

A Neural Network Approach for Online Reconstruction of Bremsstrahlung Spectra Produced by Electron Accelerator

Lucas Tasinato^{1,*}, David Tisseur², Florent Kuntz¹, Nicolas Arbor³, Abdallah Lyoussi²

¹ Aerial-CRT, 250 Rue Laurent Fries, 67400 Illkirch Graffenstaden, France

² CEA, DES, IRESNE, DER, Cadarache F-13108, Saint-Paul-Lez-Durance, 13108, France

³ Université de Strasbourg, IPHC, 23 rue du Loess, 67037 Strasbourg, France

(*) l.tasinato@aerial-crt.com

Abstract— The characterization of bremsstrahlung spectra generated by electron accelerators is becoming increasingly crucial, particularly in radiation processing applications such as sterilization of medical devices or food irradiation. The growing transition from isotopic to electric irradiators presents new challenges related to the control of beam properties. In this context, the technology resource center Aerial in collaboration with CEA/IRESNE and IPHC is looking to develop a tool and methodology enabling the online characterization of the bremsstrahlung spectra generated in its feerix[1] installation. This step is very important for their irradiation operations to ensure precise dose deposition in the sample and to precisely estimate the activation product when the photon energy exceeds the photonuclear reaction threshold. Information on the energy spectrum is also a key input for Monte Carlo simulations, which are increasingly used in radiation processing. However, conventional direct and indirect spectrometry methods are limited in meeting the challenges of Aerial’s high energy and high-power irradiation platform. In this study, we propose a new theoretical approach based on neural networks to solve an ill-posed inverse problem, enabling the reconstruction of bremsstrahlung spectra from depth-dose measurements. This approach is motivated by the limitations of previously discussed regularization methods and existing neural network approaches. We focus here on an analytical approach for generating realistic training and validation datasets, consisting of Bremsstrahlung spectra and their corresponding dose distributions in any medium. This neural network approach will also be compared with other methods reported in the literature.

Keywords — Electron accelerator, Bremsstrahlung spectra, Inverse method, Unfolding, Deep Learning, Neural Network.

I. MONITORING THE BREMSSTRAHLUNG SPECTRUM PRODUCED BY ELECTRON ACCELERATOR IN RADIATION PROCESSING

This paper is contextualized by recent trends in radiation processing. During the last decade, a shift from isotopic irradiators to electron accelerator-based irradiators has been encouraged. The reasons behind this shift are multiple, including concerns about the malicious use of nuclear material as well as the management of nuclear waste.

However, it raises new concerns regarding the monitoring of the spectrum produced by such high-energy, high-power

installations. Indeed, with isotopic irradiators, the energy and dose rate of the beam are precisely known, whereas the characteristics of beams produced by electron accelerators are subject to technical perturbations, disruptions, and component wear. Accurately characterizing the bremsstrahlung spectrum of an irradiation facility is crucial for several reasons. First, it ensures reliable and effective irradiation of samples. It also makes it possible to estimate activation products when photon energies surpass photonuclear reaction thresholds. Moreover, as Monte Carlo simulations are increasingly used in radiation processing, accurate knowledge of the input spectrum is once again essential.

However, characterizing the bremsstrahlung spectrum is at the same time very challenging due to the ultra-high dose rate and the long irradiation period in facilities used for radiation processing. For instance, in Aerial’s state-of-the-art platform feerix, the dose rate reaches no more than 100 Gy/s at 40 cm of the conversion target. Conventional spectrometers saturate or are destroyed due to those extreme conditions. Alternative inverse methods already exist and were discussed in previous paper [2]. Those methods are efficient, but they are not suitable for Aerial’s challenges as the associated experimental setup either too large to fit in feerix or require high maintenance. The Table I enumerates the advantages and disadvantages of the inverse methods found in literature.

TABLE I
A SUMMARY TABLE OF THE ADVANTAGES AND DISADVANTAGES OF INDIRECT SPECTRAL CHARACTERIZATION METHODS DEVELOPED TO DATE, IN THE CONTEXT OF AERIAL’S CHALLENGES. THIS IS DISCUSSED IN DETAIL IN [2].

Methods	Compact Device	Low maintenance	Online Measurement
Monte Carlo	+	+	-
Compton Scattering	-	+	+
Photo-activation	+	-	-
Transmission	-	+	-
Deposited Dose	-	+	-

In this paper we will discuss new insight about a method based on the resolution of the inverse problem allowing to unfold the spectra from depth dose measurement. This paper is following discussion made to develop a setup compatible with Aerial’s challenges [2].

II. UNFOLDING BREMSSTRAHLUNG SPECTRA FROM DEPTH DOSE MEASUREMENTS: THE LIMITATION OF EXISTING RECONSTRUCTION METHODS

A. Introducing the inverse problem

Before discussing the limitations of existing approaches, we can briefly review the principle behind this method. For a more detailed introduction, many papers have extensively covered this topic such as [3], [4]. If we discretize the incident spectrum in k energy groups, the depth dose measured by our device can be expressed as a contribution of the depth dose produced by each energy group in the incident spectrum, weighted by their intensity in the spectrum, as expressed in (1):

$$d = \sum_{i=1}^k M_i s_i + \dots + M_k s_k \quad (1)$$

With d , the total depth dose measured in any medium, M_i , the depth dose associated to each energy group and s_i , the intensity of the i -th energy group in the spectrum. This representation can easily be converted in a matrix form as a linear problem (2):

$$d = Ms \quad (2)$$

With $d = \begin{pmatrix} d_1 \\ \vdots \\ d_l \end{pmatrix}$ the measured depth-dose,

$M = (M_1 \dots M_k)$ the response matrix composed of k depth dose vectors M_k from each energy group and $s = \begin{pmatrix} s_1 \\ \vdots \\ s_k \end{pmatrix}$, the spectrum vector whose coefficients are to be evaluate.

Solving this inverse problem is made difficult by its ill-posed nature, where the noise on the measured depth dose is not explained by the response matrix which leads to unrealistic solutions if no constraints are applied during the resolution process. More robust methods have been applied to this problem such as regularization methods, Bayesian optimization methods or Deep Learning approaches. We previously selected two of them that appear compatible with online measurement due to their potential for fast computation.

B. Limitation of Regularization methods

In a previous paper [2], we discussed the optimization of a device compatible with online measurement through the lens of regularization methods. This method was already introduced in other papers such as [5], [6]. It basically consists of solving a least-squares problem by adding a side constraint on the shape of the solution. It can be formulated as (3):

$$J_\alpha = \min_\alpha \left\{ \|Ms - d\|^2 + \alpha \|\Gamma s\|^2 \right\} \quad (3)$$

Where α is the regularization parameter and Γ the regularization operator.

One of its advantages is the simplicity with which the solution s_α of the minimization problem can be calculated

analytically as (4):

$$s_\alpha = (M^T M + \alpha \Gamma^T \Gamma)^{-1} M^T d \quad (4)$$

The regularization operator Γ depends strictly on the nature of the problem, i.e., on the characteristics of the solution we need to unfold. Many operators can be used such as the identity operator or the first and second derivative operator. In previous work, it was shown that the first derivative operator was more suited for the spectral reconstruction [2].

As shown in our earlier work, it is possible to retrieve precise spectra as long as the response matrix is representative of the problem. However, we faced a few limitations which constraint the use of regularization method in this context. First of all, even if the reconstruction is effective overall, it performs poorly in low-intensity regions. As a result, the maximum energy of the spectra, a parameter of critical importance for Aerial, cannot be reconstructed with this approach (see Fig 1).

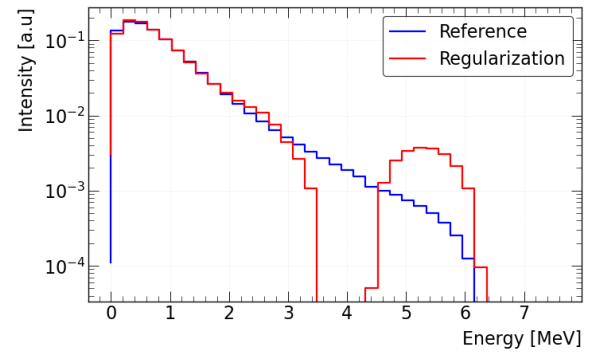


Fig 1. Illustration of the limitations of regularization methods, which fail to reconstruct the maximum of energy in low-intensities regions of the spectrum.

Another limitation of these methods is the repeatability of the measurement. To simulate the measurement of the N depth dose under the same conditions, we added random noise to the reference depth dose and evaluated the repeatability of the reconstruction.

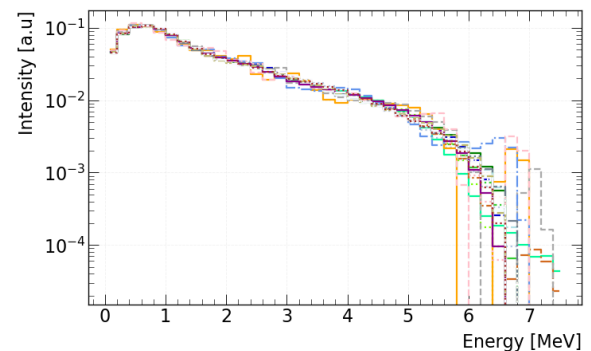


Fig 2. Impact of noise on the repeatability and stability of regularization-based reconstructions (for 100 reconstructions).

As shown in Fig 2, the reconstruction is very unstable in the last bin of the unfold spectra even if we optimize the choice of regularization parameter for each reconstruction, which is not instantaneous in practice, taking approximately 2 minutes per

reconstruction. More importantly, it is obviously not possible to assess precisely the maximal energy of our spectrum. Thus, this method is not suitable for robust online reconstruction of the bremsstrahlung spectrum in the context of Aerial's challenges.

C. Limitation of existing neural network-based methods

Another promising approach was presented in [7]. In this paper the authors presented a method based on Deep Learning and especially on neural networks. The idea is to train a neural network to learn the relationship from the depth dose to the corresponding spectra. To do so, it is necessary to have a substantial dataset, composed of spectra and their associated dose deposits defined in the same conditions as the upcoming measurement. One of the main challenges is obtaining this type of dataset. Building it from measurements is impossible due to insufficient knowledge of the spectra from each accelerator, while simulating such a large amount of data is also problematic, as we aim to generate at least 10,000 pairs of spectra and doses.

In this paper, the authors proposed an approach to build an analytic set of data by generating spectra from five different functions, all of them, combination of exponentials. The associated dose deposits are then calculated with the simulated response matrix using (2).

With this dataset, the authors are then able to train a neural network taking the different depth doses as input and the spectra as output with a hidden layer of 2000 neurons. After training their neural network they performed their first reconstruction on experimental data and managed to approach the real spectrum from different 6 MeV LINAC as shown in Fig 3.

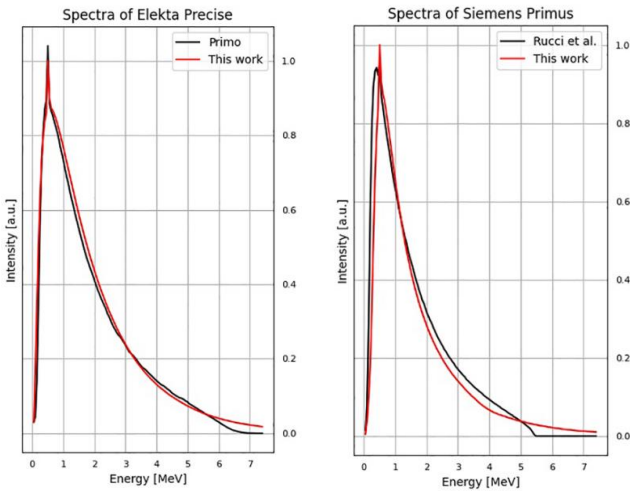


Fig 3. Illustration from Torres-Diaz et al. [6], showing experimental spectra reconstructions on two medical accelerators.

One notorious advantage of this method is the computational time to obtain the unfolded spectra once the training is done. Indeed, with such methods the unfolded spectrum can be calculated in less than a second which is compatible with our constraints of online measurement. However, the method suffers some limitations regarding our problem. Since the dataset is composed of combinations of exponential functions, none of the reference spectra display a maximum energy. It is reflected on the reconstructed spectra which cannot estimate

this key parameter since they never learned it during their training, as shown in Fig 3.

Despite these limitations, a neural network approach seems promising, which is why we decided to explore a new approach allowing for more robust and accurate reconstruction of the incident spectra

III. A MORE ROBUST AND ACCURATE RECONSTRUCTION MODEL BASED ON NEURAL NETWORKS

A. Building a realistic dataset

Herein, the objective was to propose a new method for generating a realistic dataset that accurately accounts for the maximum energy of the spectrum. For this purpose, we attempted to find a parametric function that could fit realistic spectra from simulations. We simulated these spectra using Gate 9.3 [8], taking into consideration the electron spectra from feerix and the geometry of the conversion target, along with potential variations of these parameters.

From these simulations, we attempted to find a parametric function that could fit each of the spectra. The best candidate is based on a generalized beta prime function, completed by a linear adjustment in the last bin. It can be expressed as follows, using only seven parameters:

$$s(E, bin_0, \alpha, \beta, p, q, E_{cut}, E_{max}) = s = [s_0, s_{inf}, s_{sup}] \quad (5)$$

$$\text{With } \begin{cases} s_0 = bin_0 \\ s_{inf} = \frac{p \left(\frac{E}{q}\right)^{\alpha p - 1} \left(1 + \left(\frac{E}{q}\right)^p\right)^{-\alpha - \beta}}{q B(\alpha, \beta)} \\ s_{sup} = \frac{s_{inf}(E_{cut})}{E_{cut} - E_{max}} (E - E_{max}) \end{cases} \quad (6)$$

Where bin_0 being the first bin of the spectrum, α, β, p , and q are the parameters of the generalized beta prime function, $B(\alpha, \beta)$ is the beta function, E_{cut} , is the position of the cut between the generalized beta prime function and the linear function, and finally E_{max} , the maximal energy of the spectrum. Fig 4 illustrates the role of each parameter.

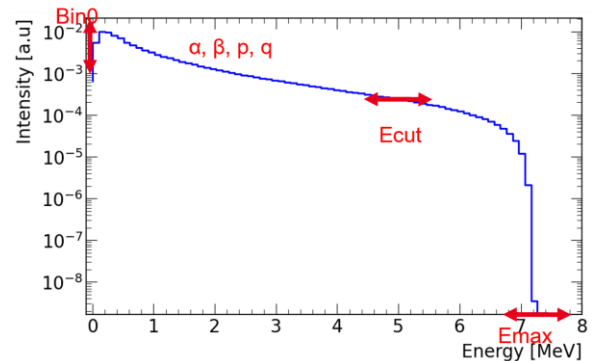


Fig 4. Illustration of the role of the 7 parameters in our parametric representation of the Bremsstrahlung spectra.

After fitting each function from the sensitivity analysis, we are able to retrieve ranges of variation for every parameter.

From these ranges, we can then randomly and uniformly select parameters to build spectra that are representative of our problem. From these spectra and with the appropriate simulated response matrix, we can build the associated dose deposits using (2). We then have a realistic dataset that represents key parameters such as the maximal energy of the spectra. Fig 5 and Fig 6 illustrate the variation range of 10 000 spectra and depth doses generated in ~ 2 seconds using this approach. The range of variation of each parameter used to build this dataset is given in Table II.

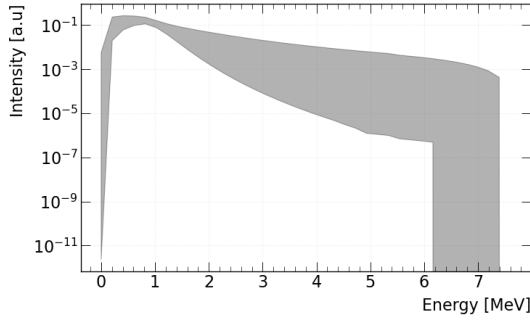


Fig 5. Variation range of the spectra produced for our dataset.

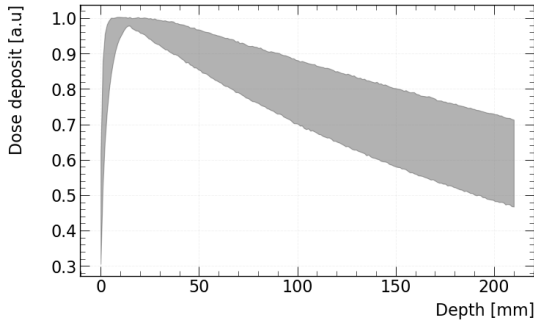


Fig 6. Variation range of the depth dose associated with each spectrum computed for the training dataset.

TABLE II
RANGE OF VARIATION OF EACH PARAMETER USED TO BUILD THE DATASET IN FIG 5 AND FIG 6.

bin_0	α	β	p
[0,02-0,03]	[0,35-0,65]	[2,87-5,38]	[1,96-3,64]
q	E_{cut}	E_{max}	
[0,53-0,99]	[3,9-7,4]	[5,6-8,5]	

B. Training our neural network

For the training of the neural network, we differ from previous methods by not learning the full spectra in the output, but rather their parametric representation (i.e., the 7 parameters as shown in Fig 7). As input, we used the 300 bins of the depth-dose profile, calculated via the response matrix.

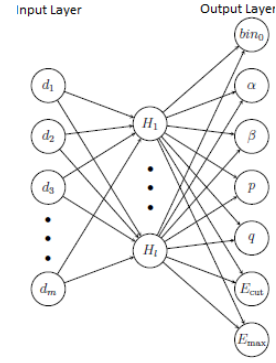


Fig 7. Architecture of our neural network, which takes the depth doses as input and outputs the 7 parameters of the parametric representation of the associated spectrum.

In terms of the architecture of our neural network, we added three hidden layers, a batch normalization layer, and a dropout layer as follows:

- Input layer (300 neurons)
- Hidden layer (256 neurons)
- Batch Normalization layer
- Hidden layer (128 neurons)
- Dropout layer (0.2 %)
- Hidden layer (64 neurons)
- Output layer (7 neurons)

As the activation function, we used the Rectified Linear Unit (ReLU). For the optimizer, we used the Adaptive Moment Estimation (Adam). Finally, we set the mean squared error as our cost function. To reinforce the stability of our training, we added L2 kernel regularization to each of our hidden layers. The neural network is then trained with a dataset of 10,000 spectra/dose pairs across 300 epochs.

C. Validating our neural network model

Once the model is trained, we proceed to its validation. To do so, we generated a validation dataset, independent of the training dataset, which we input into our trained model. For each depth dose, we reconstruct the seven parameters and then the associated spectra. An illustration of a reconstructed spectrum is presented in Fig 8.

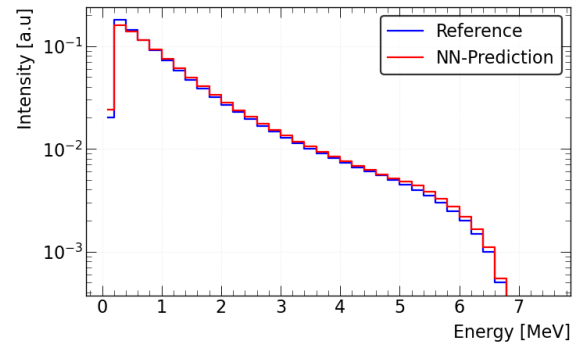


Fig 8. An example of reconstructed spectra using our model. The predicted parameters are $[E; bin_0; \alpha; \beta; p; q; E_{cut}; E_{max}] = [0.02; 0.17; 1.11; 5.12; 1.88; 6.63; 0.68]$ and the RMSE between the reference and predicted spectrum is $RMSE = 0.003$.

To assess the general efficiency of our model, we looked at the root mean squared errors (RMSE) between the reference and predicted spectra and plotted their distribution. An example is given in Fig 9, for a validation dataset of 1,000 spectra/depth dose pairs, to which we also compared the reconstruction efficiency of previously discussed methods ([2] and [7]) on the same validation dataset.

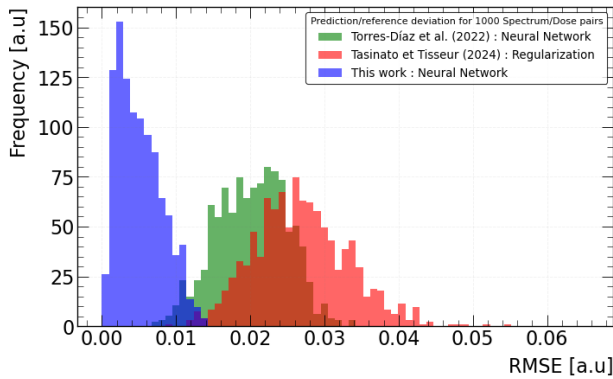


Fig 9. Comparison of the reconstruction performance of our model with that of other methods from the literature, evaluated on the same dataset. We computed the root mean square error between each predicted spectrum and its reference spectrum.

As shown in Fig 9, the overall RMSE between the reference and predicted spectra is lower with our new model than with the neural network [7] or with our previous regularization method. This illustrates a more accurate unfolding of the spectra, not only in the high-energy parts (which have low intensity and thus contribute less to the total RMSE), but mainly also in high-intensity areas of the spectrum. This improvement is most likely due to our more constrained method, where we do not reconstruct the full spectra themselves, but rather the parameters of a realistic representation of the Bremsstrahlung spectra.

As for the high-energy part of the spectra, as we discussed, an important parameter for Aerial is the estimation of the maximal energy in the spectrum. We estimate the ratio between the predicted and reference E_{max} in the same validation dataset. The resulting distribution is presented in Fig 10.

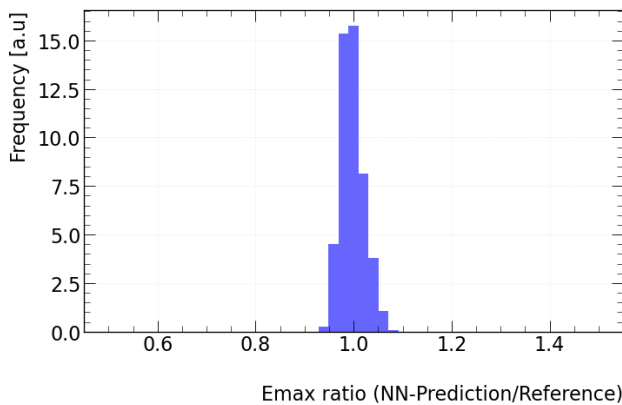


Fig 10. Ratio between the reference and predicted maximal energy E_{max} for 1000 spectra reconstructions.

Again, we observe good efficiency in the reconstruction of the maximal energy. We have a maximal deviation of $\pm 2.5\%$ at $k=1$, which is compatible with national standards and normative documents, such as NF EN ISO 11137-1 [9], which discuss the monitoring of the bremsstrahlung spectra produced by electron accelerators in the context of medical sterilization.

IV. CONCLUSIONS AND PERSPECTIVES

In this paper, we discussed a new approach for the reconstruction of Bremsstrahlung spectra produced by electron accelerators. This method has proven to be more efficient than previously developed methods (regularization and previous deep learning methods) in terms of overall reconstruction efficiency. The improvement is partly due to our constrained method, where we do not reconstruct the entire spectra themselves but rather their parametric representation. This method implies that the shape of the spectra can be described at any time by our parametric representation. This is a strong yet credible assessment for bremsstrahlung spectra produced on platforms similar to feerix, which can be endorsed by a sensitivity analysis of the spectra produced on the platform.

One advantage of this method is also its ability to retrieve key parameters of the spectra, such as their maximal energy. This parameter is important for Aerial to meet ISO standards recommendations, which require monitoring of the maximum emission of the bremsstrahlung spectra to be within $<5\%$.

A multiparametric study as well as an experimental validation of the methods are being performed. These findings will be detailed in a future publication, which will also explore how to optimize the experimental device to improve reconstruction efficiency with our new neural network approach.

ACKNOWLEDGMENT

The authors would like to thank both the ANRT (Association Nationale de Recherche et Technologie) and the CEA (RBNEW project) for co-funding this research work.

REFERENCES AND FOOTNOTES

A. References

- [1] F. Kuntz, A. Nasreddine, N. Ludwig, et A. Strasser, « Feerix, a Novel Irradiation Platform for R&D, Education and Training », 2022.
- [2] L. Tasinato et D. Tisseur, « Development of a method for the on-line spectral characterization of Bremsstrahlung photons from an electron accelerator », *Radiation Physics and Chemistry*, vol. 215, p. 111374, févr. 2024, doi: 10.1016/j.radphyschem.2023.111374.
- [3] B. Armbruster, R. J. Hamilton, et A. K. Kuehl, « Spectrum reconstruction from dose measurements as a linear inverse problem », *Phys. Med. Biol.*, vol. 49, n° 22, p. 5087, oct. 2004, doi: 10.1088/0031-9155/49/22/005.
- [4] B. Juste, R. Miró, G. Verdú, S. Díez, et J. M. Campayo, « Linac photon spectra reconstruction using a depth dose gradient TSVD methodology based on Monte Carlo simulation », in *2011 4th International Conference on Biomedical Engineering and Informatics (BMEI)*, oct. 2011, p. 786-790. doi: 10.1109/BMEI.2011.6098411.

- [5] B. Juste, R. Miró, G. Verdú, S. Díez, et J. M. Campayo, « Bremsstrahlung Spectrum Reconstruction from Gradient Depth Dose Curves Obtained in a Water Phantom », *Nuclear Technology*, vol. 175, n° 1, p. 175-181, juill. 2011, doi: 10.13182/NT11-A12287.
- [6] Z. Shafahi, S. Sina, et R. Faghihi, « Comparison of TSVD, MTSVD, and Tikhonov unfolding methods for reconstruction of X-ray spectra », *Radiation Physics and Chemistry*, vol. 166, p. 108437, janv. 2020, doi: 10.1016/j.radphyschem.2019.108437.
- [7] J. Torres-Díaz, G. B. Grad, et E. V. Bonzi, « Measurement of linear accelerator spectra, reconstructed from percentage depth dose curves by neural networks », *Physica Medica*, vol. 96, p. 81-89, avr. 2022, doi: 10.1016/j.ejmp.2022.02.019.
- [8] S. Jan *et al.*, « GATE: a simulation toolkit for PET and SPECT », *Phys Med Biol*, vol. 49, n° 19, p. 4543-4561, oct. 2004, doi: 10.1088/0031-9155/49/19/007.
- [9] ISO 11137-1:2006. Sterilization of health care products — Radiation — Part 1: Requirements for development, validation and routine control of a sterilization process for medical devices. International Organization for Standardization, Geneva.