Lodz University of Technology,

Faculty of Electrical, Electronic, Computer and Control Engineering

Institute of Applied Computer Science

DOCTORAL THESIS

Extended Abstract

Gravitational solids flow parameters estimation by the use of electrical capacitance tomography and artificial neural networks.

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1. Introduction

Measurement and monitoring of gravitational solids flow in a silo is important in many industrial applications, for example in chemical and food industry, civil engineering, pharmaceutics, etc. Ultimately, key parameters of the flow should be monitored on-the-fly to prevent possible unwanted phenomena. The proper monitoring of granular behaviour allows avoiding problems occurring during the silo discharging process, (Niedostatkiewicz et al., 2009), (Chaniecki et al., 2006), (Grudzien et al., 2010).

The behaviour of granular structures and changes in the volume of the bulk solids are related to initial density of the granular material, stress level, mean grain diameter, specimen size and direction of the deformation rate. The on-line monitoring of the process state, especially when external factors, influencing the process (humidity, temperature) are changing during the process, requires in-depth knowledge and understanding about the physical phenomena taking place during the gravitational flow of the bulk. Visualization of the material distribution in the silo seems to be the best option for understanding and monitoring of the flow. Very helpful are the tomography systems, which allow showing inner of the process in a form of an image and then determining important process parameters without disturbing the flow itself.

Electrical capacitance tomography (ECT) was considered the most performing technique for visualizing fluidised bed granulation and drying processes. This technique has the advantages to be a non-invasive and non-destructive tool to measure and monitor processes in hazardous or unreachable areas (high temperature, high pressure), to have low cost comparing to other tomography tools and to quickly respond. Limitations of this technique lie on the poor resolution of the provided image, (Zhang et al., 2014), (Tapp et al., 2003), (Abdul Wahab et al., 2015).

The aim of the PhD thesis was to elaborate new methods and algorithms which would allow on-line monitoring of gravitational solids flow and would be faster than the currently existing methods. The new approach should be accurate enough to solve the above task.

The process modelling and identification was considered with the purpose to predict the variations of characteristic process parameters.

The new approaches are based on Artificial Neural Networks (ANN) as universal approximators and powerful tools to solve nonlinear problems, (Haykin, 1999).

The thesis of the PhD dissertation was formulated as follows:

Estimation of funnel parameters of gravitational solids flow using ANN is faster than state-of-the-art methods for ECT-based process monitoring at a similar accuracy level.

In order to prove the thesis, the PhD project demanded to solve the following tasks:

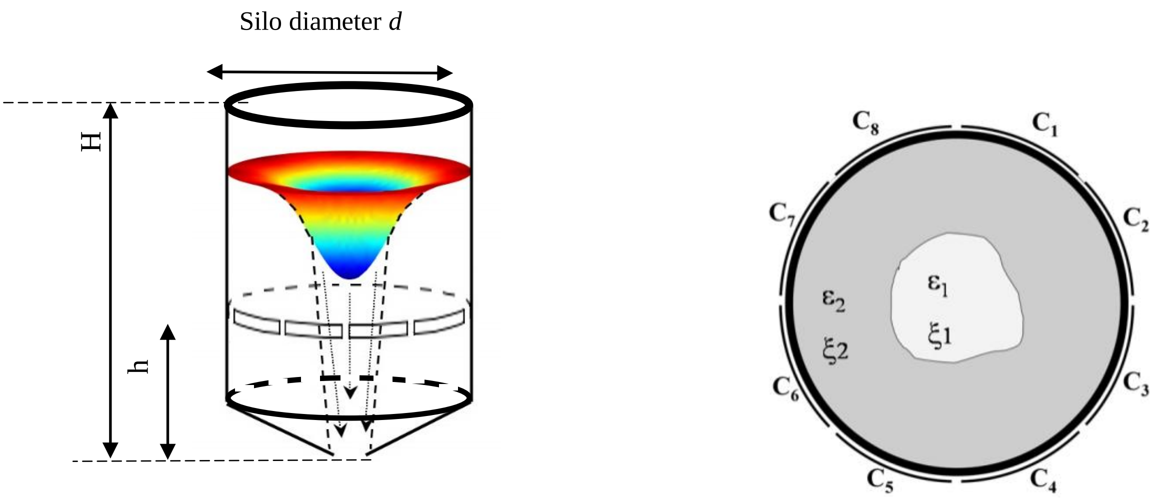
1) Design the model of the process and choose the important parameters.
2) Propose a model and design an algorithm for parameters estimation and choose the appropriate tools (ANN)
3) Prepare the data for the ANN training and which are accurate enough to build the proper ANN based model.
4) Build and test ANN models which solve the ECT inverse problem and allow crucial parameters estimation.
5) Prepare a physical model and perform experiments in TOMOKIS laboratory for the proposed method and models verification.
6) Design implement and test algorithms for the selected process parameters prediction on the basis of the measurements performed for a funnel flow of gravitational solids.

2. Concept

The behaviour of material during silo discharging process depends on granular properties and also silo construction [(Romanowski, Grudzien and Williams, 2006), (Grudzien et al., 2006)]. Two main types of flow are distinguished: mass flow, where material is moving with the same velocity in whole cross-section of silo, and funnel flow, where material is moving only in centre part of cross-section (Romanowski, Grudzien and Williams, 2006). In both situations unwanted phenomena can happen. The presented approach concerns the funnel flow. For this silo discharging type the most unwanted phenomena are arching (blocked funnel - stopping discharging process), rat holing (empty funnel – stopping discharging process). To avoid these situations the funnel area should be monitored. The movement of material in the central part of the cross-section container is distinguished by a lower packing of the material than in its other areas (Fig.1). This area is called funnel flow and is characterized by changes in shape and size during silo discharging.

In order to model the silo flow, two separate regions are identified within the cross section during discharging the container: the ‘funnel’ in the centre and the area close to the wall. One region corresponds to flowing material, e.g. funnel while the other corresponds to stagnant zone. The estimated parameters were: size of the funnel ξ_1, permittivity of the funnel ε_1, and the size ξ_2 and permittivity ε_2 of the other area.

The funnel shape was approximated by a circle and its size was estimated based on the area belonging to lower permittivity ε_1 in the centre of the silo cross-section. This form of modelling can allow direct estimation of the process parameters, and make process monitoring more efficient.



a) b)

Fig. 1 *Geometrical model of the silo, a) a simplified diagram of emptying the silo - funnel flow, (Grudzien et al., 2006), b) Geometrical modelling of hopper flow in cross section. The set of estimated parameters* $\eta = \{\xi_1, \varepsilon_1, \xi_2, \varepsilon_2\}$, *(Romanowski, Grudzien and Williams, 2006); where: H – the silo height, h – the height of ECT sensor position over the silo outlet.*

The set of parameters such as solids concentration, which corresponds to the permittivity, in the funnel and the funnel area size characterize the dynamics of hopper flow (Grudzien et al., 2006). This information asserts correct/incorrect hopper flow. Typically characteristic of material concentration changes during silo discharging process in case of funnel flow are presented in Fig.2. The permittivity distribution was normalized between 0 and 1.

Characteristic was prepared on the basis of measurement data changes (capacitance changes) taken as an average for each point of time, for opposite pairs of electrodes. The presented example of a sequence of reconstructed images placed on silo flow characteristic plot indicates the material concentration/ permittivity distribution inside a sensor. The changes of measured capacitances are associated with funnel appearing in the central part of the receptacle cross section area and these correspond to decreased material concentration in this part. In the considered case, the most important range of time of silo discharging process, from control point of view, is between 200 and 500 frames. Than a funnel size monitoring is the most important to prevent stoppages and dangerous accidents.

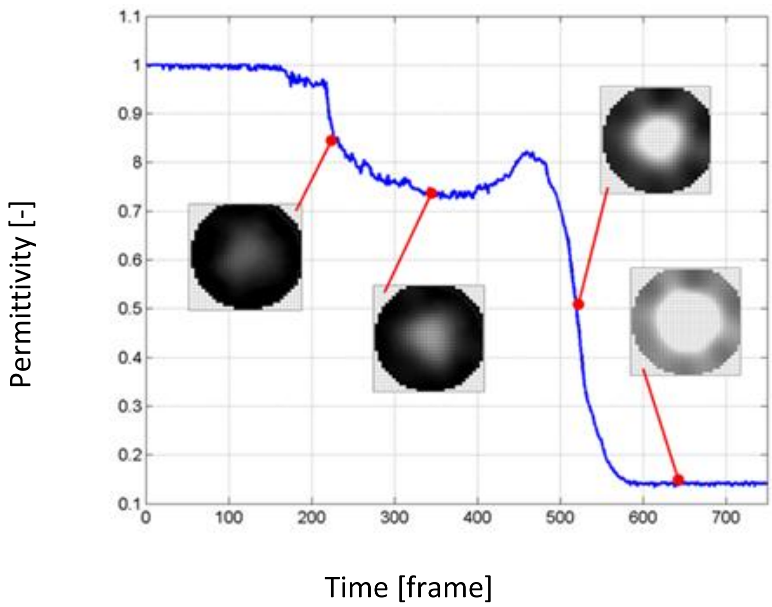


Fig. 2 *Changes of the material concentration (permittivity) distribution inside a sensor (Grudzien et al., 2006)*

State-of-the-art approaches solve the inverse problem by reconstructing pixels of the flow image. An appropriate image processing algorithm is needed to interpret the provided image and extract the useful information (Fig.3.a) such as flow parameters needed in process monitoring e.g. the area of the flow funnel, material concentration in the funnel, and the position of the funnel.

Inverse problems are in almost cases correlated to ill-posed problems since the number of the available observations or measurements to solve the handled task are limited or the solution is characterised by an instability (Kabanikhin, 2008). ANNs are known as a powerful tool for nonlinear modelling. They were used to solve several inverse problems and mapping nonlinear complex relationships within a set of data.

One class of such problems is identification of small cylindrical inclusion in the material. Shape inverse problems are usually difficult to solve in analytical way and numerical methods are complex and time consuming. Jackowska-Strumillo et al. (2002) proposed application of ANN of MLP type for the identification of cylindrical inclusion opening in a square plate.

ANNs were successfully applied to image reconstruction using Electrical Impedance Tomography (EIT) [(Ratajewicz-Mikolajczak et al., 1998), (Ratajewicz-Mikolajczak and Sikora, 2002), and (Stasiak et al., 2007)].

Artificial Neural Networks (ANN) have been used for solving both ECT problems (forward and inverse) since they represent a powerful and effective tool to dealing with complex and nonlinear computations. The type of the applied neural network differs depending on the purpose of investigations.

Comparing to iterative ECT image reconstruction techniques, ANN based algorithms are fast, however for the full image reconstruction large ANN size or large number of ANNs has to be used. Precise image reconstruction algorithms have high numerical complexity and are not suitable for long term monitoring of fast-varying industrial processes in real-time.

The present work gets the target information in a direct manner as summarised in the above bloc scheme in Fig. 3.b: an artificial neural network provides directly the funnel parameters knowing the capacitances measurements fed at the input layer.

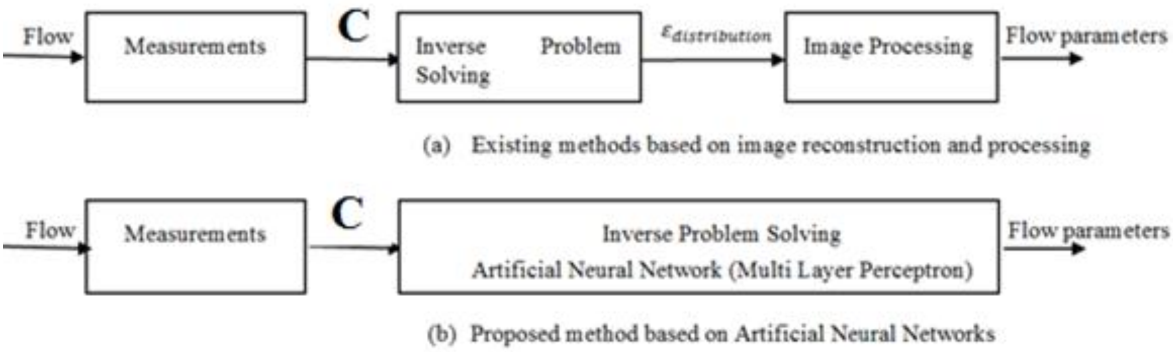


Fig. Błąd! W dokumencie nie ma tekstu o podanym stylu. *Different approaches to determine the flow parameters from capacitances data: (a) An existing methods based on image processing and reconstruction, (b) The proposed method based on Artificial Neural Networks*

3. Simulations

The data for ANN training were prepared via computer simulations. The simulation is done using ECTSIM Matlab’s toolbox, [(Smolik and Radomski, 2008), (Ectsim.ire.pw.edu.pl, 2012)]. ECTSIM was designed to evaluate existing image reconstruction algorithms applied on the field of ECT like Landweber algorithm, Levenberg-Marquardt LM and LBP method. The ECTSIM was used only for capacitance data generation. The carried out work can be described on 2 main steps: (1) Sensor modelling and capacitances generation via ECTSIM (2) Flow parameters estimation using artificial neural network: a Multi-Layer Perceptron (MLP) is applied to estimate different flow parameters during the several handled tasks (Fig.4).

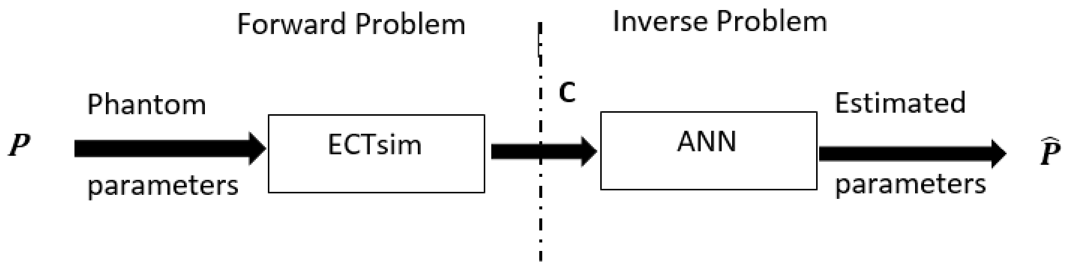


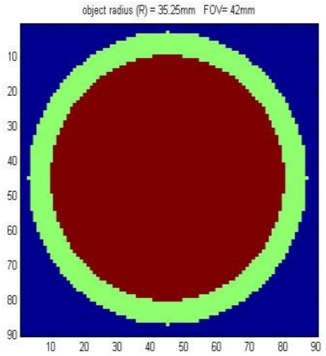
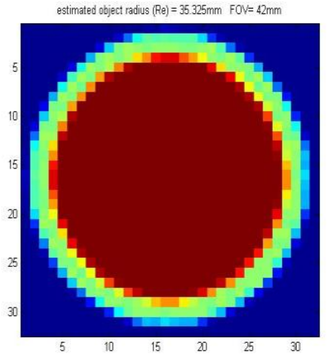
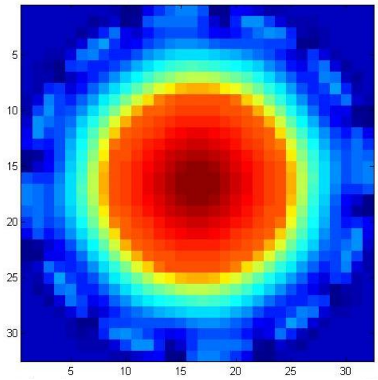
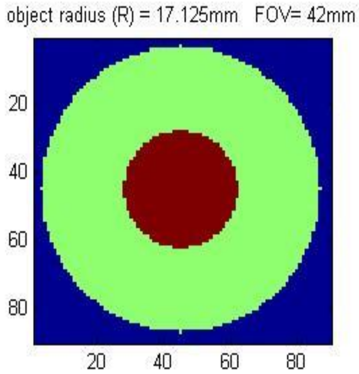
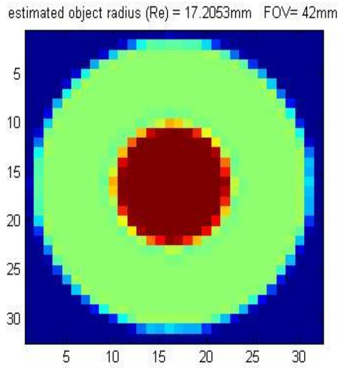
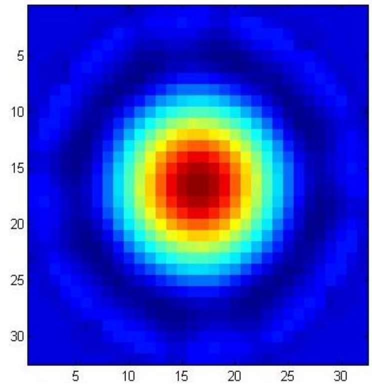
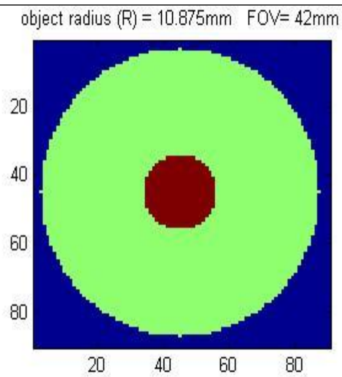
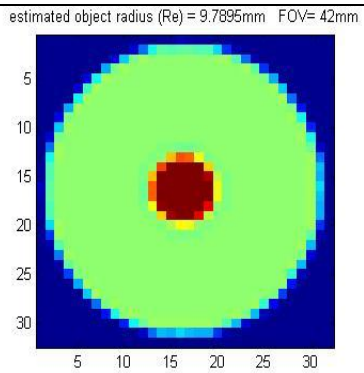
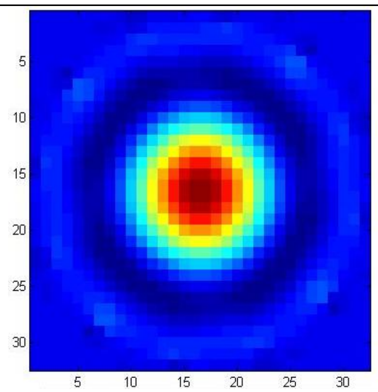
Fig.3 Forward and Inverse Problems simulation

A simplified model of gravitational solids flow geometry was proposed and crucial flow parameters needed in process monitoring were selected, such as the area of the flow funnel, material concentration in the funnel, and the position of the funnel. The funnel shape in the cross section was modelled by a circle. Large number of simulations were performed to generate the data for ANN training and testing and to evaluate the ANN performances. The proposed ANN-based method is dedicated to inverse problem in ECT and estimation of the circular flow parameters directly from the ECT raw data.

4. Flow parameters estimation

In the first attempt estimation of the radius of a circular object was considered. The obtained results for ECT sensor with 12 electrodes were promising for a simple MLP structure (66-10-1) and the back-propagation training algorithm. The ANN-based approach allowed to solve the inverse problem in a shorter computational time which is about 120 times shorter than for the Levenberg-Marquardt (LM) iterative algorithm (see Table 1).

Table 1 Reconstructed images from MLP and Levenberg-Marquardt algorithm

<table>
<tr><th>Desired Phantom/ Distribution</th><th>Image reconstructed from MLP</th><th>Image reconstructed from Levenberg-Marquardt</th></tr>
<tr><td rowspan="2"></td><td></td><td></td></tr>
<tr><td>time elapsed for reconstruction (s)
0.07</td><td>time elapsed for reconstruction (s)
10.22</td></tr>
<tr><td rowspan="2"></td><td></td><td></td></tr>
<tr><td>time elapsed for reconstruction (s)
0.076</td><td>time elapsed for reconstruction (s)
9.91</td></tr>
<tr><td rowspan="2"></td><td></td><td></td></tr>
<tr><td>time elapsed for reconstruction (s)
0.08</td><td>time elapsed for reconstruction (s)
10.11</td></tr>
</table>

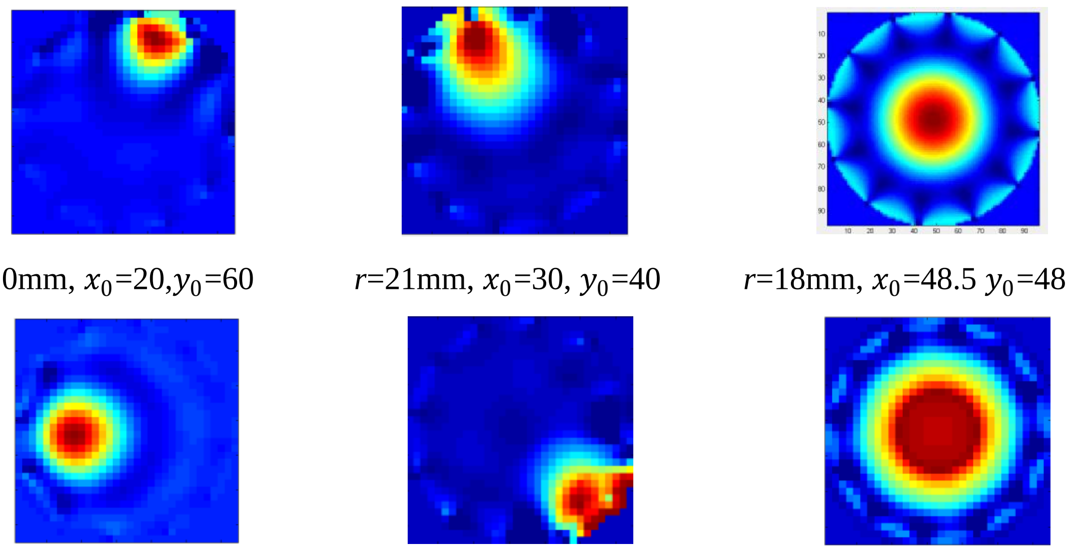
The accuracy of the ANN-based estimation of the size of the circular object was compared to two image reconstruction methods reviewed in the state of the art: the Linear Back Propagation LBP which is a fast and direct method but suffers from poor resolution of the reconstructed image and to the Levenberg-Marquard which is accurate but time consuming method. Results in Table 2 indicate that the radii of the three tested phantoms estimated by the use of MLP are close to the real desired values. Lower relative estimation errors have been achieved using the MLP than either the LBP or LM, i.e.: at least a few times smaller for small object and even 25 times smaller than the LM and 93 times lower than the LBP for larger objects.

Table 2 Comparison of the accuracy of the different methods

Method / r [mm]	MLP		LBP		LM	
	$\hat{r}$ [mm]	E_r [%]	$\hat{r}$ [mm]	E_r [%]	$\hat{r}$ [mm]	E_r [%]
35.25	35.32	0.19	29.01	17.7	33.54	4.85
17.125	17.20	0.44	12.84	25.02	18.73	9.37
10.875	9.79	9.98	12.48	14.76	16.4	50.8

The performances of the MLP were then tested in noisy environment (noise was added to the capacitance measurements constituting the input of the selected neural network). The applied ANN proved robust to noise reaching a standard deviation no larger than 7%.

Later on, the number of targeted parameters was increased. In addition to the size of the funnel, the MLP was used to estimate more than one parameter of the flow. In the next step, the size (radius) and position coordinates (x, y) of the circular shape of the funnel flow were determined. Examples of different positions and different radii of phantoms considered in the simulation are shown in Fig.5. The provided results highlight the performances of the artificial neural network based approach to direct estimation of different tomographic parameters without image processing phase in a reduced computational time offering the possibility of online cylindrical flow monitoring. The considered flow parameters were estimated 26 times faster than by the use of the Landweber method.



r=10mm, x_0=20,y_0=60 r=21mm, x_0=30, y_0=40 r=18mm, x_0=48.5 y_0=48.5

r=12mm, x_0=50, y_0=30 r=18mm, x_0=70, y_0=70 r=30mm, x_0=48.5, y_0=48.5

Fig. 5 *Examples of different positions and different radii of phantoms considered in the simulation*

Table Błąd! W dokumencie nie ma tekstu o podanym stylu. Comparison of the accuracy of the estimation of the position and radius of the funnel by the use of the MLP, LM and LBP

Phantom	Method / $p=\begin{bmatrix} r \\ x_0 \\ y_0 \end{bmatrix}$ [mm]	MLP		LBP		LM	
		$\hat{p}=\begin{bmatrix} \hat{r} \\ \widehat{x_0} \\ \widehat{y_0} \end{bmatrix}$ [mm]	E_p [%]	$\hat{p}=\begin{bmatrix} \hat{r} \\ \widehat{x_0} \\ \widehat{y_0} \end{bmatrix}$ [mm]	E_p [%]	$\hat{p}=\begin{bmatrix} \hat{r} \\ \widehat{x_0} \\ \widehat{y_0} \end{bmatrix}$ [mm]	E_p [%]
1	$\begin{bmatrix} 28.88 \\ 30 \\ 40 \end{bmatrix}$	$\begin{bmatrix} 29.37 \\ 29.11 \\ 40{,}83 \end{bmatrix}$	$\begin{bmatrix} 1.69 \\ 2.96 \\ 2 \end{bmatrix}$	$\begin{bmatrix} 24.81 \\ 15.90 \\ 53.35 \end{bmatrix}$	$\begin{bmatrix} 14.09 \\ 47 \\ 33.37 \end{bmatrix}$	$\begin{bmatrix} 27.73 \\ 25.71 \\ 50.62 \end{bmatrix}$	$\begin{bmatrix} 3.98 \\ 14.3 \\ 26.55 \end{bmatrix}$
2	$\begin{bmatrix} 24.75 \\ 70 \\ 70 \end{bmatrix}$	$\begin{bmatrix} 24.63 \\ 69.24 \\ 69.74 \end{bmatrix}$	$\begin{bmatrix} 0.48 \\ 1 \\ 1 \end{bmatrix}$	$\begin{bmatrix} 20.78 \\ 78.64 \\ 74.17 \end{bmatrix}$	$\begin{bmatrix} 16.17 \\ 12.34 \\ 5.96 \end{bmatrix}$	$\begin{bmatrix} 17.96 \\ 78.74 \\ 73.94 \end{bmatrix}$	$\begin{bmatrix} 27.43 \\ 12.48 \\ 5.63 \end{bmatrix}$
3	$\begin{bmatrix} 25{,}25 \\ 20 \\ 60 \end{bmatrix}$	$\begin{bmatrix} 25.45 \\ 19.55 \\ 61.52 \end{bmatrix}$	$\begin{bmatrix} 0.8 \\ 2.25 \\ 2.52 \end{bmatrix}$	$\begin{bmatrix} 20.12 \\ 14.59 \\ 67.05 \end{bmatrix}$	$\begin{bmatrix} 20.32 \\ 27.05 \\ 11.75 \end{bmatrix}$	$\begin{bmatrix} 18.01 \\ 14.40 \\ 64.50 \end{bmatrix}$	$\begin{bmatrix} 28.71 \\ 28 \\ 7.5 \end{bmatrix}$

This advantage of the proposed algorithm is also revealed by the accuracy level provided by the ANN-based approach (see Table 3): the smallest relative error obtained by the MLP is 0.48% against 6% and 4% by the use of the LBP and LM respectively. The highest relative error reached by the MLP is 3% while it is in the order of 33% and 29% in the case of the LBP and LM.

In a further step, in addition to the previous parameters, the concentration of the material in the funnel was considered. Concentration of the material can be evaluated using ECT on the basis of electrical permittivity estimation. ECT sensor with 8 electrodes and MLP structure (28-14-4) were taken into account. The MLP was then trained and implemented to estimate four flow parameters which give more pertinent and valuable information and then more accurate process monitoring. The accuracy and speed of the new method were compared to the existing image reconstruction based approaches. The MLP allowed to estimate the targeted parameters faster than the existing methods: over 4000 times faster than the Levenberg Marquardt nonlinear method, 2800 times faster than the Landweber and 15 times faster than the LBP re-construction method. The obtained accuracy using MLP is at the same level as for the LM method and at least a few times better comparing to the LBP. The advantage of the ANN-based approach is also an ability to perform the estimation of the fourth flow parameter, i.e. electrical permittivity of the funnel from the raw measurement data, which is a difficult problem in the case of other methods.

In all considered cases the MLP-based approach provided accurate values of the funnel flow parameters. The results are of the same level of accuracy or even better than for the state-of-the-art methods and time of calculations is significantly lower, what proves the thesis.

The revealed results performed for the different models of the funnel flow are promising and the provided speed is sufficient and gives the possibility for the online industrial process monitoring in a real time. The time required for estimating the parameters is about thirty times shorter than the acquisition time in traditional ECT measurement system and about three times shorter if compared to high performances ECT systems.

In an experimental part, described in chapter 4, measurements were performed in the Tom Dyakowski Process Tomography Laboratory in the Institute of Applied Computer science, Lodz University of Technology in order to test the performances of the proposed approach in a real environment. A physical model of the funnel was built and the measurements were fed to the selected MLP, which was trained with simulated data using ECTsim Matlab toolbox.

Fig. 6 *A physical model of a cylindrical flow process – a pipe with the object inside and ECT sensor with 8 electrodes placed around*

Parameters of sensors and phantoms considered in the performed simulations are gathered in Table 4, such as: sensor diameter, number of electrodes, object size and electrical permittivity and background permittivity. The structure of the most performing MLP is also specified.

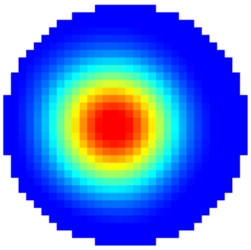
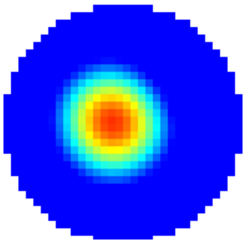
Table Błąd! W dokumencie nie ma tekstu o podanym stylu. Parameters of sensors and phantoms considered during simulations and corresponding MLP structures

Estimated parameters	Sensor diameter	Number of electrodes	Object diameter	Object permittivity	Background permittivity	MLP
r	84	12	<4; 84>	3	1	(66-10-1)
r, x, y	84	12	<20; 84>	3	1	(66-14-3)
r, x, y, ε	**142**	**8**	**<40; 142>**	**[1.6 ,2]**	**1**	**(28-14-4)**

During the experiments in the laboratory, only the third case was considered: the sensor with a diameter 142 mm, 8 electrodes and background permittivity =1. The measured capacitances were fed to the MLP of a structure (28-14-4) to test its performances in real environment.

The accuracy of the MLP to estimate the radius and permittivity of the object is about 11% in average for each estimated parameter in the case of an object placed in the centre of the pipe which corresponds to the case of the funnel flow in a silo.

Table 5 Result of parameters estimation from real measurements by the use of MLP structure (28-14-4) for two different phantoms

phantom	Considered phantom	Parameters of the phantom	Parameters estimated by MLP	Relative Errors [%]	Parameters estimated by Landwber	Relative Errors[%]
1		$P=\begin{bmatrix}31\\65\\75\\2\end{bmatrix}$	$\hat{P}=\begin{bmatrix}27{,}5\\64.1\\64.7\\1.8\end{bmatrix}$	$\begin{bmatrix}11.3\\1.38\\13.7\\10\end{bmatrix}$	$\widehat{P}=\begin{bmatrix}40\\45.78\\49.75\\-\end{bmatrix}$	$\begin{bmatrix}29\\29.56\\33.66\\-\end{bmatrix}$
2		$P=\begin{bmatrix}25\\62\\68\\2\end{bmatrix}$	$\hat{P}=\begin{bmatrix}27{,}4\\64{,}3\\64.7\\1{,}8\end{bmatrix}$	$\begin{bmatrix}9.6\\3.7\\4.85\\10\end{bmatrix}$	$\hat{P}=\begin{bmatrix}31\\44.8\\49.6\\-\end{bmatrix}$	$\begin{bmatrix}24\\27.78\\27{,}06\\-\end{bmatrix}$

In the first case, the object has a diameter 62 mm, r =31mm, and is placed near to the centre of the pipe. The relative error for radius estimation by the use of the MLP is 11.3% and 10% for permittivity which are satisfactory. The highest relative error is obtained for the position y_0, 13.7% but is lower than the error when the parameters are estimated after processing the reconstructed image by Landweber method. Lower relative errors are obtained for the smaller object with diameter d=50 mm and the relative errors do not exceed 10% for radius and permittivity estimation and 5% in average for the position. The level of the accuracy of the ANN-based method is higher than Landweber method.

5. Flow dynamics prediction

Also a new ANN-based model for application in ECT was proposed for the prediction of the variations of the characteristic parameters of gravitational solids flow. Electrical Capacitance

Tomography (ECT) was applied for non-invasive process monitoring. A sequence of artificial neural networks (MLP and Nonlinear-Auto-Regressive (NAR) neural network) is implemented to estimate and predict important flow parameters knowing the measured capacitances: The first ANN of MLP type solves the ECT inverse problem directly by mapping the nonlinear relationship between the set of inputs − the measured capacitances and outputs − the crucial parameters of the considered gravitational solids flow.

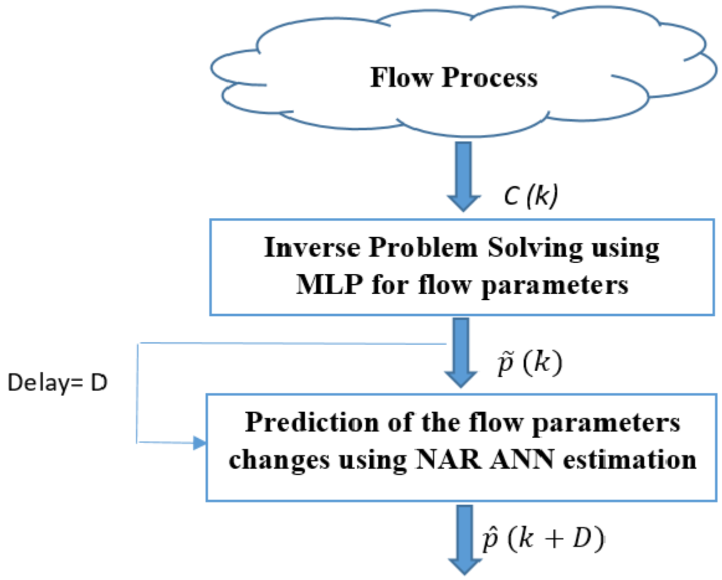


Fig. 7 Proposed ANN-based approach for flow parameters estimation and prediction

The provided estimated parameters at the MLP output are then sent to the second neural network of nonlinear autoregressive type, which predicts the parameters variations and the dynamics of the funnel. The proposed approach provided a rapid parameterization of the funnel flow. The simulation of the silo discharging process is performed relying on real flow behaviour obtained from the previous work in the field (Romanowski et al., 2006). The simulated data are used to new approach testing and verification.

During the experiments two cases of the silo behaviour were considered: a normal flow and a flow with a blockage, when a stagnant zone is present inside the silo. The estimated changes of the funnel area and permittivity at the height 45 mm for both cases: with and without the blockage are shown in Fig. 8. A delay of the changes (frames) and small changes of the signal magnitude are noticed when an obstacle appears during the discharging process.

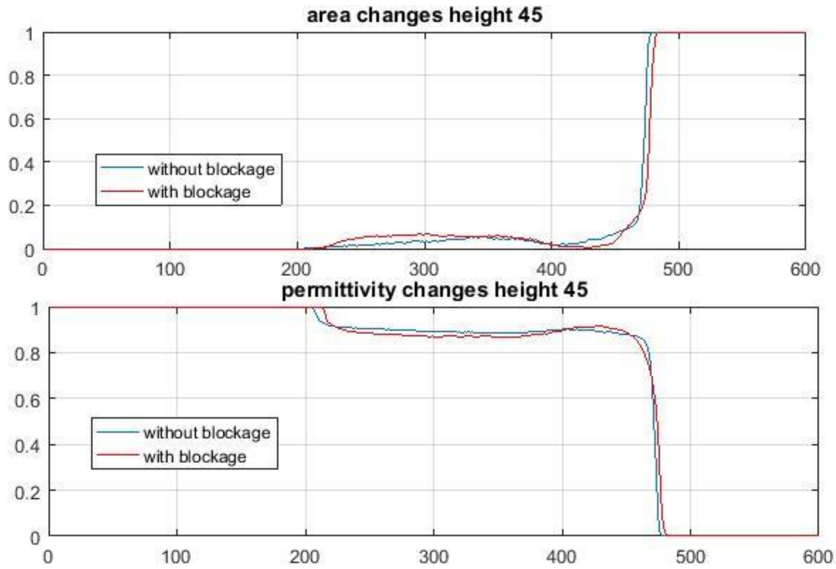


Fig. 8 *Changes in area and permittivity for two cases of the funnel flow: with and without the blockage with the same height of the sensor (h=45mm).*

The concentration and the area of the funnel are the crucial flow parameters considered during the experiments. According to the proposed approach (see Fig. 7) these parameters are estimated at first by the MLP and then are fed to the NAR neural network, which predicts their future changes. The prediction was performed using the Matlab and Neural Network Toolbox. The Levenberg-Marquardt training algorithm was applied and initial state of the NAR model was set using a random function.

The predicted variations of the funnel parameters for the sensor's height h=45 mm and in the case of an obstacle present inside the silo are shown in Fig 9 and Fig. 10. Larger errors can be noticed for the characteristic parameters changes. This could be used in the future for the flow abnormality detection and diagnosis.

The obtained accuracy $2{\cdot}10^{-7}$ in average is satisfactory and proved that proposed ANN-based method will allow online tracking of the silo discharging process and earlier recognition of the process phases and abnormalities.

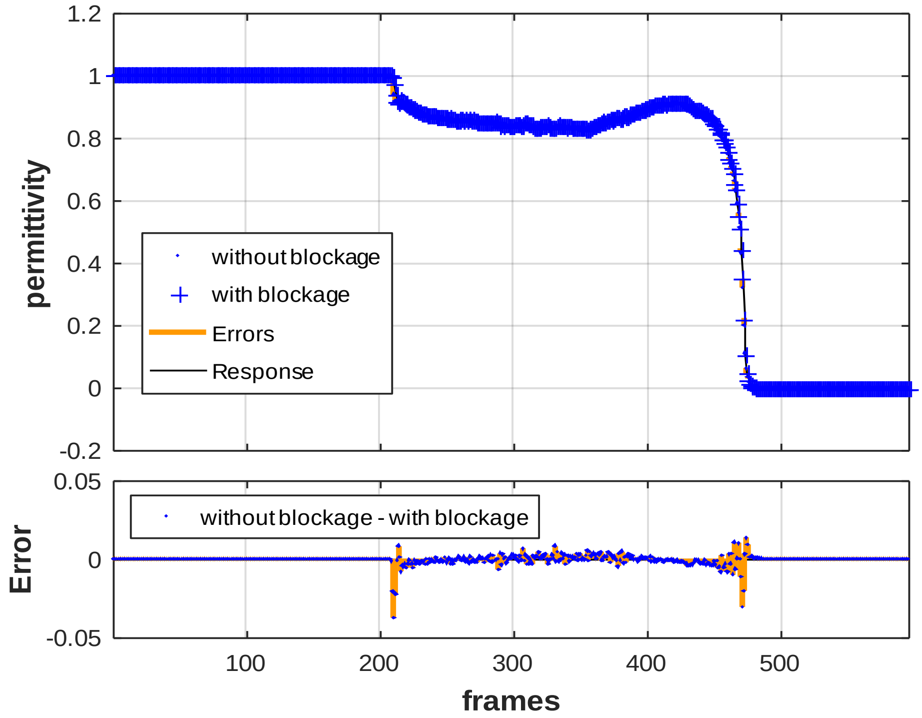


Fig. 9 Predicted changes of the funnel concentration and obtained errors for the sensor's height of 45mm in the case of the blockage.

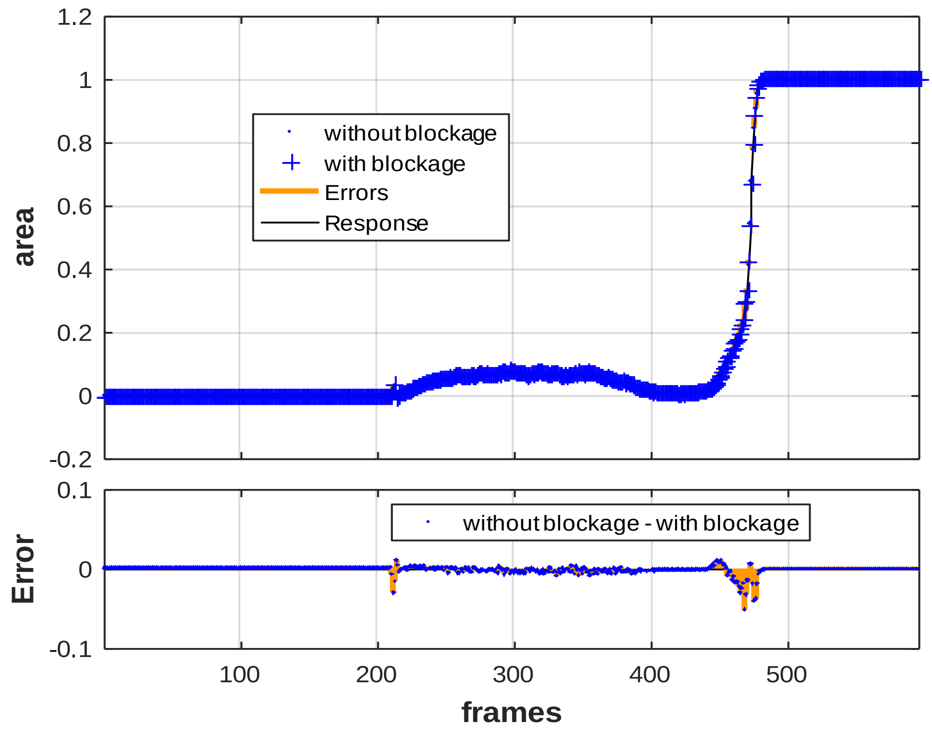


Fig. 10 Predicted changes of the funnel area and obtained errors for the sensor's height of 45mm in the case of the blockage

6. Conclusions

The aim of this PhD thesis was to develop and implement new methods that enable on-line monitoring of gravitational solids flow in real time.

The main achievement of the thesis is elaboration of the new method for estimation of crucial flow parameters based on artificial neural networks, with the following advantages:

1) Parameters of the flow are directly estimated from the measured capacitances with no need to implement image reconstruction algorithms, 2) faster than the existing image reconstruction methods and 3) of a good accuracy to solve the ECT inverse problem.

In all considered cases the MLP-based approach provided accurate values of the funnel flow parameters. The results are of the same level of accuracy or even better than for the state-of-the-art methods and time of calculations is significantly lower, what proves the thesis.

The revealed results performed for the different models of the funnel flow are promising and the provided speed is sufficient and gives the possibility for the online industrial process monitoring in a real time. The time required for estimating the parameters is about thirty times shorter than the acquisition time in traditional ECT measurement system and about three times shorter if compared to high performances ECT systems.

In the case of real environment, the accuracy of the MLP to estimate the radius and permittivity of the object is about 11% in average for each estimated parameter in the case of an object placed in the centre of the pipe which corresponds to the case of the funnel flow in a silo.

In addition, new ANN-based method was proposed for prediction of the gravitational solids flow parameters variations during the silo discharging process and the provided accuracy proved that proposed ANN-based method will allow online tracking of the silo discharging process and earlier recognition of the process phases and abnormalities.

7. References

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