

<b>ITC 3/48</b> Journal of Information Technology and Control Vol. 48 / No. 3 / 2019 pp. 464-486 DOI 10.5755/j01.itc.48.3.22189	<b>Computer Methods for Non-invasive Measurement and Control          of Two-phase Flows: A Review Study</b>	
	Received 2019/08/16	Accepted after revision 2019/08/20
	 <a href="http://dx.doi.org/10.5755/j01.itc.48.3.22189">http://dx.doi.org/10.5755/j01.itc.48.3.22189</a>	

# Computer Methods for Non-invasive Measurement and Control of Two-phase Flows: A Review Study

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Nowadays, the application of advanced technologies in modern production systems is the main trend of development and technological progress in many industrial sectors. It is due to the still growing trends of energy-saving and production quality enhancement. Wherever in the production process, the phase mixture is transported and it is not optimal or not economical, there is a need to develop a system which would be able to prevent any construction disaster, unexpected production line stopping or situation where for reasons of bad flow parameters, the final product is defective. This paper studies various sensors, measurement techniques and computer methods for signal processing and analysis to diagnose and control two-phase flows. Due to the possibility that the invasive measurement disturbs the process and changes its parameters and behaviour especially in the location just after the measurement point and simultaneously does not provide any information about these changes it is unreliable for the diagnosis or control. Therefore, the non-invasive techniques commonly used for measurement of flows parameters are described. Depending on the industrial demands, many applications examples for non-invasive two-phase flows measurement and monitoring are given. This description for identifying the flow parameters is divided into features categories of this phenomenon as void fraction distribution, velocity profile and flow regime. However, from these methods the high accuracy and short processing time are expected. The continued observation and monitoring of the process deliver knowledge about the dynamic states of the flow to control it more efficiently. Therefore, the development of advanced process control is one of the most important challenges to keep the flow regime on the given level and for instant and long-term energy saving, quality improvement.

**KEYWORDS:** identification, control, non-invasive measurement, process tomography, 3D electrical tomography, two-phase flow.

## 1. Introduction

The two-phase flow (TPF) process is a part of many technological lines in the industry and still, it is one of the most studied phenomena in fluid and particles mechanics [38]. Numerous research works have been done in order to learn and describe this phenomenon what may be testified not only by the sophisticated simulation models e.g. Computational Fluid Dynamics (CFD) [9] but also by new concepts of diagnostics systems. Furthermore, new optimisation methods and computer algorithms for control are also being designed.

The still growing interest strongly depends on their great practical significance in many industrial branches like food, biotechnology, bioprocess, environmental, chemistry and petrol engineering. That is because the TPFs are an important and ubiquitous component of numerous industrial processes like the aeration processes [144, 68], chemical reactors [72], processes of flotation [147]. Some examples of TFP applications are summarized in Table 1.

From the hydrodynamic point of view, the TPF mixtures identification is focused on evaluations of flow patterns, flow resistance and void fraction of the mix-

ture [34, 125, 26]. Additionally, to describe the mass transfer it is required to determine other flow parameters like mass transfer coefficient, gas bubbles coalescence and finally the interfacial surface area. So far, many of research works presented in the literature have been done to solve these issues. On the other hand, due to the complicated mechanism of flow dynamics, often connected with difficulties in its description from the mathematical point of view and due to the complicated measurement methods the further and new studies are highly expected.

The correct and optimal functioning of the industrial processes involving the TPFs depends on various, sophisticated tasks of measurement, diagnosis and control as it is depicted on the flow diagram in Figure 1.

The growing needs of industry for a simple, versatile, relatively inexpensive, non-invasive and rapid method of process monitoring and control for TPFs remain apparent. The knowledge of the characteristics and types of flow is required while designing production lines or numerical modelling algorithms [106,69] to predict or/and to prevent the malfunctioning of the process.

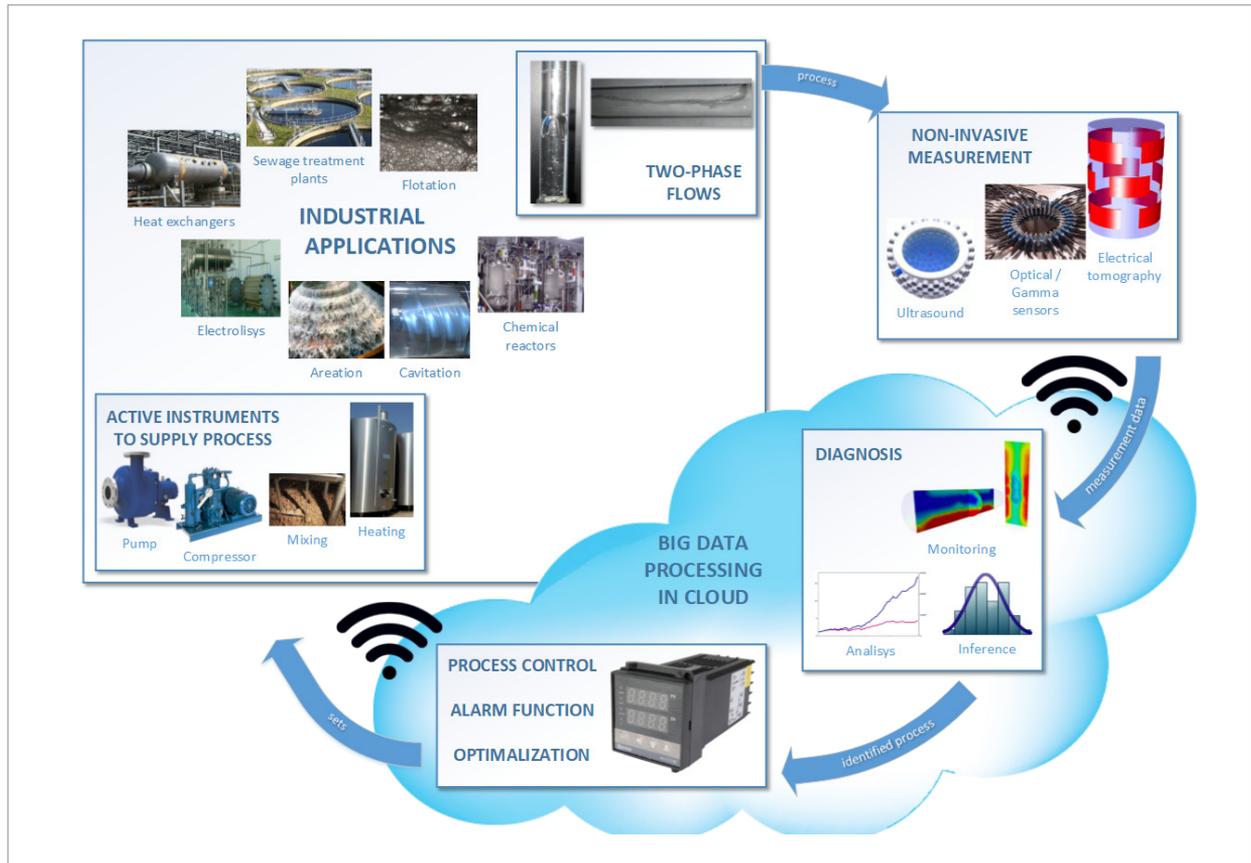
**Table 1**

Examples of TFP applications in the industry

industry / phenomena	application	description
aeration systems	sewage aeration	biological sewage treatment plants [16,46]
	aerobic bacteria	injection of free oxygen to ensure the bacteria growth [112]
bio- and petrochemical processes	bubbles columns in physical and chemical processes	identification of bubbles to study mass transfer in chemical reactions [30,101], evaluation of air-bubbles plumes existence [2]
	air-lift columns	intensity of the process depends on the bubbles size [5,71,19]
		control of the gas stream to force the liquid movement [12,20]
	ejectors	flotation processes in the extractive industry [166]
sedimentation processes to precipitate some fractions of the liquid [93],		
chemical reactors	electrolysis	the intensity of the process identified from the gas phase [109,81], evaluated size of the gas bubbles indicates the process quality
heating devices	heat exchange	gas existence is undesirable and denotes the boiling liquid [139]
cavitation	rotational pump	detection of this phenomena warns of pump's blades erosion or leakage [85,169]

**Figure 1**

The flow diagram with measurement, diagnosis and control tasks processed in the cloud for TPFs handling in the innovative industry of 4<sup>th</sup> generation



Nowadays, the application of advanced technologies in modern production systems is the main trend of development and technological progress in many industrial sectors. It is due to the growing trends of energy-saving and production quality enhancement. Wherever in the production process, the phase mixture is transported and it is not optimal or not economic, there is a need to develop a system which would be able to prevent any construction disaster, unexpected production line stopping or situation where for reasons of bad flow parameters, the final product is defective. Such a solution could also be irreplaceable when a flow process requires constant supervision, or when the work environment would be a danger to the safety or employees' health and simultaneously it is required a continued, automated, non-invasive and efficient monitoring of inaccessible parts of pipelines.

### Lessons Learned from the Review

This review provides the reader with the fundamentals and new applications of diagnosis and control of TPF processes as well as points out the future development directions in the context of advance and innovative information technologies. The summarised state-of-the-art given in this review for numerous engineers and young researches starting their adventure with the TPF s would deliver valuable lessons about:

- the non-invasive measurement techniques commonly applied for TPF scanning categorised regarding their physics phenomena,
- the TPF parameters categorisation,
- the computer methods of measurement data processing and analysis involved for TPF identification,

- the artificial intelligence techniques applied for inferencing about TPF parameters and process control strategy,
- the directions of IT innovations developments for TPF handling in a frame of industry 4.0 revolution.

## 2. Two-phase Flows Non-invasive Measurements Techniques

The main aspect of many identification and control systems is a measurement of industrial flows' features. Since many years the research conducted on the two-phase gas-liquid flows still does not deliver consistent answers to many questions according to this phenomenon [38]. It is because of its stochastic nature as well as its dynamics but also it is related to the research capabilities. In the case of these flow processes, the diagnostic methods developed so far are based on usage of most sophisticated measurement techniques [22]. Just as a technical advancement grows many flow measurement techniques were developed starting from mechanical through the electrical unto radiation. The measurement precision has continuously raised and its variety differed concerning the liquid or gas. In the beginning, most of them interfered with changing of the process features [160, 148] e.g. mechanical, manometric, impulse flow-

meters or rotameters. Though, the development in this field has been focused on non-invasive methods using electric, ultrasound (Doppler Effect) or hard radiation sensors. Since the invasive measurement disturbs the process and changes its parameters and behaviour in the location just after the measurement point and simultaneously does not provide any information about these changes it is unreliable for the diagnosis or control. However, there are some kinds of methods which involve a special tracer system to expand the flow features by the assumption that it is less intrusive.

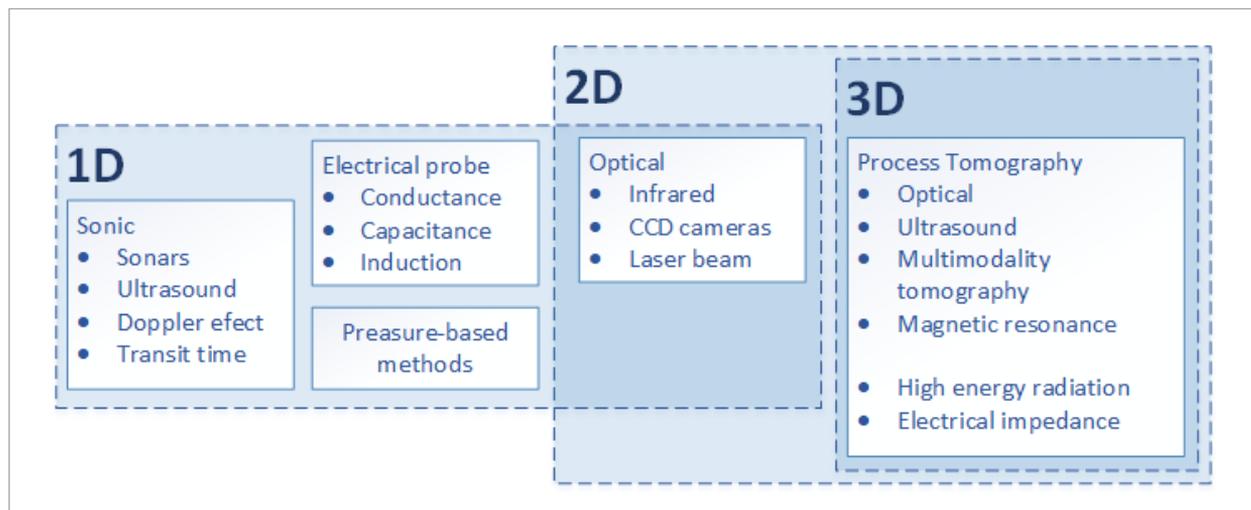
Below, the state of the art in a field of flow measuring is provided. This description, however, focusing only on non-invasive groups of methods, is divided considering the sensors' physical matter and starts from single-measurement based method (1D) through the tomographic based methods (2D and 3D). Figure 2 shows the diagram of possible non-invasive sensing techniques grouped by their physical matter and dimension abilities.

### Electrical methods

The flow can be characterized by electrical properties. The flowing phases can be conductive, dielectric or magnetic. The usage of a conductance sensor for phases identification between gas and liquid is not an innovative solution. In the past, it was commonly applied in multiphase flows to evaluate the local velo-

**Figure 2**

Non-invasive sensors for flows diagnosis with dimension measurement strategies



city distribution or volume of gas fraction. Still, there are lots of limitations or required assumptions using conductance-based measurements as it has actually been reported in [88]. The authors of this work examined the oil-in-water bubbly vertical flow to evaluate the oil velocity distribution and distribution of oil fraction in the basis of conductance probe composed of two sensors. This type of radial sensors was successfully used also by [49]

for the flow pattern and holdup phenomena investigation of low-velocity oil-water flows in a vertical upward small diameter pipe.

If the conductive phase is the solid phase and non-conducting phase isolates electrodes from the conductive phase, inductive sensors are more suitable. This technique based on an induced voltage across a liquid moving through a magnetic field has been successfully used to measure the mean velocity of the conductive fluid in the single-phase flows [133].

Similar, the proven solution in case of non-conductive phase is the measurement of electrical capacitance. Such a method was successfully applied in [57] to measure the water holdup based on water layer thickness in horizontal pipes. In [167], in turn, the authors designed the capacitance sensor in the form of double helix and similarly were able to evaluate the holdup in the oil-water horizontal flow. The liquid holdup of cryogenic TPF measurement system with a capacitance (2 electrodes) sensor was designed [25]. The same shape of electrodes can be seen in the system in [8].

### Optical, vision

Another group of methods that are definitely non-invasive but require transparent part of the pipeline are methods based on photography. There are numerous solutions where this approach only supports the measurements performed using other techniques [61] or may play the main role in monitoring. In [155], the authors used the high-speed camera and the images of flow structure of different flow regimes were caught to visual analysis or visual assessment. Some examples of image analysis for identification of flow patterns in oil-water upward flow may be found in [48]. Moreover, in the literature, some examples that apply complex algorithms of image processing to investigate the flow specificity may be found. do Amaral *et al.* [7] captured the series of flow images using a high-speed camera and designed a computer

method to extract quantitative parameters of turbulent flows in horizontal pipes. The different steps of the segmentation phase for captured images were implemented. It was shown there that this method provided the results of bubble dimensions, velocity and frequency.

The visual observation of the flow patterns becomes difficult when the mixture velocity increases or the pipe-wall is no longer clear. Under these conditions, there is a need to search other techniques to clarify the flow regime identification.

### Tomographic techniques for non-invasive flows measurement

One of the methods for the dynamic processes monitoring is the Process Tomography (PT). This technique of process (object) imaging provides the possibility of an investigation of structural complexity of physical and chemical phenomena without the need for interference in it. It is widely applied for visualisation and monitoring of various processes due to its variety of physical quantities. It collects measurements from sensors located around the process volume and reconstructs 2D (two Dimensional, cross-sectional) or 3D image of character, density or components distribution inside the measurement volume. PT significantly differs from other classical methods based on e.g. photo or thermo vision cameras. The most demanded feature of PT is its non-invasive (sensors should not be mounted inside the process) and non-intrusive (should not interfere the process and change it) measurement.

Previously described measurement techniques have not engaged any sophisticated computer methods and algorithms. Computers have been used mostly for collecting and organising measurement data for purposes of future analysis determining required flow parameters.

The process tomography applies computer techniques just on measurement stage. First, the raw acquired measurement data need to be reorganised removing duplicated and negligible values. Then, to reconstruct the image of the examined space, the complex computer methods are applied which involve advanced computational challenging algorithms for computer modelling, statistical calculations and artificial intelligence [14, 149, 152].

According to the applied energy source PT can be categorised into two main groups [138]: hard-field (optical, ultrasound, magnetic resonance imaging, high-energy X and gamma rays) and soft-field tomography (electric and magnetic phenomena). PT techniques are classified as hard-field when the path of the transmitting signal is in a straight line pattern. In this case, mostly the signal strength factor regarding the attenuation phenomenon of the material is measured. For soft-field tomography, the phenomena have non-linear nature and the medium distribution perturbs the transmitted signal path. This induces additional computer methods to be implemented during the image reconstruction process considering i.e. a second-order partial differential equation (Poisson's or Laplace's equation) supported with Dirichlet's and Neumann's boundary conditions.

### Optical sensors

Optical tomography provides a tool for the determination of the spatial distribution of materials with a different optical density in a volume by non-intrusive measurement. The wide spectrum of light from infrared to ultraviolet can be applied. The receivers can measure the level of light beam absorption, reflection, diffraction or refraction and then reconstruct the image of components distribution. This technique was successfully applied to the flow processes in '80 of last century. The simple multi-angular technique which involves making light's beam absorption measurements (projections) can be read in [131] and the application of holographic interferometry in [136]. The laser-based tomography technique used for flow visualisation in supersonic ejectors was described in [20]. One of the examples of optical fibre process tomography can be found in [162]. This technique, to acquire enough projections, involves rotatable scanning. In [58], the concentration of gas bubbles in a water column was measured using an optical tomography system. Besides, a hybrid back-projection algorithm was applied to provide a tomographic image of the measurement cross-section and to calculate concentration profiles. The algorithm combined the characteristic of an optical sensor as a hard field sensor and the linear back projection algorithm. The significant disadvantage of this technique is a requirement of mounting the transparent part of the pipeline.

### Quantitative magnetic resonance flow imaging

Magnetic resonance method assumes the use of radio-frequency signals. The molecular species of the examined medium are placed inside the magnetic field and in a result of excitation are changing the magnetic field frequency providing the spectral information about the organic compounds distribution and dynamic information such as diffusion and flow inside the measurement volume [29, 141].

### Ultrasound

Instrumentation systems employing a variety of ultrasonic techniques have been widely applied to the industrial flow processes. The transducers mostly are composed of a set of transmitter-receiver pairs. One of the numerous examples of applications may be found in [161]. The authors designed a system involving a fan-shaped beam scanning geometry and a fast binary back-projection filtering algorithm. Kurniadi and Trisnobudi [80] proposed in their work a flow meter based on a multi-path ultrasonic transit time evaluation for velocity profile measuring of the gas flow. A set of transmitter-receiver pairs was located around the pipe wall. To reconstruct the velocity profile, the algorithm of filtered back-projection was implemented. Similarly, the same image reconstruction technique and the Ultrasound Tomography (UST) was used in [28] to imagine the flow from the line-averaged velocity distribution in Radon space. The method of ultrasonic pulse echo reflected from the pipe's internal wall is proposed in [82] for flow pattern identification in a horizontal pipe with gas-liquid TPF. Moreover, Abbagoni and Yeung [1] designed the neural network for classification of gas-liquid two-phase horizontal flow regimes from ultrasonic measurement data.

### High energy rays tomography

Computer Tomographic (CT) imaging technique, developed as a medical diagnostic system found its application as a tool for industrial non-destructive evaluation. This industrial brother of CT contributed to this field providing the three-dimensional inspection of defects, their location and size. In this matter, the high energy (X or gamma)-ray source together with the detectors array are necessary to apply. Then, to reconstruct the cross-sectional 2D or spatial 3D high quality image the set of transmitter-receivers needs

to be rotated or replicated. In 1999, Luggar *et al.* [89] designed energy-dispersive X-ray scatter for measuring oil and water concentrations in a bulk liquid. The designed system had a relative error up to 0.6% in the oil/water ratio measurement.

Ultrafast electron beam X-ray computed tomography is a powerful imaging technique for the analysis of two- and multiphase flows. In the basis of this, in work [42], a specific system was designed whereas the scanning mode the beam was circularly guided across the target to produce a rapidly moving X-ray spot. The detector had a sampling rate of up to 1Msample/s. The measurement data were processed by the algorithm based on the filtered back-projection technique and produced cross-sectional images with the maximum rate about 7 kHz. This rate was limited by the capability of the deflection coil amplifiers to adjust the required elliptical beam deflection pattern. Bieberle *et al.* [18] in turn implemented the method to obtain virtual 3D CT images from the two-plane measurement of a buoyancy-driven water-air flow within a packed bed. Then, the phase segmentation was performed by adequate thresholding and the phase fraction profiles as well as velocity profiles were calculated. Barthel *et al.* [15], using the same measurement technique, evaluated velocity profile as well. The slice images were reconstructed, with a spatial resolution of approximately 0.6 mm per pixel and were pre-processed by selecting a region of interest, enhancing contrast and removing background.

Many applications of high energy radiation also use gamma rays. The studies [11, 98, 129] describe the developments of multisource gamma CT systems which proved to be useful tools to evaluate multiphase systems by volume fractions and flow regime identification. Hjertaker *et al.* [53] designed the multimodality sensing system for monitoring of multiphase hydrocarbon flow where there was a need to measure the quantity of oil, water and gas in a cross-section of a pipe originating from an oil well.

Multimodality tomographic systems consisted of electrical capacitance and gamma-ray sensing provide component specificity of oil/water/gas. For these purposes, the algorithm with dual-modality tomograms to three component tomogram mapping procedure needs to be implemented. The three-phase flowmeters are now becoming a demanded part of many

production systems in the oil and gas (petroleum) industry. In [145], there is accomplished a comparison of commercial flowmeters, which by merging the abilities of hard-field sensing with the methods of image reconstruction and processing can meet the growing demands of applications.

### Electrical tomography

Electrical Impedance Tomography (EIT) technique delivers the two- and three-dimensional imaging on the basis of electric features (permittivity, conductivity, inductivity) of the process' components e.g. flow. The first Electrical Capacitance Tomography (ECT) systems [120, 113, 158, 79], Electrical Resistance Tomography (ERT) systems [33, 32, 147, 127] as well as the Magnetic Induction (MI) [90,119] allowed to obtain only the rough evaluation of the process state because the information encoded in measurement data represents merely the fragment of the process which additionally was approximated into the cross-section surface through the sensor (2D ECT) [60, 163, 78, 128, 135]. This kind of imaging, however still commonly applied in many industrial applications [50, 66, 67, 104, 75, 65], occurs to be insufficient from the process control point of view. The cross-sectional image does not reflect enough the spatial phase distribution or flow structure in a measurement volume. It is because the image is generated according to the approximated measurement values from the whole electrodes surfaces. In the case of long electrodes, the high level of approximation prevents the precise measurements. Moreover, the spatial electrostatic field distribution is neglected. Therefore, the ECT monitoring was developed in the direction of other data processing methods like cross-correlation [103, 84, 87, 31], image processing and analysis, multi-layered tomography [100, 55, 154, 45] or even rotatable sensor [86] etc. Nevertheless, independently of the mentioned extensions still the classic 2D ECT measurement suffers from the limitations of the cross-sectional approximation. Many of the industrial processes are characterised by the spatial features and their reduction to the planar solution results in undesirable simplifications. One of the first efforts to produce 3D images using tomographic algorithms from 3D ERT measurements data applied to two production pressure filters can be found in [164, 114]. Moreover, the authors implemented the dynamic sensitivity maps recalculation algorithm. The maps evolve according

to the conductivity changes that occur in the filter during a batch. Analogously, some first 3D imaging system was designed based on ECT measurements [96, 156, 150, 137].

### Multimodal tomography

Due to the complex nature of processes the power of process tomography can be multiplied to measure several physical properties. Then, data from more than one sensor are superimposed together with data from other sensors. In case of multimodal systems, lots of issues must be considered. First, the multimodal sensor, capable of detecting various properties based on differing modalities needs to be designed. Next, these different types of sensor hardware need to be combined into a single data acquisition system. Finally, a specialized reconstruction algorithm that differentiates between components needs to be implemented. Marashdeh *et al.* [95] designed the system of dual imaging modality (permittivity and conductivity distributions) of granular flow based on ECT sensors. Capacitance and power measurements were acquired by an ECT sensor located around the vessel and then reconstructed and presented in a form of the 2D cross-sectional images. The inverse problem was determined using the optimization technique based on neural network. A design of conductance and capacitance dual-modality tomography applied for flow measurements can also be read in [153, 157].

A dual-modality tomography for air bubble detection with fusion of resistance and UST was proposed in [165]. ERT sensing was influenced by air bubbles but UT, in turn, was highly influenced by interruption of the transmission path. Fusion of both techniques provides improved ability of objects detection because two different images of the same volume can be obtained simultaneously.

However, such hard-field and soft-field modalities combination is commonly encountered especially in the petroleum industry to distinguish gas, oil and water fractions. Snakowski *et al.* [130] patented a method and a device for measuring conductive and/or non-conductive component fractions in a flow. The designed three-phase flow meter based on combining three modalities: ECT, ERT and gamma ray radiation is able to determine the flow composition of a mixed flow in vertical and horizontal pipelines.

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## 3. Flows Parameters Identification

To describe a TPF, it is usual to specify the total flow regime and to characterize the fractions that the flow consists of. A complete description of a TPF contains also the phase distribution and its velocity. In this section, the solutions for identifying the flow parameters are provided. The knowledge is divided into features categories of this phenomenon as void fraction distribution, velocity profile and flow regime.

### Holdup measurement and void fraction distribution

The liquid holdup is significant parameters for TPF. In such a process, each fraction moves at a different speed. To determine the void fraction distribution and flow rates, one of the methods is to measure the holdup of flow components. In the world literature, there are presented many of solutions for liquid holdup determination. An intrusive example of the Quick Closing Valves method (QCV) is presented in [64, 57, 49].

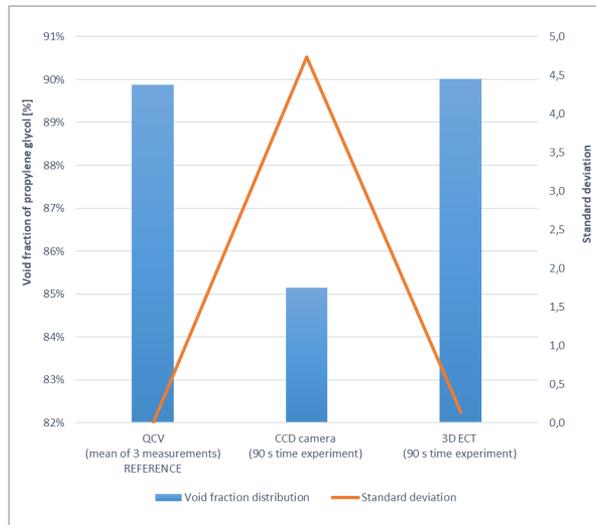
However, void fraction is a very important parameter in multiphase flows. The QCV method interrupts the process while the EIT allows keeping out of this undesirable effect. Hua *et al.* [56] measured the volume and velocity of oil fraction in vertical flow applying dual-plane ERT and dual-sensor conductance probe. To reconstruct the distribution of the flow, they adopted the algorithm of back-projection. To obtain the oil velocity, the correlation-based method was additionally applied. The presented method suffers from some limitations. The method requires some time (up to 30 seconds) to form the flow. Moreover, if the flow could not be stable enough, the method results with significant differences. A similar approach may be found in [67] where the authors designed algorithms based on a linear approximation of the sensitivity back-projection method for handling full void fraction range in two-phase flow ERT measurement with the error less than 2%.

Similar high accuracy of electrical tomography has also been reported in [151]. In this work, the reader may find results of experiments on the two-phase horizontal flow that aim to compare various diagnosis techniques like QCV as a reference method, CCD-based edge detection system and 3DECT-based fuzzy logic classification. The measured void fraction dis-

tribution together with a calculated standard deviation is depicted in Figure 3.

**Figure 3**

Comparison of accuracy of void fraction measurement methods [151]



### Velocity profile

The non-invasive tomographic techniques supported additionally by computer methods like tomograms processing and analysis, cross-correlation etc. designate a standard in velocimetry. The most common solutions are based on resistance and ultrasonic diagnosis. The three-path ultrasonic flow meter for fluid velocity profile identification was proposed in [62]. The ability of the first method is sensitive to the flow profile. In case of non-axisymmetric flow, the metering device has to be reinstalled. Otherwise, it indicates that the flow rate is of reduced accuracy and may be unreliable. Similar approach read in [143] can detect the Doppler shift frequency as a function of time. The authors of this method gave many examples where their solution has already been applied e.g. Flow Mapping of a Recirculating Flow in a Square Cavity, stirring and mixing processes in a hyperboloid stirrer vessel, detecting the velocity field in the vicinity of a mechanical valve substitute for simulating pulsatile flow as well as in a 10-mm pipe with raw chocolate and many others. Likewise, UST and extra convolution algorithm for parallel scan data were applied in [76] to visualise the velocity profile of air flow. In [105], the multiwave ultrasonic excitation was shown to be applied to the autocorrelation pulsed-Doppler velocity profile measurement of

counter-current two-phase bubbly flow in a vertical pipe. In this case, the system is able to measure both the liquid- and bubble-velocity profiles saving the spatial resolution below 0,8mm. The last example of a UST velocimeter can be found in [83]. This device is capable to provide quantitative images of axial flow fields in pipes and to detect the flow in various directions and positions. The filtered back projection (FBP) algorithm has been employed to reconstruct the axial flow field. The method was validated using CFD simulation and the velocity relative error was 1,1%.

Naturally, other tomography techniques are also appropriate for this task. Many of the proposed methods for velocity profile determination are based on EIT monitoring. For instance, an application of ERT for shampoo velocity measurement is presented in [121]. According to the conductivity changes the functionality of in-line rheometer was achieved on the basis of ERT technique. The further analysis of the shampoo flow velocity was also investigated. Moreover, the flowmeter which uses measurements of electrical conductance, electrical capacitance and density of the three-phase mixture in the petroleum industry was designed in [145]. The cross-correlation technique was used to measure the velocities of the three phases. Similar, the cross-correlation method by using parallel-wire capacitance probe was designed in [168] to measure velocities of six flow patterns in horizontal oil-water TPF in the petroleum industry. Authors noted that the accuracy of the cross-correlation technique strongly depends on the relationship between the velocity inferred from the correlation function's peak position and the mean velocity of the flow. To overcome this issue, they predict the homogeneous velocity of oil-water TPFs upon kinematic wave model.

However, the most advanced cross-correlation-based algorithm was implemented in [103]. The authors, using reconstructed data acquired from a twin-plane ECT system, were looking for the best-correlated pixel on the second sensor plane in the neighbourhood of the corresponding pixel. This concept without the requirement of any additional assumption is not limited only to determine the velocity vector that is perpendicular to the pipe axis.

### Flow regime identification

During an industrial flow process monitoring, an identifying the flow regime and determining its struc-

tures are of great importance. It can be determined by flow patterns which can vary for different kinds of flows components i.e. gas / liquid / solid and can be organized in so-called flow maps. This map indicates the most likely flow regime for the given regime of single phase streams and is provided in many research works [110, 94, 118]. The pattern of the flow depends on many factors like flow components, pipeline (its diameter, length, position, arrangement and shape etc.), supply devices (pumps, compressors etc.). The TPF type identification task is valuable especially while designing new productions lines. It may provide knowledge about the dynamic states of the flow to control it more efficiently.

Some works have widely adopted image processing techniques. Flow images used to be captured with camera and to be pre-processed. After then, to identify flow regime some image processing algorithm such as watershed segmentation, top-hat filtering and H-minima transform etc. can be applied [146, 7]. The processing allows determining the bubble velocity, shape, length and frequency with the standard error of 7%. In [132], the authors implemented additional post-processing based on the Artificial Neural Network (ANN) and supported vector machine. The network can reflect both the dynamic and complex characteristics of the TPF with the accuracy of 98.03. There are also solutions which are using stochastic models to model randomly changing processes. The works [91, 124, 123], to identify TPF regimes, propose methods of the on-line fluid phase signals analysis implementing hidden Markov model.

Many solutions based on artificial intelligence become more and more popular in the industrial applications. It is due to their ability to perform various tasks similarly as the humans think. The intelligent algorithms are trying to solve a problem, and then are using the outcomes of this study as a basis for their next inference. One of the most common research areas in this domain is the ANNs. In [102], the authors proposed a flow regime identification methodology with the supervised and self-organising ANN and TPF models. The ANN was used as well in [111, 36] for estimation of flow patterns and frictional pressure losses of two-phase fluids in horizontal wellbores. The ANN may support tomographic techniques by providing a mechanism for image reconstruction and analysis [74]. Figueiredo *et al.* [41] applied an ultra-

sonic technique and ANNs to identify the flow pattern and volume of the gas fraction. ANN executes a non-linear mapping and cross-correlation of input and output signals. Similarly, in [52], the application of an ANN was designed to analyze and to classify the measurement signals of a bubbles length function obtained from the conductivity sensor. The self-organized ANN was used as the mapping system.

Another and most reliable intelligent method repeatedly applied for industrial monitoring and control purposes is fuzzy logic. Classical logic considers two states mostly given as 0 and 1 (false and true). Such an approach can e.g. handle the flow as air or liquid phases with the clear boundary between them. Fuzzy logic allows understanding the problem in a "more human" way [77]. It assumes the existence of more values or states between 0 and 1 (e.g. almost true, probably) blurring (fuzzing) the boundaries so far considered as crisp. Some works have been done to determine flow patterns using fuzzy inference on image analysis. In [99], the authors implemented image pattern classification systems based on simple features using a fuzzy inference system. The TPF regime identification system to manage heat transfer of the nuclear reactor coolant was designed in [23]. The image segmentation process was used to divide the image into sub-regions and then the fuzzy image processing was applied to detect bubbles in the natural circulation system.

Other research team performed boiling regime classification on low-resolution, low-speed images using simple machine learning and image processing techniques [54]. The classifiers were trained on the measurement data. Both support vector machines and ANNs were able to identify pool boiling regimes with about 99% precision.

The first use of a fuzzy pattern recognition technique in basis on tomographic measurement was introduced in [47, 159] to solve the flow pattern identification. The images captured by the ECT system are analyzed through image processing and a pattern recognition technique. However, the fuzzy logic inference was applied for the first time to the three-dimensional reconstructed images as an efficient evaluator [13, 151]. In this study, the two-phase vertical and horizontal flow regimes classification was obtained from spatial analysis of a set of objects from 3D reconstructed images. The developed system allowed

the real-time non-invasive determination of the void fraction and structure identification thanks to the specialized parallelized algorithms for fast processing of measured data. The implementation of forward and inverse problem computations was done using CUDA technology.

### Imaging or not imaging?

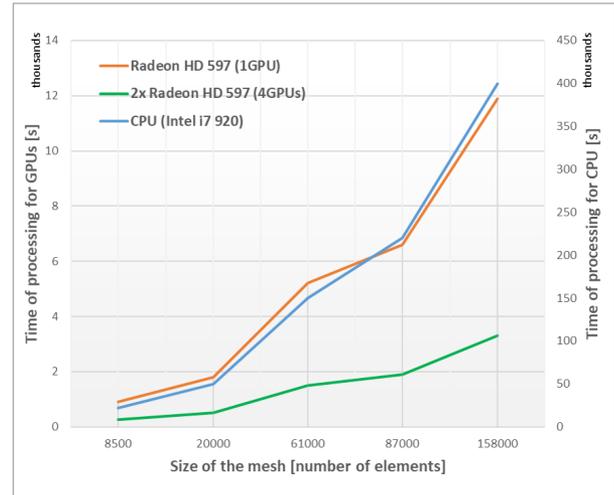
Most of the research works based on the tomographic techniques have implemented the image reconstruction methods. In many industrial applications supported by the tomographic diagnosis, beside the accurate measurement devices the key role plays the data processing and image reconstruction methods. From these methods, it is expected the high image quality together with the short processing time. These challenges concern the essential computer issues like the image resolution enhancement saving quality and processing time what definitely results in the computation complexity, computer modelling of measurement sensors, numerical errors and finally in the necessity of development of new algorithms for efficient management of resources as well as computation power. If the image is especially important for the issue of monitoring and visualization, the image reconstruction and processing tasks can be performed on graphical processors. Kapusta *et al.* [70] developed an effective method called a General Purpose computing on Graphics Processing Units that involves a hybrid algorithm for rapid, parallel determination of the solution of forward problem implementing CUDA API and OpenCL libraries by uses of both x86/x64 class and graphics processors.

How significantly efficient the parallel computing is, it can be read in the work [92] where authors described expedients while under the same conditions they performed 100 iterations of the Landweber's image reconstruction algorithm for ECT. The processing was executed on various computational platforms ones based only on CPU and next on 1 and 4 GPUs. As can be seen in Figure 4, the total computational time was reduced even up to 0,8% for the densest mesh.

There are some researches that perform direct flow-pattern identification from measurement data. In [65], the general idea for flow-pattern classification relied on the finding of geometrical properties hidden in a measurement frame corresponding to a set of

**Figure 4**

100 iterations of the image reconstruction algorithm for ECT executed under the same conditions on various computational platforms [92]



ECT measurements without the need of imaging. The decision was made on the basis of one frame only to ensure the process to be as quick as possible. A similar approach was studied in [122] where to develop a new strategy for flow systems monitoring the contextual processing of the ECT measurements data was implemented. The signal processing refers to methods and algorithms taking advantage over classical approaches by using context-aware, context-enabled or context-driven features in order to enhance computer systems or applications.

The analysis of the tomographic raw measurement data for TPF type identification is actually more effective (not only in terms of processing time). The methods based on the 3D reconstructed images analysis [13] gave mostly satisfying results but because of its lower speed there is a risk to miss (not detect) some specific features of the dynamic flow such as plugs or foam which are important to recognize the current type of the flow. The same group of researchers in [40] designed a fuzzy logic based method for 3D ECT raw measurement data processing dedicated for the identification task of the dynamic TPF processes ensuring the accuracy as good as the human expert work. It was proven that this solution is a sufficient alternative to the methods commonly used in this field and stands out with its effectiveness, low recognition time and full scalability.

## 4. Flow Control

The task of flow control is of substantial meaning in any branch of industry where these processes are used for production, transport etc. Because of the applications' variety in each case the needs and demands are different. Nevertheless, the important thing is to keep the flow regime on the given level or to avoid of e.g. slugs' occurrences. Severe slugging may have undesirable effects on the many processes causing problems including unstable pressure, kinetic force or insufficient phase separation. In case of too large slugs the pipeline flooding or damage is possible. That is why the highly important is to identify the slugs and to determine their frequency, size and velocity.

However, in case of such dynamic, stochastic and non-linear processes like flows one needs to be remembered: holding the same level of phases' streams supply does not guarantee the flow regime stability [142]. Therefore, there is a necessity to process the continued monitoring and to immediately react in case of any abnormalities. In the world literature, many research works may be found which, using various modelling techniques, provide the tools for control process simulation or even for threats estimation. The example showing the control task's complexity is the mathematical flow control scheme introduced in [3] to minimize the turbulences in the basis of four different models. Next, in [17], the readers may find out the discussion on the interdisciplinarity of the algorithms development process for flow control purposes issuing requirements and limitations while working out the optimality of this task in the context of different applications. Furthermore, some problems in the flow modelling and control in the basis of the flow pattern and flow map using the specified Eötvös number classification have been demonstrated in [21]. Havre and Dalsmo [51] deal with the results from simulations with the feedback flow control which show how to avoid slugs and hold on the stable conditions both at the pipeline inlet and outlet, whereas without control severe slug flow was experienced. In [134] in turn, the authors made the exhaustive analysis on control models commonly used by industrial control engineers. The discussion about the advantages as well as the limitations of the single input single output (SISO) in contrast to the multi-input multi-output (MIMO) feedback control systems may be found. The case study on the controllability prop-

erties of a typical pipeline-riser system of two fluid flow with the PDE-based (partial differential equations) model was described in [140].

Besides the theoretical achievements, some works have been performed to design the feedback control solutions based on PID [44, 117, 4] or PI [107] controllers to demonstrate that this strategy can guarantee the stability of the flows whereas the manual choking occurred insufficiently. The production (subsea) choke is used to control the offshore flow and stabilize the flow line pressure. The controllers mostly measure the bottom-hole and top pressure. The authors noted that to avoid riser slugging a strategy to control the pure inlet pressure for pipelines with limited length is most recommended. Otherwise, more advanced cascade controller should be employed combining e.g. flow line pressure and volumetric flow control. Many of functional examples may be found in [44].

Also in [108] the auto-tuned PI controller algorithm based on a perturbed First-Order-Plus Dead-Time (FOPDT) delay model of the riser system was introduced which was developed and implemented for severe slugging control focusing on achieving stable operation and maximizing production. The author indicates that the solution has the ability to stabilize the unstable riser system at a valve opening that is larger than that achieved with the original (conventional) controller algorithm. Moreover, the linearization closed in a feedback loop in a combination of pressure drop was used in [63] for the control design of the production choke valve to prevent severe slugging flow conditions. Thanks to the authors' solution it was possible to successfully maintain the stability of large valve opening in the experimental rig without the need of re-adjusting it. Nevertheless, Di Meglio *et al.* [97] analyzed the disadvantages of the production choke control system based on non-collocated PI-controller in contexts of their new approach of the nonlinear state-feedback control law based on a first principles model of the slugging phenomenon. In this case, only one parameter (the gas pressure) was adjusted. Elsewhere, the detailed analysis and the discussion about the problems and optimization of the linear controllers were performed in [73] and especially in case of slug attenuation in [35]. Generally, after studying the referred works one conclusion may be drawn. Due to the complexity of the flow processes (especially severe slug flows in offshore

multiphase oil & gas pipeline transportation systems), the design of the robust control system based on an active feedback control makes a major challenge to achieve the desired performance and optimal efficiency [126].

What is more, for the non-linear systems such as flow processes, PID controllers do not exhibit good performance. Therefore, in order to satisfy the need for system stability and to optimize production simultaneously some other solutions for flow control were developed. The comprehensive review study of non-linear controller theory together with some examples may be found in [59]. Authors deal with the differential algebra and multivariable calculus to explain the mathematical basis of nonlinear controllers.

Another computer technique which may successfully compete with the linearized feedback systems is fuzzy inference. The fuzzy controllers surely belong to the group of predictive controllers and have already been applied many times including scheduling and controlling electrical operators [27], the maintenance a floating level in a tank on top of the atmospheric distillation unit of the refinery [43] or the boiling water reactor as a recirculation flow control system [10]. The usage of artificial intelligence in the industrial applications allows avoiding any random errors as well as breakdowns and human mistakes which suffer from a lack of objectivity. To know the differences between the PID and fuzzy controllers, some research works as comparative studies have been done like [24] or [116]. In both cases, the PID controllers were characterised with the slower response time also with the tendency of oscillating convergence. Much more advantages of fuzzy controllers may be found in [115]. The contributors of this work simulated fuzzy and neuro-fuzzy controllers to obtain better performance in flow process regulation in comparison to the PID. Likewise, to overcome the occurrences of unpredictable disturbances from PID regulators AL-Qutami and Ibrahim [6] designed the fuzzy controller for flow application in tanks. It can be read here that this type of controller is flexible and can handle any sudden changes or disturbances on the system and can overcome the presence of process nonlinearities, operation variability and measurements noise.

Despite many examples for fuzzy logic controllers each time the systems are dedicated for specific applications. A lot of work always needs to be per-

formed to adjust such controller to the process conditions. In [39], the intelligent system for the TPFs monitoring and control on the basis of raw 3D ECT data was developed. In a frame of this study, the universal approach of the fuzzy logic controller is described that is characterised by the easy adaptation to the work conditions by the maintenance staff of the flow rig what is guaranteed in the result of sharing the individual sets of parameters and the intuitive inference rules.

The control module works in a feedback loop and keeps the sets of required flow regime. In the inference process, it considers not only the current flow type and the flow type set by the user but also the current state of the flow rig (i.e. the current values of the control signal). It is possible to change the TPF type changing only one control parameter about the minimum value which is required to achieve the set flow type and simultaneously without excessive overcharging the flow rig and the supply units. This approach allows the user of the system to avoid looping over in case when the algorithm would try to reach the unsupported or undesirable flow type. It is not required to determine any of complicated computer models of the flow rig, what is unfortunately necessary when using the classic regulators.

An additional feature of this system is the universal mobile multi-touched monitoring-control panel which gives the opportunity to build a user-own virtual model of the flow rig to monitor and control the process efficiently.

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## 5. Conclusions and Future Directions

The advanced industrial processes automation and control play the key role in competitiveness enhancement. If expensive technical devices and production lines mean the heart of the industrial production, the control systems and information technologies will become their brain. They ensure the flexibility in case of their fast adaptation to any industrial processes taking into account the volatile demands and provide the safety and efficiency respecting sustainable consumption of energy and resources. Therefore, the development of advanced process control is one of the most important challenges for instant and long-term energy saving, quality improvement. Finally, it guides

to the economic growth in conventional and new industrial areas.

Nowadays, the meaningful progress in massive parallel computational systems enables the real-time data processing additionally distributed among the external environments (i.e. clouds). Therefore, now the process tomography, known so far only from its significant computational complexity, has the opportunity to be the demanded powerful multi-sensor technique. This conception, of course, still requires new data processing strategies to be developed.

Similar, the immeasurable capabilities are hidden in distributed systems. The cited works (both for diagnosis and control purposes) which involved the methods based on artificial intelligence (e.g. ANN, fuzzy inference) dealt with aspects from computational intelligence theory. A very attractive and innovative issue would be applications on swarm intelligence. The significant improvement in accuracy (highly demanded in case of process diagnosis) together with the increase of efficiency would be expected. Such solutions could comprise the convolutional ANNs or various algorithms of deep learning as well [37].

Finally, we cannot forget that we are living in a world of the fourth industrial revolution. The new trends and technologies are developed extremely fast and the ongoing barrier between human and the machine disappears. This revolution is accelerated by the development of Internet of Things (IoT) conception,

mobile 5G communication, big data and cloud computing. This leads us to integration with the diagnostic and control systems in basis of the wide usage of internet's resources. Industry 4.0 surely would not discount the TFP processes, which often take place under the inaccessible and dangerous conditions and therefore would gain them in new technologies based in computer methods, artificial intelligence and distributed processing listed in this review. Reading this work provides with not only the fundamental insight into the existing solutions for TFP diagnosis and control techniques but also with the future directions in the context of innovative information technologies applications. The given state-of-the-art as well as the new development trends make this review as a valuable resource for engineers and young researchers who start dealing with TFP processes.

### Acknowledgements

Author wants to thank Prof. Dominik Sankowski, Prof. Jacek Kucharski, Robert Banasiak, Paweł Fideriek, Tomasz Jaworski and Jacek Nowakowski for support and their fruitful advices.

This work was financed by the Lodz University of Technology, Faculty of Electrical, Electronic, Computer and Control Engineering as a part of statutory project No. 501/12-24-2-5416 and by The Polish National Centre for Research and Development – project no. POIR.04.01.02-00-0089/17-00.

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