1. Krzysztof KRÓL[1,2], 2. Konrad NIDERLA[1,2], 3. Edward KOZŁOWSKI[3]

Netrix S.A., Research & Development Centre (1), University of Economics and Innovation in Lublin(2), Lublin University of Technology, Faculty of Management (3)
ORCID: 1. 0000-0002-0114-2794, 2. 0000-0003-1280-0622, 3. 0000-0002-7147-4903

doi:10.15199/48.2023.02.29

Multisensor platform using industrial tomography for monitoring and control of technological processes

***Abstract**. The article covers the process of developing intelligent mechanisms for monitoring and controlling industrial processes using modern measurement techniques and process tomography. The solution proposed in this work focuses on analysing, monitoring and controlling technological processes using industrial tomography.*

***Streszczenie.** Artykuł obejmuje proces opracowywania, inteligentnych mechanizmów monitorowania i sterowania procesami przemysłowymi z wykorzystaniem nowoczesnych technik pomiarowych, tomografii procesowej. Rozwiązanie zaproponowane w niniejszej pracy skupia się na analizie, monitorowaniu i kontroli procesów technologicznych za pomocą tomografii przemysłowej (**Platforma wielosensorowa wykorzystująca tomografię przemysłową do monitorowania i sterowania procesami technologicznymi**).*

Keywords: electrical capacitance tomography, cyber-physical systems sensors, process tomography.
Słowa kluczowe: elektryczna tomografia pojemnościowa, czujniki systemów cyber-fizycznych, tomografia procesowa.

Introduction

This article presents a multisensor industrial tomography platform used for diagnostics and control of technological processes. The concept of the whole platform has been developed as a system of Industry 4.0. The main intention is to prepare the whole in such a way that it is possible to add individual sensors cooperating with the system of an intelligent cyber-physical platform of open architecture [1,2,3].

An important element is a free configuration and cooperation with external systems. Experimental work has developed a platform that allows individual subsystems to work together. The cyber-physical system consists of integrated computing, communication, control and physical elements. The system's general assumptions can indicate the ability to manage data stored on the server. It is possible to read current data as well as historical data [4,5,6]. The data coming from the measuring sensors are sent to the database, and it is possible to check and read them at any time. As part of the system's construction, individual sensors that communicate through an established standard can be combined at will. In our case, it was the Kafka system.

The system is built based on smart sensors that measure basic physical quantities but also more complex tomographic sensors such as electrical impedance tomography. The industrial tomography sensor itself makes measurements related to either current flow or potential distribution on the component under test. However, in order to make measurements capable of displaying information about the object under study, appropriate algorithms are needed to control the measurement process, and on the other hand, appropriate algorithms must be applied to analyze and diagnose technological processes [7-18].

EIT measurement

Various sensors have been used to build the multisensor platform, but in this article, we focus on the impedance tomography sensor. The use of this type of sensor allows you to look inside the object without destroying it, and with up-to-date knowledge of the process taking place, you can control it, and control the processes [19].

All sensors allow direct or indirect data collection from various sources related to the production process. We use a tomographic device for different objects (e.g., a field of view in the form of a circle with different diameters). Using ML techniques, we should first create a learning set. Analyzing the correlation coefficient value map, we see that the predictors are highly correlated. In order to reduce the dimensions, we usually use techniques such as Tikhonov regularization, LASSO, Elasticnet [20], Principal Component Analysis [21], wavelet decomposition (signal projection for the i-th level, we choose scaling factors), etc.

The approach used is similar to SVM, except that, using SVM, we select support vectors that constitute the learning set, while here, we first define support vectors and select kernel values (e.g., the square of the norm of the difference between the measurement and the base vector) as pre-kernel values. In this way, we construct a learning set in which the number of predictors is equal to the number of base vectors.

Used technique

The viewing area consists of k finite elements, while the vector of measurements obtained from the electrodes contains m values. For a learning set containing n cases, we define $Y \in \mathbb{R}^{n\times k}$ and $X \in \mathbb{R}^{n\times m}$ of the form

$$(1)\qquad Y=\begin{bmatrix} y^{(1)} \\ y^{(2)} \\ \dots \\ y^{(n)} \end{bmatrix}=\begin{bmatrix} y_{11} & y_{12} & \dots & y_{1k} \\ y_{21} & y_{22} & \dots & y_{2k} \\ \vdots & \vdots & \vdots & \vdots \\ y_{n1} & y_{n2} & \dots & y_{nk} \end{bmatrix},\quad X=\begin{bmatrix} x^{(1)} \\ x^{(2)} \\ \dots \\ x^{(n)} \end{bmatrix}=\begin{bmatrix} x_{11} & x_{12} & \dots & x_{1m} \\ x_{21} & x_{22} & \dots & x_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n1} & x_{n2} & \dots & x_{nm} \end{bmatrix}$$

we define a matrix of baseline measurements

$$(2)\qquad B=\begin{bmatrix} b^{(1)} \\ b^{(2)} \\ \dots \\ b^{(n)} \end{bmatrix}=\begin{bmatrix} b_{11} & b_{12} & \dots & b_{1m} \\ b_{21} & b_{22} & \dots & b_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ b_{d1} & b_{d2} & \dots & b_{dm} \end{bmatrix}.$$

This matrix consists of a baseline measurement and measurements corresponding to the position of inclusions at specific locations. Of course, the number of base measurements d<m<<n.

In order to reduce the dimension, we apply a transformation $F_B\colon \mathbb{R}^m \to \mathbb{R}^d$ of the form $F_B(x^{(i)}) = \left(f_{b^{(1)}}(x^{(i)}), f_{b^{(2)}}(x^{(i)}), \dots, f_{b^{(d)}}(x^{(i)})\right)$
where

$$(3)\qquad f_{b^{(j)}}(x^{(i)}) = exp\left(-||b^{(j)} - x^{(i)}||\right)$$

for any 1≤j≤d, 1≤i≤n In view of the above, the matrix of predictors $W=F_B(X)$ of the form

$$W = \begin{bmatrix} w^{(1)} \\ w^{(2)} \\ \dots \\ w^{(n)} \end{bmatrix} = \begin{bmatrix} w_{11} & w_{12} & \dots & w_{1d} \\ w_{21} & w_{22} & \dots & w_{2d} \\ \vdots & \vdots & \vdots & \vdots \\ w_{n1} & w_{n2} & \dots & w_{nd} \end{bmatrix} = \begin{bmatrix} F_B(x^{(1)}) \\ F_B(x^{(2)}) \\ \dots \\ F_B(x^{(n)}) \end{bmatrix} \tag{4}$$

After applying the FB transformation of the ML technique, we apply to a learning set containing n cases: a matrix of finite element values $Y \in \mathbb{R}^{n \times k}$ and a matrix of predictors $W \in \mathbb{R}^{n \times d}$, d<m.

Model

The two-dimensional model represents a circle of radius 1. All electrodes are placed on the edge of the circle.

Parameters of the model:

- 1338 number of calls;
- 2502 number of finite elements;
- 16 number of electrodes;
-point electrodes

The number of measurements obtained from the electrodes is 96.

Below are examples of field inclusions and measurements from the electrodes, which are the basis vectors in the B matrix (Fig.1-8).

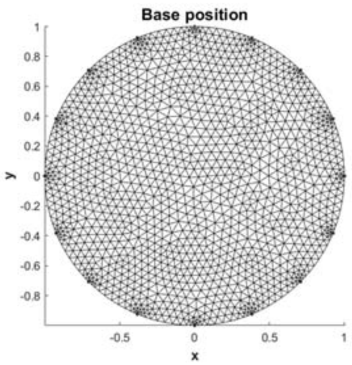

Fig.1. The two-dimensional model, and base position for basis vector 1

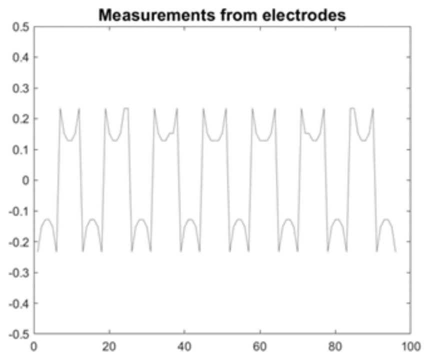

Fig.2. Reference measurement from electrodes for vector 1.

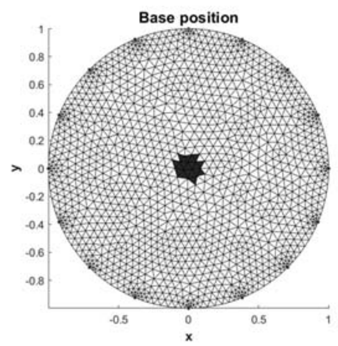

Fig.3. Reference as basis vector 2.

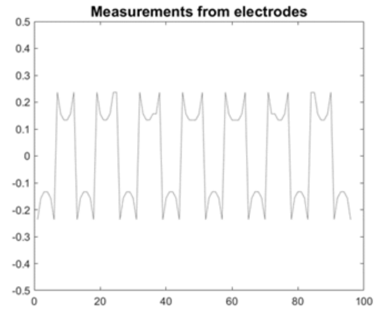

Fig.4. Reference measurement from electrodes for vector 2

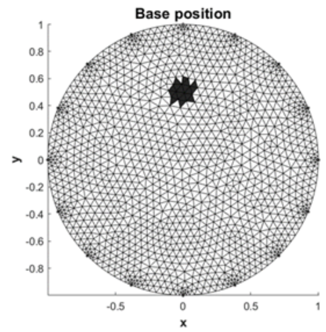

Fig.5. Reference as basis vector 3

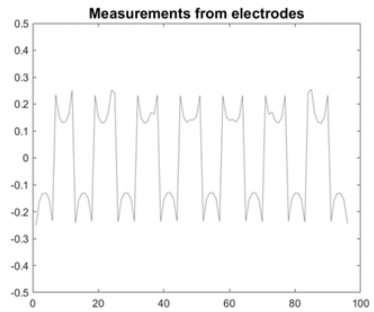

Fig.6. Reference measurement from electrodes for vector 3

Then the measurements at each electrode.

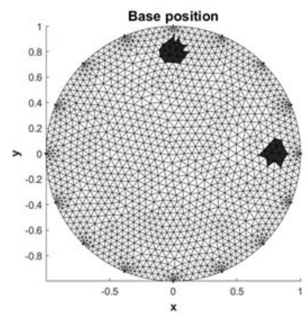

Fig.7. Reference as basis vector 19.

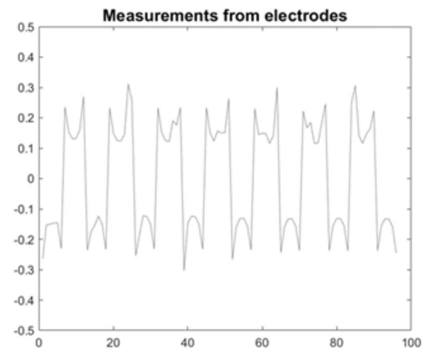

Fig.8. Reference measurement from electrodes for vector 19

Examples of reconstructions

Models were identified for each finite element:

- linear regression with Elasticnet;
- logistic regression with Elasticnet.

Estimation of the structural parameters of the models for each finite element was performed in the programming language R. The glmnet function from the glmnet package was used to determine the coefficients.

Example reconstruction results are given below (Fig.9-18).

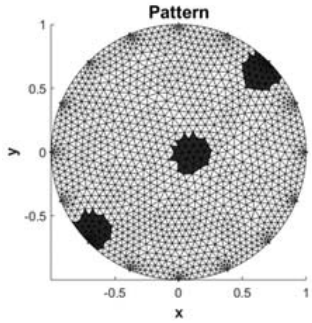

Fig.9. Example 1 Pattern

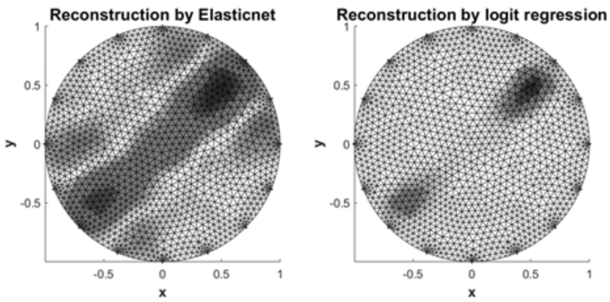

Fig.10. Example 1 Reconstruction

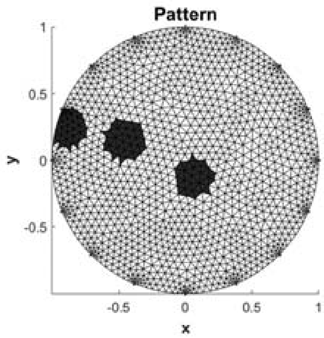

Fig.11. Example 2 Pattern

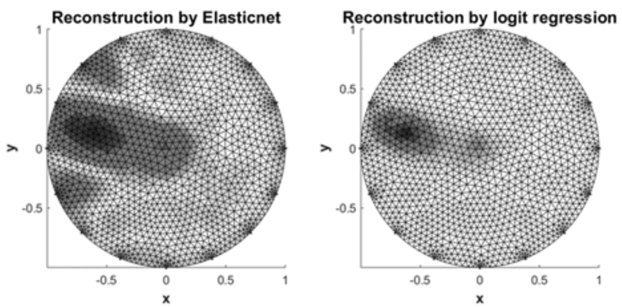

Fig.12. Example 2 Reconstruction

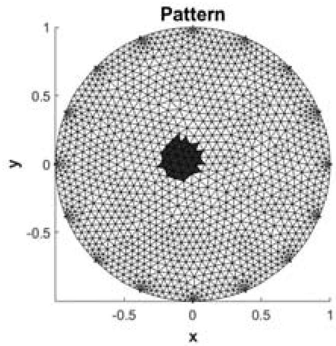

Fig.13. Example 3 Pattern

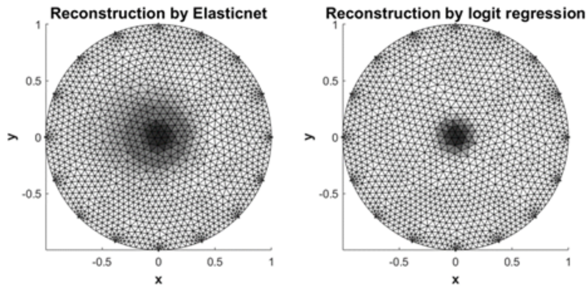

Fig.14. Example 3 Reconstruction

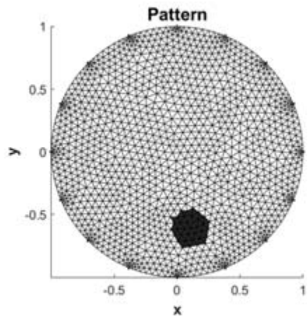

Fig.15. Example 4 Pattern

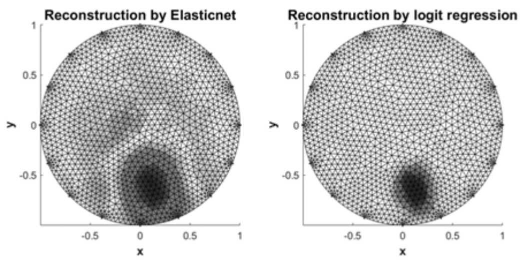

Fig.16. Example 4 Reconstruction

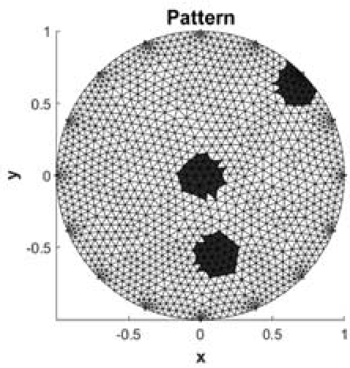

Fig.17. Example 5 Pattern

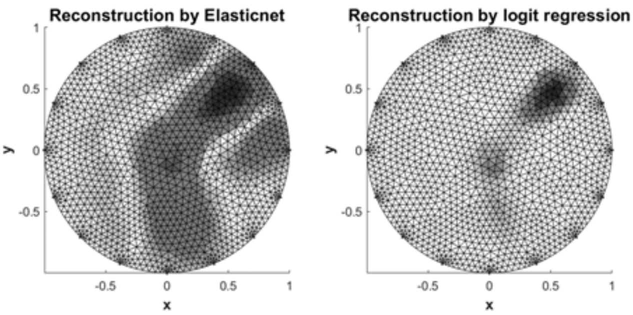

Fig.18. Example 5 Reconstruction

Conclusions:

The presented technique allowed to reduce the dimensions of the predictors (from 96 to 24). The presented technique allows to detect the location of the inclusion in the viewing area, while the boundaries of the inclusion are not clear, the use of additional filters is required. The method's main purpose is to use a tomographic device to view areas in the form of a circle of different diameters. By recording the baseline measurements, we determine the basis vectors necessary for the transformation of the predictors. Disadvantage: regression also requires regularization techniques because the resulting predictors—further research: using other transformations to obtain predictors that are less correlated with each other.

Authors: *Krzysztof Król, Research&Development Centre Netrix S.A., Email: krzysztof.krol@netrix.com.pl; Edward Kozłowski Ph.D.Eng.,Lublin University of Technology, Nadbystrzycka 38, Lublin, E-mail: e.kozlowski@pollub.pl; Konrad Niderla, University of Economics and Innovation, Projektowa 4, Lublin, Poland E-mail konrad.niderla@netrix.com.pl;*

REFERENCES

[1] Akhtari S, Pickhardt F, Pau D, Pietro AD, Tomarchio G. Intelligent embedded load detection at the edge on industry 4.0 powertrains applications. 2019 IEEE 5th international forum on research and technology for society and industry (RTSD2019:427-30
[2] Król K., Marciniak A., Gudowski J., Bojanowska A., Intelligent Sensor Platform with Open Architecture for Monitoring and Control of Industry 4.0 Systems, European Research Studies Journal Volume XXIV, Special Issue 2, 2021, 597-606
[3] Rymarczyk T., Król K., Zawadzki A., Oleszek M, Kłosowski G., An intelligent sensor platform with an open architecture for monitoring and controlling cyber-physical, Przegląd Elektrotechniczny,97(2021) nr 3, 141-145
[4] Kong XT, Zhong RY, Zhao Z, Shao S, Li M, Lin P, et al. Cyber physical ecommerce logistics system: an implementation case in Hong Kong. Comput Ind Eng 2020;139:106170
[5] He J, Jia G, Han G, Wang H, Yang X. Locality-aware replacement algorithm in flash memory to optimize cloud computing for smart factory of industry 4.0. IEEE Access 2017;5:16252-62
[6] Lins T, Oliveira RAR. Cyber-physical production systems retrofitting in context of industry 4.0. Comput Ind Eng 2020;139:106193.,59
[7] Manavalan E, Jayakrishna K. A review of internet of things (iot) embedded sustainable supply chain for industry 4.0 requirements. Comput Ind Eng 2019; 127:925-53
[8] Occhiuzzi C, Amendola S, Nappi S$, D'Uva N, Marrocco G. Rfid technology for industry 4.0: architectures and challenges. 2019 IEEE international conference on RFID technology and applications (RFID-TA) 2019:181-6
[9] Poor P, Basl J, Zenisek D. Predictive maintenance 4.0 as next evolution step in industrial maintenance development. 2019 international research conference on smart computing and systems engineering (SCSE) 2019:245-53
[10] Kłosowski G., Rymarczyk T., Kania K., Świć A., Cieplak T., Maintenance of industrial reactors supported by deep learning driven ultrasound tomography, Eksploatacja i Niezawodnosc – Maintenance and Reliability; 22 (2020), No 1, 138–147.
[11] Koulountzios P., Aghajanian S., Rymarczyk T., Koiranen T., Soleimani M., An Ultrasound Tomography Method for Monitoring CO2 Capture Process Involving Stirring and CaCO3 Precipitation, Sensors, 21 (2021), No. 21, 6995.
[12] Rymarczyk T., Kłosowski G., Hoła A., Hoła J., Sikora J., Tchórzewski P., Skowron Ł., Historical Buildings Dampness Analysis Using Electrical Tomography and Machine Learning Algorithms, Energies, 14 (2021), No. 5, 1307.
[13] Kania K., Rymarczyk T., Mazurek M., Skrzypek-Ahmed S., Guzik M., Oleszczuk P., Optimisation of Technological Processes by Solving Inverse Problem through Block-Wise-Transform-Reduction Method Using Open Architecture Sensor Platform, Energies, 14 (2021), No. 24, 8295.
[14] Rymarczyk T., Niderla K. Kozłowski E. Król K., Wyrwisz J. Skrzypek-Ahmed S., Gołąbek P., Logistic Regression with Wave Preprocessing to Solve Inverse Problem in Industrial Tomography for Technological Process Control, Energies, 14(2021), No. 23, 8116.
[15] Kania, W., Wajman, R., Ckript: a new scripting language for web applications, Informatyka, Automatyka, Pomiary W Gospodarce I Ochronie Środowiska, 12(2022), No. 2, 4-9.
[16] Styła, M., Adamkiewicz, P., Hybrid navigation system for indoor use. Informatyka, Automatyka, Pomiary W Gospodarce I Ochronie Środowiska, 12 (2022), No. 1, 10-14.
[17] Korzeniewska, E., Sekulska-Nalewajko, J., Gocawski, J., Drożdż, T., Kiebasa, P., Analysis of changes in fruit tissue after the pulsed electric field treatment using optical coherence tomography, EPJ Applied Physics, 91 (2020), No. 3, 30902.
[18] Korzeniewska, E., Krawczyk, A., Mróz, J., Wyszyńska, E., Zawiślak, R., Applications of smart textiles in post-stroke rehabilitation, Sensors (Switzerland), 20 (2020), No. 8, 2370.
[19] Sankowski, D., Sikora, J. 2010. Electrical capacitance tomography: Theoretical basis and applications. Warszawa: Wydawnictwo Książkowe Instytutu Elektrotechnik
[20] Zou, H.; Hastie, T., Regularization and variable selection via the elastic net, Journal of the Royal Statistical Society: Series B (Statistical Methodology), 67 (2005), 301–320
[21] Hastie,T.; Tibshirani,R.; Friedman, J., The elements of statistical learning, Springer-Verlag New York Inc., 2009