery of the vessel, [3]. A schematic showing the assembly of all the electrodes on the sensor head is shown in Fig. 1 (b).

As shown in Fig. 1, the electrodes are arranged very often symmetrically taking necessary precautionary measures to improve the signal to noise ratio. These measures are mainly based on avoiding spurious capacitance values, e.g. inclusion of guard electrodes, shielding etc. In the context of this paper, the arrangement shown in Fig. 1 is called the ECT sensor module. In our application, the ECT sensor consists of one circumferential set of N capacitance electrodes placed around the pipe separator (in the experiments described below, N=12). During the experiments performed in conjunction with this study, the pipe is kept horizontal, as shown in Fig. 1 (b).

B. Multi-phase flow loop

Simple flow Diagram of the testing section of experimental flow-rig used in this study is shown in Fig. 2. Experiments were performed using water and air at room temperatures and atmospheric outlet pressure. Differential pressures between the points marked in red arrows were captured from sensors PDT120 and PDT121.water is circulated using volumetric pumps. The mass flow, density and temperature were measured for each phase, before the components enter the test section using Coriolis flowmeters. The test section is a 15m long steel pipe with inner diameter 56mm. with the test section of the pipe having adjustable inclination in the range of -10º to +10º to the horizontal. Liquid and air flow 12.5 m from the inlet of the test section to pass the first tomography sensor plane. Distances between points where the differential pressure is measured are also given in the same figure. Coriolis flowmeters provide high accuracy with uncertainty ± 0.01kg/min. PID controllers implemented in LabVIEW controls the liquid flow rates. In this experimental study, the inlet air and water flow rates were maintained at 0.25kg/min and 50kg/min while the pipe inclination was fixed at +1º to the horizontal.

Volume ratio, α_w can be calculated using (1) based on inter-electrode capacitance measurements as explained in [3] and [5].

$$\alpha_w = \frac{1}{N(N-1)} \sum_{i=1}^{N} \left(\sum_{j=1}^{N} C_{ij} \right) \qquad \forall\ i < j \qquad (1)$$

Where N=12 and C_{ij} is the capacitance between electrodes *i* and *j*.

III. DYNAMIC TIME WARPING (DTW)

Dynamic Time Warping is implemented in many algorithms in the field of speech and image processing for establishing similarities in two or more sequences of observations (Usually measurements) in the form of time series. DTW is a versatile tool in data mining applications, where there is a need for detecting "matches" in many sets of time series. The sets of time series are warped in the temporal domain somewhat non-linearly under some constraints. As such, DTW is a useful tool in sensor data fusion in process industries, where the tags can run into thousands and data can run into TB regions.

The use of DTW is to compare two time series signals. Here the warping path and two time series signals are defined as $P_w = (p_1, p_2, \ldots p_L)$, $X = (x_1, x_2, \ldots x_r)$ and $Y = (y_1, y_2, \ldots y_s)$ respectively. *r* and *s* are number of elements in the X and Y time series and L is length of the warping path. Warping path aligns the points in time series *X* and *Y* in such a way that the distance between them are minimized. Squared distance between two elements can be defined as:

$$\delta(x_i, y_j) = (x_i - y_j)^2 \tag{2}$$

Then total cost Co_δ of a warping path P_w between *X* and *Y* signals with respect to δ can be defined as:

$$Co_\delta(X, Y) = \sum_{k=1}^{L} \delta(x_i - y_j)_k \tag{3}$$

Here, *i* and *j* corresponds to the location in the $Co_\delta(X, Y)$ matrix and *k* is the corresponding point of the warping path P_w. Then the best alignment between *X* and *Y*, is found following the path through the minimum points of the $Co_\delta(X, Y)$ matrix [4].

$$DTW(X, Y) = \min_{P} \sum_{k=1}^{L} \delta(p_k) \tag{4}$$

The DTW given in (4) is found using dynamic programming [5].

IV. CHARACTERIZATION OF FLOW REGIME AND SLUGS

Under the experimental conditions given above slug flows can be observed. Water volume ratio signal (α_w) calculated from ECT measurements using (1) can then be used to estimate liquid slug parameters. As shown in Fig 3, a threshold value is selected to locate t_s. In this analysis, a threshold of 0.7 was selected. When the volume fraction α_w reaches the threshold value of 0.7 from lower values of α_w, the corresponding time stamp is picked. When the volume fraction α_w reaches the threshold value of 0.7 again in the descending mode, on its way back to the stratified region, the second time stamp is picked. Then the difference between these two time stamps is calculated giving the value of t_s. Then this time difference t_s is used in the slug length L_s calculation as given in (5). Here V_s is the velocity of the slug.

$$L_s = V_s t_s \tag{5}$$

Similarly, L_s of each slug observed using the time series of pressure Dp and volume fraction α_w is calculated. Since a twin plane ECT sensor is used in these measurements, two time series of α_w can be calculated. Cross-correlation of those two α_w signals gives the time lag, τ , between two signals corresponding to the correlation peak. Since the distance between two sensor planes is known (d =190mm). The slug velocity V_s can easily be calculated using (6) as explained in [7].

$$V_s = \frac{d}{\tau} \tag{6}$$

Differential pressure signal (Dp) from DP121 sensor was also recorded along with the capacitance measurements from ECT-module. Then the sets of time series consisting of differential pressure Dp and water volume fraction α_w signals are warped to get the optimum alignment. The warping of Dp signal on to the α_w is selected here for the estimation of the magnitude of Dp (h_{Dp}) at the liquid slug region as shown in Fig 4. As illustrates in Fig 4 the warped Dp signal indicates its peak within the corresponding liquid slug body. Hence, maximum Dp value (h_{Dp}) can easily be selected. Similarly h_{Dp} values correspond to all slugs can be selected.

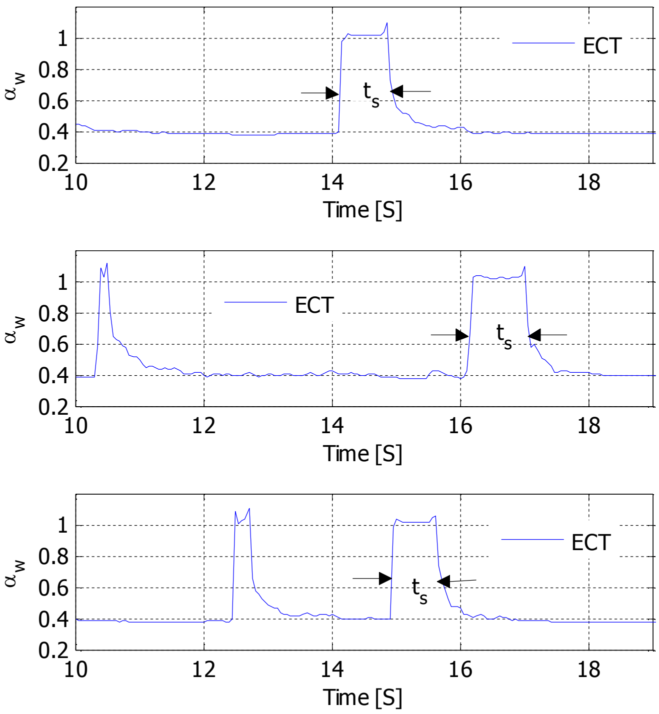


Figure 3. Typical slug pulse as obtained from ECT-module based water volume fraction, shown here as part of a time series with characteristic features depicting slug formation

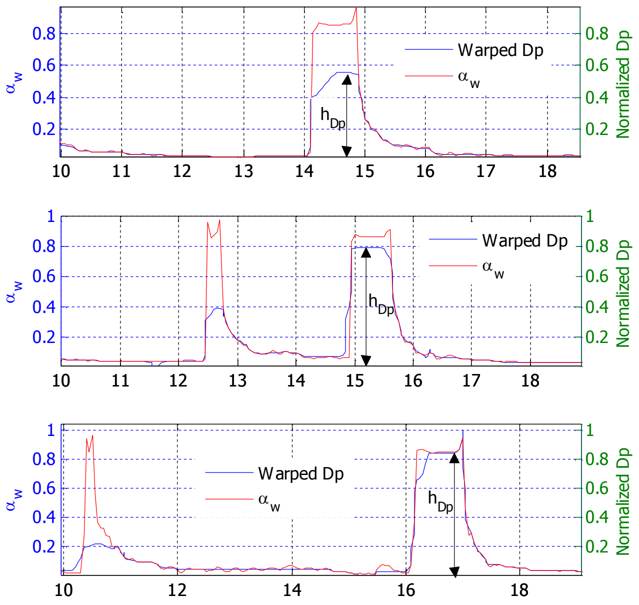


Figure 4. Warping Dp on to α_w signal and selection of h_{Dp}

V. EXPERIMENTAL RESULTS

Signals used in the analysis are given in the Fig 5. Warping path p_w is indicated in white of Co_δ matrix plot shown in Fig 6. Then the warped Dp signal with reference to water volume ratio signal is extracted from the warping path information. Fig 7 illustrates the mapping of differential pressure signal Dp onto the volume fraction signal α_w

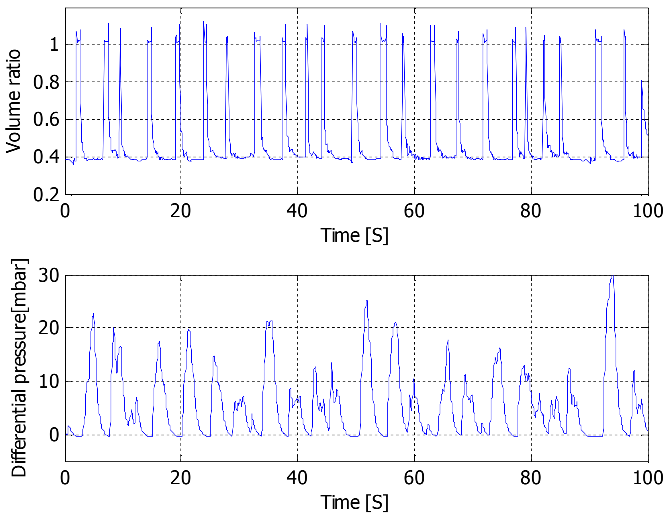


Figure 5. Typical sets of time series (water volume fraction α_w and differential pressure Dp signals) used in the data mining algortihms

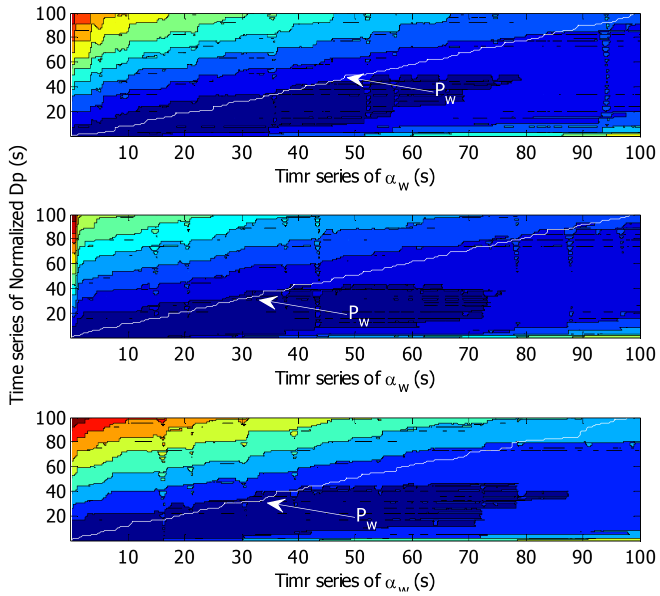


Figure 6. The cost matrix and warping path (white line) using the time series of differential pressure Dp and water volume fraction α_w

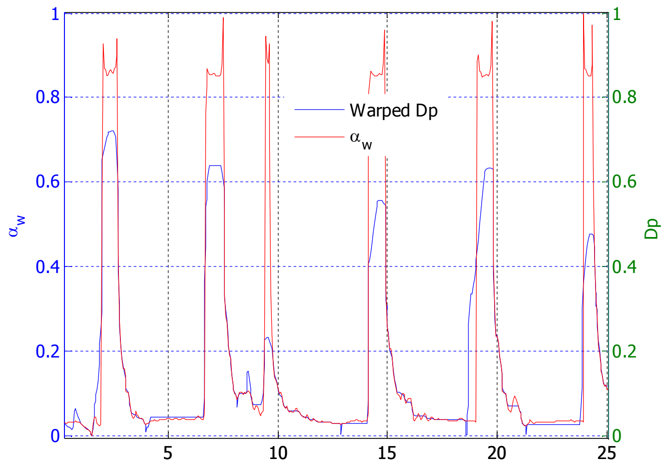


Figure 7. The warped versions of Dp and α_w signals represented using a common time axis.

It can be seen from Fig 7 that positive-going and negative going flanks of water volume fraction α_w and warped Dp are aligned properly with the plateau parts of these two time series also falling in the same time slots. It is interesting to note that for plateaus for water volume fraction α_w with wider time slots, higher amplitudes of differential pressure signals Dp can be observed.

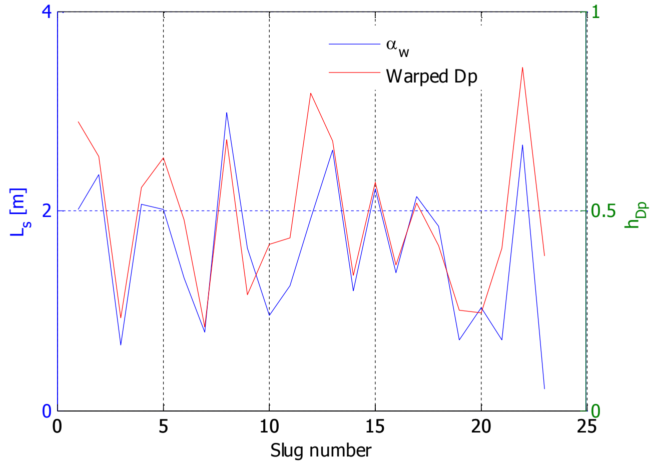


Figure 8. Slug lengths as calcualted using slug velocities for slugs found using Figure 7

The lengths of different slugs (L_s) calculated using (4) with the help of the slug velocities are given in Fig. 8. The liquid slug length (L_s) and magnitude of the *D*p peak which lies within the corresponding slug body (h_{Dp}) is then studied both with respect to the time slots and their respective amplitudes. The results for 23 slugs observed are presented in Fig 8. From Fig. 8, it can be seen that for longer liquid slugs higher h_{Dp} values are generated, whereas for shorter slugs the values of h_{Dp} are lower.

The variations of slug lengths for different inflow conditions of air and water as estimated using the DTW based algorithm is given in Table 1.

TABLE I. PRESSURE PEAK VARIATION UNDER DIFFERENT SLUG LENGTHS

Slug Length (m)	Pressure peak ($\bar{h}_{Dp} \pm \sigma_{h_{Dp}}$)	
	Inlet Flow rates Air -- 0.25kg/min Water-- 50kg/min	Inlet Flow rates Air -- 0.10kg/min Water -- 50kg/min
0-0.5	0.38	--
0.5-1	0.30 ± 0.09	0.31 ± 0.11
1-1.5	0.37 ±0.09	0.406
1.5-2	0.49 ± 0.2	0.55 ± 0.14
2-2.5	0.61± 0.07	0.62 ± 0.15
2.5-3	0.73± 0.10	0.78 ± 0.21

The pressure peaks observed using the DTW algorithm follow the trend shown in Fig 9. The lengths of slugs and corresponding pressure peaks were then classified into 6 different groups as given in Table l. The mean of h_{Dp} and their deviations are given in the other columns for the experimental conditions given.

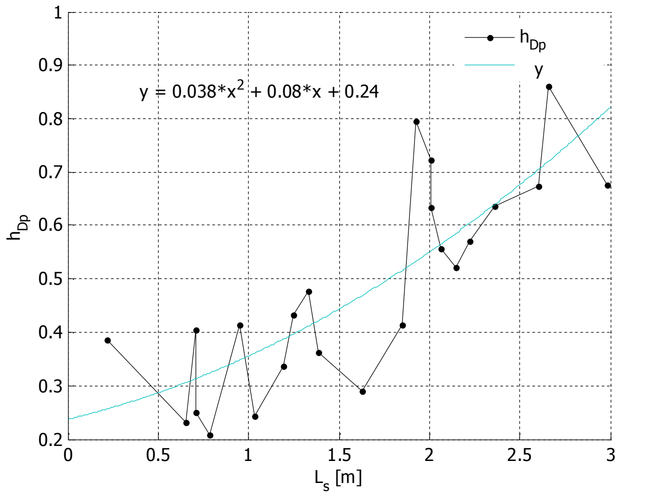


Figure 9. Variation of Normalized pressure peak (h_{Dp}) with increasing Slug lengths

VI. SOFT SENSOR APPROACH USING PROCESS TOMOMETRY

The results from the multimodal tomometric approach involving capacitance values from ECT-module and differential pressure sensors indicate that useful information on flow regime and slug can be extracted from a fusion of these two sets of time series. This is an example of a soft sensor approach giving the process engineer parameters such as V_s, L_s and the time slots of the occurrences of slugs. The system integration of the differential pressure Dp and ECT-sensor with the soft sensor outputs related to the flow regime/slug are shown in Fig 10 with a schematic of the control architecture for mitigating the detrimental effects of heavy slug formation and its transportation to sensitive hardware like valves and pumps is a multiphase loop.

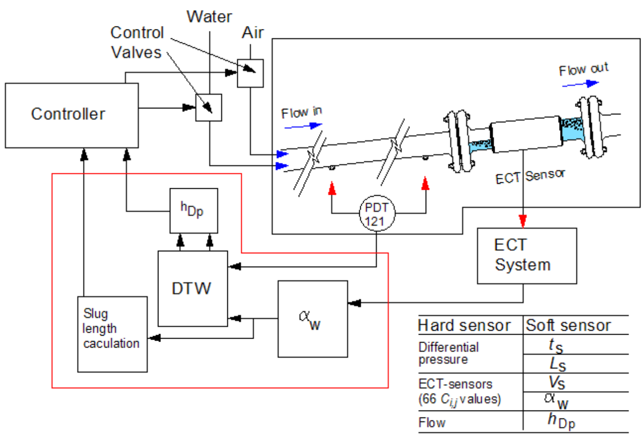


Figure 10. Block diagram for the system with soft sensor outputs in a control scenario to ascertain slug length and mitigate slug induced flow problems.

VII. CONCLUSIONS

The simultaneous observations of differential pressure and capacitance values form an ECT-module in a pipe section in multiphase flow gives the process engineer a set of time series, which can then be subjected to data mining using various procedures. In the present study, differential pressure signals and water volume fraction signals as estimated with capacitance values from ECT-sensor modules form a good set of cooperative sensor data for data fusion. The data mining and data fusion are done using dynamic time warping (DTW). With the dynamic time warping, some physical phenomena are clearly captured and their characterizations are facilitated, especially with respect to slug and pressure peaks. The aligned signals of pressure and volume fractions clearly indicate the possibility of identifying the time of occurrence and the extent of slugs. With a set of two time series, based on two physical measurands, viz. pressure and capacitance, the soft sensor approach described in this paper gives rise to water volume fraction, flow regime identification, slug velocity, frequency and length and the time of occurrence and duration of these flow regimes. The interdisciplinary group in the Telemark University College looking into CFD codes for multiphase flow is looking into the ways and means of unambiguously identifying input parameters giving rise to certain type of slugs. These could be compared with the results given in this paper, especially those given in Table 1 and Fig 10.

This is a valuable tool for the process engineer in making decisions as to what kind of control actions are to be taken.

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