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# A ROBOTIC-ASSISTED SPUTUM COLLECTION BOOTH

**Bogdan GHERMAN, Ferenc PUSKAS, Paul TUCAN, Cecilia ROMAN, Adrian PISLA, Calin VAIDA, Iosif BIRLESCU, Doina PISLA**

***Abstract:*** *The collection of biological samples containing airborne pathogens may be a dangerous process in closed spaces, since it may lead to the spread of bacteria and viruses within the environment. The paper presents a solution for a safety collection process of biological samples within the testing procedure for lung tuberculosis infection. A collaborative robot has been integrated within a sputum collection booth, having the task to manipulate the sputum container until its evacuation for further analysis. A control algorithm targeting the safety wrapping of the container has been proposed, consisting in the implementation of convolutional neural networks using a vision system for the classification of the qualitative screw fastening process.*

***Keywords:*** *biological sample manipulation, robotics, control system, safety*

## 1. INTRODUCTION

Tuberculosis (TB) is an infectious disease affecting mainly the lungs [1]. Mycobacterium tuberculosis, the bacterium causing TB may affect the kidney, spine, or brain as well and is spread usually through the droplets released in the air the infected person though coughing, sneezing, etc. Although TB has been almost eradicated in developed countries, it re-emerged since 1985 with the spread of HIV. In 2018 alone, TB has made about 251.000 victims within the HIV infected people, which means about 30% of all deaths [1].

In the case of pulmonary infection, the recommended steps to stop the spread of TB include taking the prescribed medicines, perform regular doctor appointments, keep the social distancing, get fresh air, and cover the mouth when sneezing or coughing [2]. The standard procedure for the bacteriological examination assumes a specimen collection. This is usually achieved by collecting three different sputum specimens into a sputum container [2]. The recommendation is to perform the sputum collection either in a well ventilated are, away from other people (which is difficult to find in a general hospital) or in a Sputum Collection Booth (SCB).

From the architectural point of view, the SCB is similar to a Biological Safety Cabinet, which uses laminar air flow to protect the patient and environment from exposure to biohazards. In the case of the SCB, the level of isolation is defined by the cleanliness degree, standardized by the ISO clean room class (1 to 10). The SCB targets at least a class 5 clean room, which is a super clean cleanroom classification. The particles should have a micron size between 0.5µm and 0.3µm, a maximum number of 3520 particles/m$^3$, with the recommended air changes/hour between 250-300 using HEPA filters [3]. In addition, a negative pressure is required to prevent the aerosol generated at sputum collection from leaking out, in the surrounding environment.

Such SCBs have been previously developed, mostly by Japanese companies. Dai-Dan [4] through their DTB-01 model, offer a simple and easy to operate booth, fulfilling the class 5 cleanroom conditions. The VCM-1500N2 model produced by [4] has slightly larger dimensions and uses a UV lamp for disinfection. The one produced by [5] uses high quality stainless steel, coated with an antimicrobial

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coating (ISOCIDE), making it highly secured. The downside of the already developed SCB consist in the fact that the patient needs to manipulate the sputum container (SC), which increases the chance of cross-contamination. To avoid such events, the current paper proposes the integration of a robotic manipulator within the SCB, to handle the SC.
The paper is structured as follows: section II presents the layout of the automated SCB, integrating the robotic system and section III presents a deep learning based control algorithm for the robotic system. A conclusion section summarizes the work achieved until now and future directions of development.

## 2. THE SPUTUM COLLECTION BOOTH

The robot integration into the SCB is performed strictly based on a predefined sputum collection protocol, developed precisely for the designed booth. The main steps within the proposed protocol for the robotic-assisted sputum collection are [7]:
1. Patient data registration (into the system).
2. Patient enters the SCB.
3. The robot takes the SC from the biohazard container (placed previously in the SCB) and places it in a support in front of the patient. The robot unscrews the cap of the SC.
4. The patient provides the biological sample in the SC and exists the SCB.
5. The robot screws the cap back on the SC and places the SC back into the biohazard container.
6. The SCB is disinfected and prepared for the next patient.
Since the robot works in the close vicinity of the patient, safety becomes an important concern. To eliminate this issue, a collaborative robot (cobot) has been considered for the completion of the task, since they have implemented safety features such as collision detection or force feedback, which can be used to work in the same area with a human operator. The main When unexpected force is detected, the arm stops operating. Specific models will freeze their position at this point, others will release all joints causing the arm to “collapse”. Other safety features include a programmatic bounding box for operation to define where the arm is not allowed to come and emergency switches. Collaborative robots are also safer due to the lower speeds at which they move.
Usually in applications involving robots, the robotic system serving the task is isolated from the human operator, inside the SCB the robot performs manipulation tasks close to the patient and the patient may enter the workspace of the robot, hence use of collaborative robots is required and safety system of the robot must be supervised by external safety system. The SCB layout may be observed in figure 1.

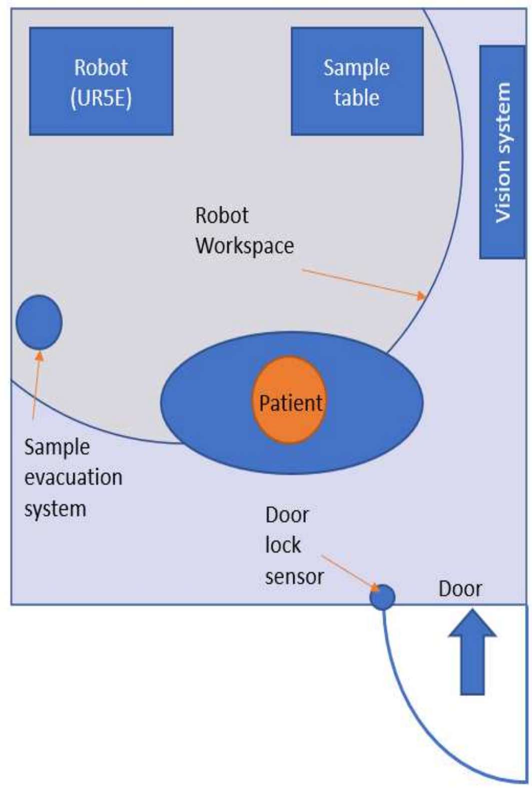


**Fig. 1.** SCB Layout

The robotic system is placed in the left corner of the SCB opposing the entry inside the cabin. The workspace of the robot is graphically represented using the gray circle. The entire robotic task is triggered by the door locking system and the vision system when a patient enters the SCB. The entire sampling process starting from the door lock trigger is presented in figure 2. Before entering the SCB the patient receives a SC tagged with his personal data. After receiving the SC the patient enters the SCB and when the door is properly closed to ensure the isolation and non-contamination of the sample the entire process is triggered.

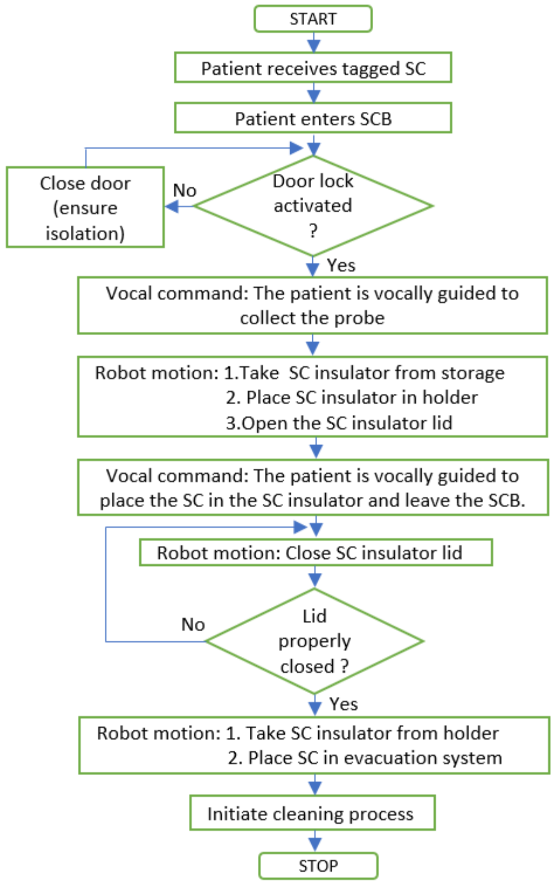


**Fig. 2.** Automatized/guided sample collection

The patient is vocally guided by a prerecorded message on how to collect the sputum inside the tagged SC and after collecting the sputum to close the lid of the SC. Meanwhile the robotic system starts its task by taking a SC insulator from the storage and place it in the SC insulator holder. When taken from the storage, the SC insulator has its lid on, next robot task is to unscrew the lid of the SC insulator. Placing he SC insulator and unscrewing the SC insulator lid is performed under vision system supervision, that detects if the SC insulator is placed correctly in its holder and the lid has been properly unscrewed. After the opening the lid, the robot waits for the patient to place the SC in SC insulator. The patient is vocally guided on how to place the SC in the SC insulator and to leave the SCB. After the patient leaves the SCB the robot closes the lid of the SC insulator. Vision system is again used to check if the lid is properly closed, and the SC is inside the insulator. After the robot receives validation from the vision system, it takes the SC insulator from its holder and delivers it to the sample evacuation system. After evacuating the SC from the SCB the trigger for the cleaning process is raised and the entire procedure stops after the entire SCB is cleaned.

The vision system, beside checking the robot tasks regarding the SC insulator manipulation, it also supervises the interaction between the patient and the robotic arm to avoid any collision between them. Beside the integrated safety system of the collaborative arm the vision system may also send command to the robotic system and activate safety mode if it predicts an unsafe situation for the robot (wall collision, table collision) or for the patient (collision with the robotic arm). The vision system may also check the patient state during the sampling process (observe patient position and alarm medical personal if the patient falls, signal any unrequired interaction between the patient and the SCB).

Fig. 3 shows the experimental model of the SCB with the UR5e robotic system installed, manipulating the SC.

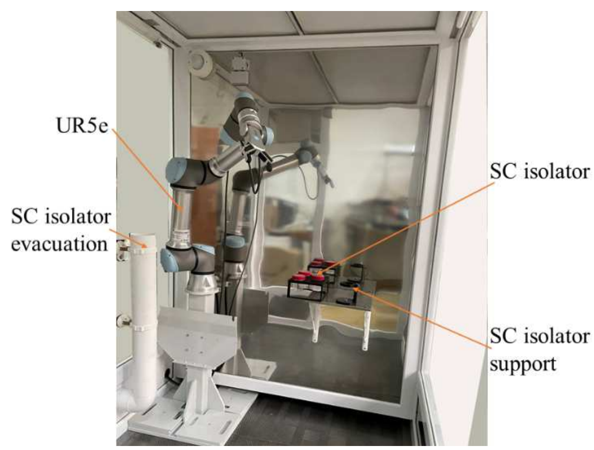


**Fig. 3.** The SCB and the UR5e robotic system

## 4. A CONTROL ALGORITHM FOR THE ROBOTIC-ASSITED SPUTUM COLLECTION BOOTH

During the initial tests, several issues have been encountered, the most annoying of them being related to the screwing of the SC insulator cap: the process could not always be completed successfully. This is mainly due to the elasticity of the SC and the gripping pose of the gripper relative to the SC. Unfortunately, this anomaly could only be observed from the outside of the SCB by a human operator, either through the cabin glass walls or the used vision system. This event would trigger an interruption of the normal flow of the sputum collection process, so that the fastening of the SC cap could be performed again, starting from the current position of the cap. This would even suggest some knowledge regarding the programming of the UR5e by the human operator, which most of the times has a medical training and might find it difficult to operate the robotic system in this way. Therefore, a control algorithm is proposed, to alleviate some of the previously described issues. It consists in developing a vision-based system that inspects the SC isolator after the cap fastening/screwing and look for anomalies. Examples of such anomalies are presented in fig. 4 but any other position, different from the correct one (fig. 5) can be called as “anomaly”.

**Fig. 4.** SC insulator cap anomalies

**Fig. 5.** SC insulator cap screwed in the “correct” position

Previous work [8], [9] mention process curves as the main method to monitor screw fastening, using envelope curves, process windows, or process limits for the evaluation of the process curves. However, since fig. X.0 shows only a few examples of the multiple cases which could be classified as anomalies, there is a high level of expertise needed to inspect if the cap screw fastening has been achieved correctly, leading to the conclusion that the monitoring system needs to learn to recognize the “anomalies”, as a different pattern than the “correct” one.

Machine Learning (ML) techniques have become increasingly used for this type of purpose [10], using labeled data to identify the patterns and classify new, unlabeled data. Deep Learning (DL), a subfield of ML, uses multiple layers to extract increasingly high levels of features from raw, unlabeled data. Instead of using the domain knowledge to obtain and characterize a certain feature, DL is capable of processing data for an extensive feature abstraction, which makes it very useful in fields like image recognition/classification and natural language processing [11].

To solve the screw fastening issues of the SC isolator cap, the paper presents an algorithm targeting the detection of anomalies within the SC (after screw fastening) a single class classification Neural Network. Since the training of the network is achieved using data consisting of images without anomalies, the training is semi-supervised. The model is designed to learn to classify and discern between the “correct” fastened images and the ones with anomalies. This kind of model can provide certain advantages:

- ✓ Sometimes is difficult to discern between the “correct” and anomalous images (because the anomalies within the image are difficult to detect).
- ✓ Due to the rather large domain of anomalies, these can change over the lifetime of the application. The developed model should be able to learn and distinguish the new anomalies, which have not appeared before.

### 4.1 The Vision System

The vision system is real-time based and is required for the image processing/transformation within the DL algorithm. Using a video camera, the robot task is continuously supervised. When performing manipulation tasks, the collaborative robot always waits for vision system validation. The system checks if the robot placed correctly the SC insulator in his holder, and if the lid of the SC insulator has been properly closed. The system is also able to detect if the SC insulator contains a SC inside or not. Figure 6 presents an image captured by the vison system of the SCB.

The image captured by the vision system is further analyzed using machine learning algorithms. Using pattern recognition, the gripper fingers are recognized on the image, the lid of the SC insulator, the SC insulator, and the SC inside the insulator.

**Fig.6.** Image recorded by the vision system

Firstly, the real image is converted to a grayscale image and a Canny [12] edge detection operator is applied. The Canny operator is able to find edges by searching for local maximum of gradient of the recognized object. The operator calculates the gradient by means of Gaussian filter. Two thresholds are used to detect week and strong edges, hence the Canny is less sensitive to noise than other methods. The identified objects are presented in figures 7 -10.

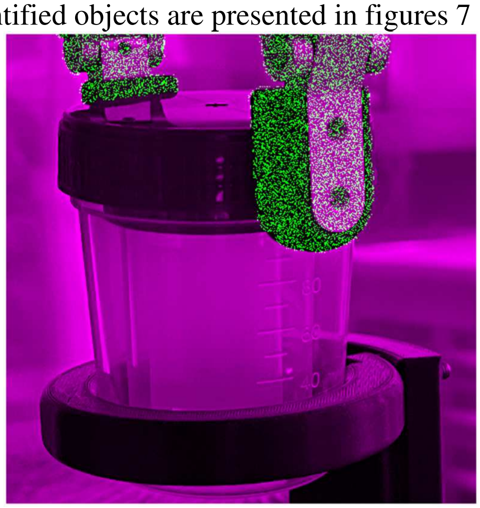

**Fig.7.** Detection of gripper fingers

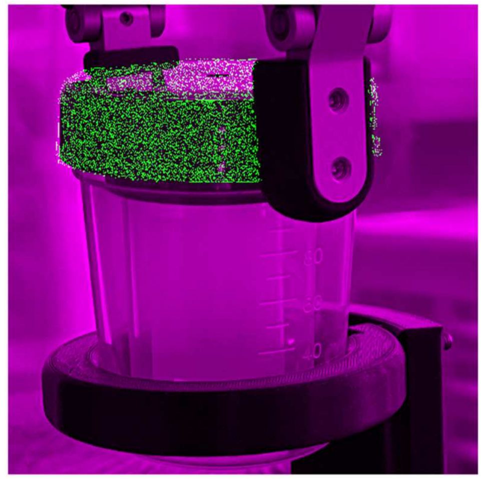

**Fig.8.** Detection of the lid of the SC insulator

In order to detect the relative position between the recognized objects further analysis is required.

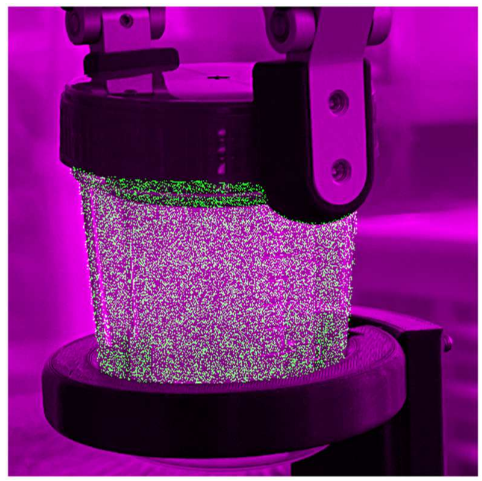

**Fig.9.** Detection of the SC insulator

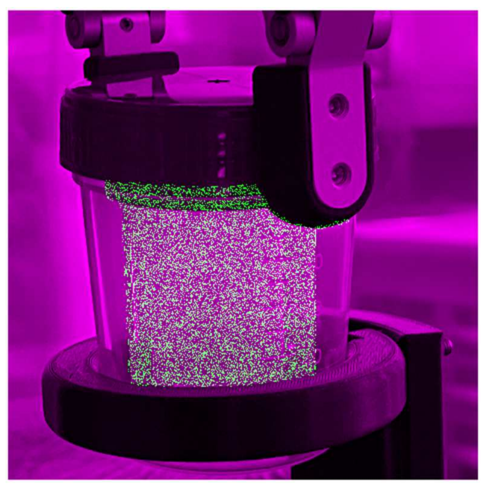

**Fig.10.** Detection of the SC inside the insulator

The image containing the lid of the SC is overlapped with the image containing the SC insulator in order to detect intersecting edges. This is used to detect if the lid of the insulator has properly been screwed on the SC insulator. The result of the overlapping is presented in figure 11.

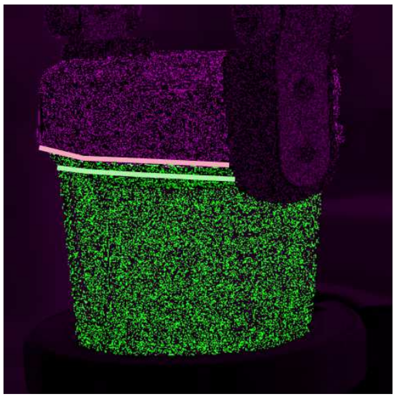

**Fig.11.** Check the position lid -SC insulator

The two lines that appear in figure 11 represent the edge of the lid (pink line) and a buffer edge from the SC insulator.

### 4.2 The Convolutional Neural Network algorithm

The main steps within the development of the proposed algorithm are:

1. Preprocess data. The images are labeled based on the quality of the screw fastening as "Correct" or "Anomaly".
2. Data set designation into: Training, Validation and Testing. A set of 200 "Correct" images have been used; 10 "Anomalies" images have been further included to increase the training classification results; a set of 1000 images from both classes have been used for testing; 150 images from both classes have been used for validation.
3. Augment and Process the Training Images. The data has been augmented and processed using the methods described within subsection 4.1 and [13].
4. Create a Mini-Batch gradient descent from the training data set (using a set of 128 images).
5. Input Normalization. The zero-mean normalization is applied for faster results.
6. Develop a fully convolutional description model [14] (FCCD) that can output a heatmap using the input image. The VGG-16 network is used as in [15].
7. Train the network. Specify the training options using 70 epochs and the Adam optimization, due to a high quality of the results and a fast response.
8. Create the classification model, considering that a classifier can return a certain probability that an image is an "Anomaly" based on the heatmap of the trained network. The mean anomaly score is then obtained knowing the real labeling of the image (as "Correct" or "Anomaly") from the validation set. The threshold for the "Anomaly" classification is chosen based on the validation set of data. Using a sigmoid activation function (fig. 12) regarding the anomalies and the respective class labels, yields a probability function whose values higher than 0.5 are considered "Anomaly".
9. Evaluate the model evaluation. The confusion matrix (fig. 13) has been chosen for this task, based on the prediction of the anomaly heatmap and computing the mean value for each anomaly score within the test set of images.

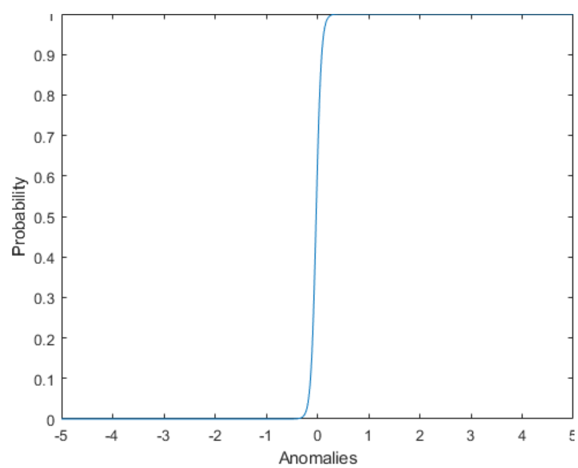


**Fig. 12.** The applied sigmoid function

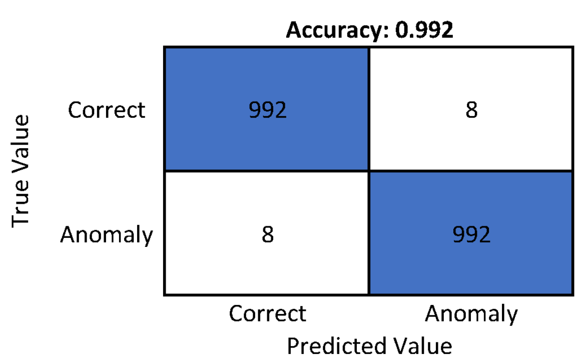


**Fig. 13.** The confusion matrix of the model

The model accuracy of 0.992 shows promising results for further implementation within the robotic system control for a safety full automated screw fastening of the SC cap.

## 6. CONCLUSIONS

The paper presents the automation of a sputum collection booth designed for patients suspected of tuberculosis. A UR5e collaborative robot has been used to manipulate the sputum container for safety evacuation from the booth. To solve the detected issues within the manipulation process which can severely damage the safety of the whole booth, a process imaging technique within a deep learning algorithm has been proposed to be further integrated in the robot control system. Future work targets the implementation of the proposed algorithm in a fully functional prototype of the automated sputum collection booth.

## 7. Acknowledgement

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**Cabină de protecție asistată robotic pentru prelevarea probelor biologice din spută**

**Rezumat:** Colectarea probelor biologice care conțin agenți patogeni aeropurtați poate fi un proces periculos, mai ales în spații închise, putând duce la răspândirea bacteriilor și a virușilor în mediu. Lucrarea de față prezintă o soluție pentru un proces de colectare a probelor biologice în cadrul procedurii de testare în vederea detectării infecției cu tuberculoza pulmonară. Un robot colaborativ a fost integrat într-o cabină destinată prelevării sputei, având sarcina de a manipula recipientul cu spută până la evacuarea în siguranță a acestuia pentru efectuarea analizelor. S-a propus un algoritm de control care vizează ambalarea în condiții de siguranță a recipientului cu probe biologice, constând în implementarea rețelelor neuronale convoluționale utilizând un sistem de viziune în vederea clasificării procesului de asamblare filetată a capacului recipientului.

**Bogdan GHERMAN,** Assoc. Prof., Technical University of Cluj-Napoca, CESTER research center, Bogdan.Gherman@mep.utcluj.ro, 103 Muncii Blv. Cluj-Napoca, Romania

**Ferenc PUSKAS,** Ing., managing director and co-founder of Electronic April S.R.L., april_private@yahoo.com , 3-5 Pasteur, Cluj-Napoca, Romania

**Paul TUCAN,** Lect., Technical University of Cluj-Napoca, CESTER research center, Paul.Tucan@mep.utcluj.ro, 103 Muncii Blv. Cluj-Napoca, Romania

**Cecilia ROMAN,** Dr. Ing., R&D manager of the INCDO-INOE 2000 subsidiary Research Institute for Analytical Instrumentation ICIA, cici_roman@yahoo.com, 67 Donath, Cluj-Napoca, Romania

**Adrian PISLA,** Professor, Technical University of Cluj-Napoca, CESTER research center, Adrian.Pisla@muri.utcluj.ro, 103 Muncii Blv. Cluj-Napoca, Romania

**Calin VAIDA,** Professor, Technical University of Cluj-Napoca, CESTER research center, Calin.Vaida@mep.utcluj.ro, 103 Muncii Blv. Cluj-Napoca, Romania

**Iosif BIRLESCU,** Dr. Ing., Technical University of Cluj-Napoca, CESTER research center, Iosif.Birlescu@mep.utcluj.ro, 103 Muncii Blv. Cluj-Napoca, Romania

**Doina PISLA,** Professor, Technical University of Cluj-Napoca, CESTER research center, Doina.Pisla@mep.utcluj.ro, 103 Muncii Blv. Cluj-Napoca, Romania