

Optimization strategies for CNN's aiming crosstalk mitigation in finely segmented calorimetry systems

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Abstract—Calorimeters with fine sensor segmentation used in High Energy Physics experiments suffer from mutual interference due to electromagnetic coupling between neighboring sensor cells. Crosstalk affects the characterization and measurement of incident particle properties, like energy and time of flight, degrading the quality of event reconstruction. This work proposes different optimization strategies for a convolutional neural network using simulation-generated events, aiming to mitigate crosstalk effects. Using a strategy with per cell normalization, it was possible to enhance the timing estimation for the central cell, with a mean R^2 of 0.893, in comparison with 0.721 from the baseline.

Keywords—Convolutional Neural Networks, Calorimetry, High Energy Physics, Crosstalk.

I. INTRODUCTION

High-Energy Physics (HEP) experiments, such as ATLAS (A Toroidal LHC Apparatus) [1] and CMS (Compact Muon Solenoid) [2] at the Large Hadron Collider (LHC), are designed to validate established frameworks like the Standard Model of Particle Physics and to probe the frontiers of current knowledge, either validating other theories or unveiling unknown physics events [3], [4]. Their goal is to resolve outstanding questions regarding the subatomic nature of matter [5]. Achieving these objectives requires experimental facilities comprising concentric layers of subdetectors around a beam axis, each with a distinct purpose and design principle.

Among the subdetectors, calorimeters are engineered to halt incident particles and measure their energy deposition profiles [6]. Electromagnetic calorimeters (EMCal), in particular, are tasked with absorbing and quantifying the energy of particles that interact predominantly via the electromagnetic force, i.e., electrons (e^-), positrons (e^+), and photons (γ) [7].

In the ATLAS experiment, the Liquid Argon (LAr) EMCal is composed of readout cells with fine granularity, in a dense multichannel arrangement that is essential for determining the impact position and trajectory of particles within the detector volume [8]. However, the high granularity of the readout cells, together with the high collision rates of the accelerator with energy levels from the order of tera-electron-volts (TeV), introduces a critical interference challenge. Adjacent cells

experience electromagnetic coupling, causing a phenomenon known as crosstalk, which induces charge leakage and distorts the signals read from the sensors, introducing systematic biases that directly degrade the reconstruction of properties of the observed particle, such as the deposited energy and the time of flight [9], [10]. Because traditional signal processing algorithms, such as the Optimal Filter (OF) [11], do not account for crosstalk in their coefficient calculations, these errors cascade into the event reconstruction process. Consequently, parameters that characterize the energy deposition profile are adversely affected, compromising overall data quality and affecting the observation of rare events.

Developing robust mitigation strategies to counteract crosstalk effects is important for improving particle identification and ensuring accurate recovery of energy and timing information. Due to technical constraints associated with extracting crosstalk profiles directly via hardware in a detector in operation, recent efforts have shifted toward simulation-based approaches and toy experiments integrated with machine learning techniques [10], [12]. Utilizing computational environments like the Lorenzetti Showers framework [13], it is possible to simulate physics events, development of electromagnetic cascades and inter-channel coupling mechanisms.

This work brings a comparison between optimization strategies for a Convolutional Neural Network (CNN) designed for crosstalk mitigation in a 3×3 cell cluster. A traditional cost function was compared to a normalized version to compensate energy level differences between the cells of a cluster. The OF was also included in the model training, and its results were compared to sample-level optimization. The normalized cost function, together with the inclusion of OF in the training process, returned the best results.

This paper is organized as follows. In Section II, calorimeters and crosstalk effect are better explained. The methodology is detailed in Section III, with results exhibited and discussed in Section IV. Conclusions and perspectives are in Section V.

II. CROSSTALK IMPACTS IN HEP CALORIMETERS

Calorimeters are a class of subdetectors that measure and characterize the energy deposition profiles, and provide valuable information for particle identification [4], [6], [14]. The Lorenzetti Showers framework [13], used here and in other works (e.g. in [15]) to simulate HEP events and detectors, has a general purpose calorimeter model inspired by the ATLAS experiment (shown in Figure 1), but with some differences regarding constructive aspects. It comprises three layers of

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EMCal and three layers of HCal. While the first layer of the EMCal (EM1) has a fine granularity to improve impact position information, the second layer (EM2) is designed to absorb most part of $e^\pm/\gamma$ energy.

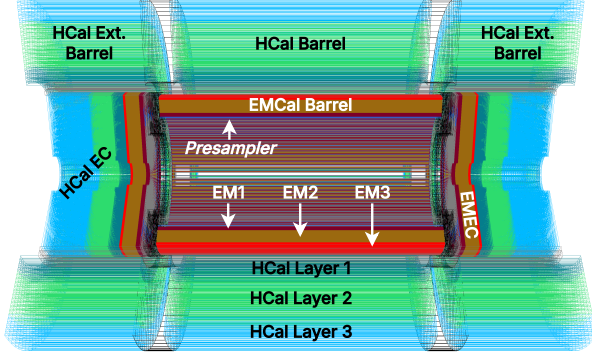


Fig. 1

LORENZETTI SHOWERS' GENERAL PURPOSE CALORIMETER [13].

The coordinate system used for particle trajectory and impact position identification is illustrated in Figure 2, where the z-axis represents the beam, and the origin is the nominal point of particle collision. Two coordinates are frequently used: ϕ , the angle related to the circumference of the detector, and η (pseudorapidity), defined as $\eta = -\ln(\tan(\theta/2))$.

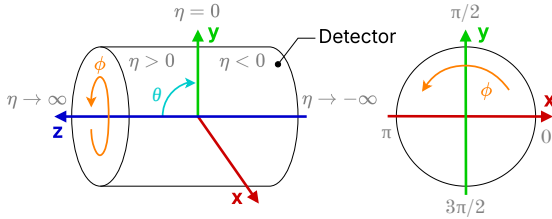


Fig. 2

COORDINATE SYSTEM FOR THE GENERAL PURPOSE CALORIMETER [12].

Each calorimeter layer is divided in cells with a given $\Delta\eta \times \Delta\phi$ granularity. These cells interfere with each other due to capacitive and inductive couplings, as represented in Figure 3. These couplings cause distortions in the pulse signals from the readout cells, both in amplitude (Δ_{Amp}) and in phase ($\Delta\tau$), as seen in Figure 4. These distortions in the energy deposition profile propagate errors in the estimation of particle's energy and time of flight, and by consequence, propagate errors to the event reconstruction.

The strategy currently used to reconstruct energy and time of flight of a particle is the Optimal Filter (OF), based in Lagrange multipliers applied over samples of the pulse signal of each cell (more details in [9], [10], [11]). The OF already receives a contaminated signal S_j^{rec} for each cell, defined as

$$S_j^{rec}(t_i) = S_j^{truth}(t_i) + \sum_k XT_{k \rightarrow j}(t_i) + b_j(t_i), \quad (1)$$

in which i represents the sample index, j represents a given cell and k represents the neighbor cells that interfere on the j cell.

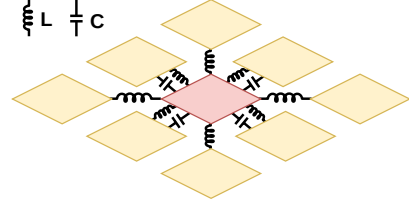


Fig. 3

CROSSTALK REPRESENTATION IN EMCAL CELLS (ADAPTED FROM [10]).

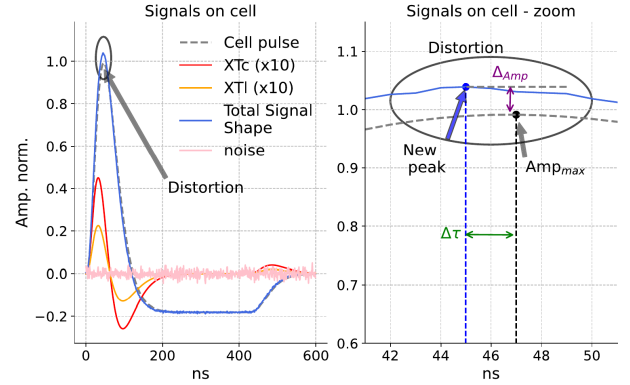


Fig. 4

CROSSTALK DISTORTION IN ATLAS LAR CALORIMETER CELL [10].

$S_j^{rec}(t_i)$ represents the contaminated signal, $S_j^{truth}(t_i)$ is the true amplitude of the signal if no interferences were present, $XT_{k \rightarrow j}$ represents the crosstalk influence of the k cell over the j cell, and b_j is a stochastic thermal noise component.

III. METHODOLOGY

The experiments consist in the use of simulated events to train CNN in supervised strategies, and analyzing the outcome of the same network with different optimization strategies.

A. Dataset

The dataset employed in this work contains events simulated with Lorenzetti Showers. Each event comprises the signal with crosstalk (input) and without crosstalk (target), representing the incidence of a single e^- with 50 GeV of energy in the centroid of a EMCAL cell in the EM2 layer. The simulation was configured to consider that the incident e^- originated from the nominal point of collision. For the crosstalk effect, the intensities considered were 1.1% of inductive component and insignificant capacitive component, considering the peak-peak definition [9], in consonance with measurements made in [16]. The stochastic thermal noise was also modeled as a gaussian distribution with zero mean and standard deviation of 60 MeV.

The inputs and targets of the dataset correspond to cell clusters of 3×3 format, each cell with 5 samples over time, considering a sampling period of 25 ns. The clusters are located around $\eta \approx 0.7125$ and $\phi \approx 1.828$, with cell granularity of 0.025×0.025 . A representation of the clusters, together with relative (η, ϕ) coordinates adopted for cell identification, is seen in Figure 5. A total of 65,536 events were used for training with cross-validation, and 50,000 for test.

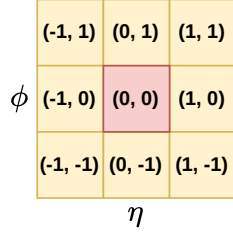


Fig. 5

 CLUSTER CELL (η, ϕ) INDEX REPRESENTATION.

B. Neural Network Model

The proposed neural network for crosstalk mitigation is shown in Figure 6. Bidimensional convolutional layers were used in order to possibly capture patterns correlated to interference between adjacent cells. This choice was inspired by the matrix disposition of the data, representing the calorimeter cell grid. The model receives a $3 \times 3 \times 5$ tensor as input, with the channels representing the time samples of the cluster cells, and returns as output a dense layer with 45 numeric outputs (later reshaped to a $3 \times 3 \times 5$ tensor), representing the filtered cluster samples. Convolutional layers were dimensioned with 2×2 kernels because of the small cluster size. Two bifurcations were implemented to avoid eventual limitations due to asymmetric padding; one of the paths receive a rotated version of the input, in order to compensate asymmetries in the quality of reconstruction. In the end, the bifurcations are concatenated and propagated through dense layers.

C. Optimization Strategies and Hyperparameters

A supervised training approach was adopted and two different loss functions were used: the classic Mean Squared Error (MSE), as an orthodox optimization method, and a Normalized version of MSE (NMSE), in which the squared errors of each cluster cell variables are divided by the cell's variance. For a given batch $\hat{y}$ of predicted variables for a cluster and a batch y of targets, each with N dataset entries, being σ^2 the variance, MSE and NMSE are defined as

$$\text{MSE}(\hat{y}, y) = \frac{1}{N} \sum_{i=1}^N \left[\sum_{\text{cells}} (\hat{y}_i^{\text{cell}} - y_i^{\text{cell}})^2 \right], \quad (2)$$

$$\text{NMSE}(\hat{y}, y) = \frac{1}{N} \sum_{i=1}^N \left[\sum_{\text{cells}} \frac{(\hat{y}_i^{\text{cell}} - y_i^{\text{cell}})^2}{\sigma^2(y^{\text{cell}})} \right]. \quad (3)$$

For each loss function $\mathcal{L} \in \{\text{MSE}, \text{NMSE}\}$, two different training strategies were tested: $\mathcal{L}(\hat{S}, S)$, with the optimization occurring directly over time samples (represented in Figure 7), and $\mathcal{L}(\hat{E}, E) + \mathcal{L}(\hat{\tau}, \tau)$, in which the OF was attached to the output and the network and the optimization was executed over recovered energy and time of flight (represented in Figure 8). In total, four different training strategies were executed; for simplification, they will be called MSE (S), MSE (E+ τ), NMSE (S) and NMSE (E+ τ). The summary of hyperparameters for all trainings is present in Table I.

 TABLE I
TRAINING HYPERPARAMETERS

Train set size	65,536	β_1	0.9
Batch size	2,048	β_2	0.999
Cross-validation	K-Fold	Learning rate	1×10^{-3}
Fold amount	5	Weight decay	10^{-5}
Iterations/Fold	5	Maximum epochs	1000
Optimizer	Adam [17]	Early stopping	50 epochs

D. Performance Evaluation

The quality of energy and time estimation per cell was evaluated over test data with Root Mean Squared Error (RMSE = $\sqrt{\text{MSE}}$) and R^2 . The RMSE provides a quantification of the error. R^2 is dimensionless, and is related to the correlation between the predictions and the targets, being defined as

$$R^2 = 1 - \frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}. \quad (4)$$

For RMSE, the lower, the better; for R^2 , the higher, the better (preferably with values close to 1).

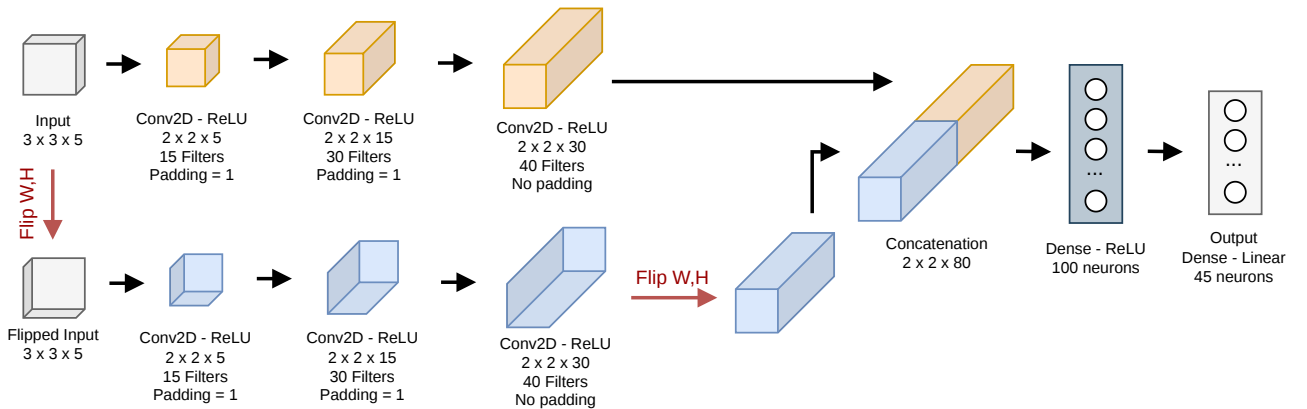


Fig. 6

ARCHITECTURE OF THE TRAINED CONVOLUTIONAL NEURAL NETWORK.

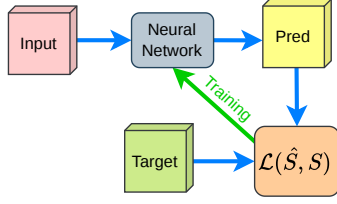


Fig. 7

TRAINING OVER SAMPLES.

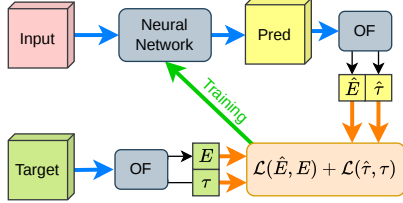


Fig. 8

TRAINING OVER RECOVERED ENERGY AND TIME.

IV. RESULTS

Tables II and III contain the mean and standard deviation, over the folds, for R^2 and RMSE of the energy estimations for each of the four trainings, in comparison with the OF as the baseline. The values highlighted in bold represent the best results for each cell. All the trainings had mean $R^2 > 0.985$ for the central cell, with a small advantage for the model trained with MSE ($E+\tau$). The energy estimations for the neighbor cells were better for the models trained with NMSE. The model optimized with NMSE ($E+\tau$) returned the best energy estimations for the cells that are horizontally or vertically adjacent to the central cell, while the training with NMSE (S) had the best performance for the diagonally adjacent cells. Comparing the RMSE between the two trainings with NMSE, they had similar performance in energy estimation, with the higher RMSE difference around 11 MeV in the cell (0, 1).

Tables IV and V show the R^2 and RMSE metrics over folds for time estimation, for each training, with the OF estimation as baseline. For the hottest cell, only the training with NMSE ($E+\tau$) had a better performance than OF, with mean $R^2 = 0.893$; the other trainings had a poor quality, with R^2 far below from the 0.721 from OF. The MSE ($E+\tau$) optimization delivered the better performances for most of the neighbor cells, but the performance of the NMSE ($E+\tau$) training is not too far away, so, if it was necessary to choose only one of the trainings, the NMSE ($E+\tau$) would be the best choice. Figure 9 shows histogram comparisons for each cell between baseline, target and the best initialization of NMSE ($E+\tau$).

Figure 10 synthesizes the normalized error between the energy/time predictions and the targets, considering all cells in a cluster, as in the equation

$$\text{Err}_{\text{norm}}(\hat{x}, x) = \frac{\hat{x} - x}{x}. \quad (5)$$

The values from the x-axis in the left represent $\text{Err}_{\text{norm}}(\hat{E}, E)$, and in the right plot, $\text{Err}_{\text{norm}}(\hat{\tau}, \tau)$.

TABLE II
 R^2 OF ENERGY ESTIMATION OVER FOLDS

Energy estimation – R^2					
Cell	OF	MSE (S)	MSE ($E+\tau$)	NMSE (S)	NMSE ($E+\tau$)
(-1, -1)	-1.892	0.374 $\pm$ 0.184	0.553 $\pm$ 0.090	0.809 $\pm$ 0.043	0.793 $\pm$ 0.083
(-1, 0)	-1.497	0.502 $\pm$ 0.051	0.502 $\pm$ 0.013	0.622 $\pm$ 0.012	0.632 $\pm$ 0.019
(-1, 1)	-1.809	0.579 $\pm$ 0.100	0.618 $\pm$ 0.059	0.833 $\pm$ 0.004	0.833 $\pm$ 0.006
(0, -1)	-0.213	0.642 $\pm$ 0.028	0.644 $\pm$ 0.048	0.687 $\pm$ 0.026	0.727 $\pm$ 0.018
(0, 0)	0.510	0.990 $\pm$ 0.001	0.992 $\pm$ 0.000	0.985 $\pm$ 0.005	0.985 $\pm$ 0.007
(0, 1)	-0.030	0.678 $\pm$ 0.025	0.686 $\pm$ 0.030	0.713 $\pm$ 0.010	0.768 $\pm$ 0.011
(1, -1)	-1.888	0.594 $\pm$ 0.100	0.608 $\pm$ 0.161	0.846 $\pm$ 0.007	0.841 $\pm$ 0.005
(1, 0)	-1.043	0.582 $\pm$ 0.037	0.612 $\pm$ 0.036	0.712 $\pm$ 0.017	0.733 $\pm$ 0.008
(1, 1)	-1.743	0.376 $\pm$ 0.199	0.725 $\pm$ 0.038	0.849 $\pm$ 0.006	0.804 $\pm$ 0.064

TABLE III
RMSE (MeV) OF ENERGY ESTIMATION OVER FOLDS

Energy estimation – RMSE (MeV)					
Cell	OF	MSE (S)	MSE ($E+\tau$)	NMSE (S)	NMSE ($E+\tau$)
(-1, -1)	172	79 $\pm$ 12	67 $\pm$ 7	44 $\pm$ 5	45 $\pm$ 8
(-1, 0)	231	103 $\pm$ 5	103 $\pm$ 1	90 $\pm$ 1	88 $\pm$ 2
(-1, 1)	171	66 $\pm$ 8	63 $\pm$ 5	42 $\pm$ 1	42 $\pm$ 1
(0, -1)	211	115 $\pm$ 4	114 $\pm$ 7	107 $\pm$ 4	100 $\pm$ 3
(0, 0)	2223	313 $\pm$ 13	286 $\pm$ 7	384 $\pm$ 67	379 $\pm$ 84
(0, 1)	210	117 $\pm$ 4	116 $\pm$ 5	111 $\pm$ 2	100 $\pm$ 2
(1, -1)	177	66 $\pm$ 9	64 $\pm$ 13	41 $\pm$ 1	41 $\pm$ 1
(1, 0)	238	107 $\pm$ 5	103 $\pm$ 5	89 $\pm$ 3	86 $\pm$ 1
(1, 1)	176	83 $\pm$ 14	56 $\pm$ 4	41 $\pm$ 1	47 $\pm$ 7

TABLE IV
 R^2 OF TIME ESTIMATION OVER FOLDS

Time estimation – R^2					
Cell	OF	MSE (S)	MSE ($E+\tau$)	NMSE (S)	NMSE ($E+\tau$)
(-1, -1)	-0.429	0.313 $\pm$ 0.089	0.901 $\pm$ 0.001	0.891 $\pm$ 0.014	0.876 $\pm$ 0.041
(-1, 0)	-2.369	0.372 $\pm$ 0.050	0.559 $\pm$ 0.044	0.506 $\pm$ 0.037	0.571 $\pm$ 0.016
(-1, 1)	-0.468	0.600 $\pm$ 0.047	0.896 $\pm$ 0.006	0.897 $\pm$ 0.002	0.891 $\pm$ 0.011
(0, -1)	-2.621	0.305 $\pm$ 0.012	0.504 $\pm$ 0.003	0.214 $\pm$ 0.132	0.488 $\pm$ 0.021
(0, 0)	0.721	0.133 $\pm$ 0.165	0.239 $\pm$ 0.220	-0.010 $\pm$ 0.011	0.893 $\pm$ 0.077
(0, 1)	-2.794	0.288 $\pm$ 0.026	0.461 $\pm$ 0.057	0.180 $\pm$ 0.130	0.480 $\pm$ 0.019
(1, -1)	-0.321	0.569 $\pm$ 0.258	0.904 $\pm$ 0.001	0.903 $\pm$ 0.001	0.901 $\pm$ 0.005
(1, 0)	-2.198	0.327 $\pm$ 0.046	0.573 $\pm$ 0.022	0.511 $\pm$ 0.043	0.570 $\pm$ 0.018
(1, 1)	-0.366	0.132 $\pm$ 0.147	0.900 $\pm$ 0.003	0.893 $\pm$ 0.007	0.820 $\pm$ 0.176

TABLE V
RMSE (ns) OF TIME ESTIMATION OVER FOLDS

Time estimation – RMSE (ns)					
Cell	OF	MSE (S)	MSE ($E+\tau$)	NMSE (S)	NMSE ($E+\tau$)
(-1, -1)	3.184	2.204 $\pm$ 0.146	0.838 $\pm$ 0.005	0.879 $\pm$ 0.055	0.928 $\pm$ 0.145
(-1, 0)	1.964	0.847 $\pm$ 0.033	0.709 $\pm$ 0.035	0.752 $\pm$ 0.029	0.700 $\pm$ 0.013
(-1, 1)	3.121	1.626 $\pm$ 0.096	0.830 $\pm$ 0.022	0.827 $\pm$ 0.009	0.849 $\pm$ 0.040
(0, -1)	1.544	0.677 $\pm$ 0.006	0.571 $\pm$ 0.002	0.717 $\pm$ 0.063	0.581 $\pm$ 0.012
(0, 0)	0.030	0.052 $\pm$ 0.005	0.048 $\pm$ 0.008	0.056 $\pm$ 0.000	0.018 $\pm$ 0.006
(0, 1)	1.482	0.642 $\pm$ 0.012	0.558 $\pm$ 0.029	0.687 $\pm$ 0.058	0.549 $\pm$ 0.010
(1, -1)	3.341	1.852 $\pm$ 0.519	0.901 $\pm$ 0.004	0.905 $\pm$ 0.007	0.916 $\pm$ 0.022
(1, 0)	2.031	0.931 $\pm$ 0.032	0.742 $\pm$ 0.019	0.793 $\pm$ 0.036	0.744 $\pm$ 0.016
(1, 1)	3.238	2.573 $\pm$ 0.216	0.875 $\pm$ 0.012	0.908 $\pm$ 0.028	1.093 $\pm$ 0.477

It is noticeable that the trainings with NMSE resulted in predictions that are closer to the target, in comparison with pure OF and with the trainings with MSE. For time, the plot indicates that the estimations are better for all the four trainings, but this is due to the results of the neighbor cells, that have better estimations with the neural network rather than the pure OF. But the central cell, which is critical for determining the time of flight of a particle, had better results only in the training NMSE ($E+\tau$), as seen in the Tables IV and V.

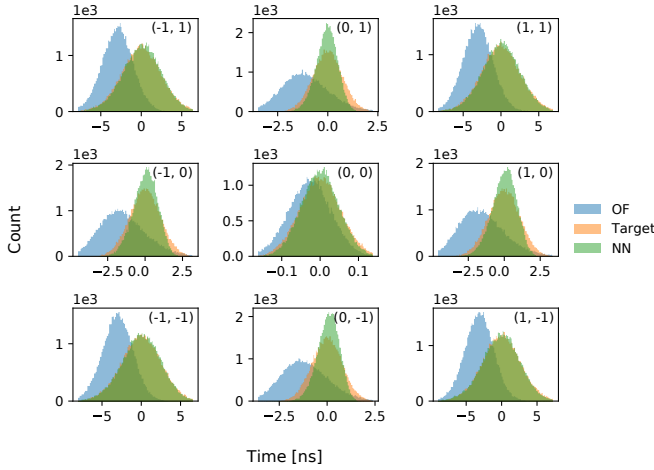


Fig. 9

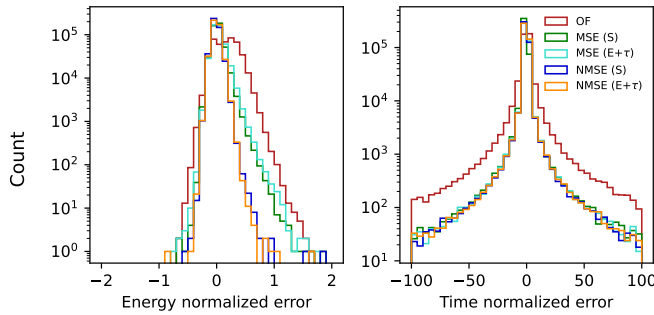
 HISTOGRAMS FOR TIME ESTIMATIONS WITH OF AND NMSE ($E+\tau$).


Fig. 10

NORMALIZED ERRORS FOR ENERGY AND TIME RECONSTRUCTION.

V. CONCLUSIONS

Experiments were conducted in this work with simulated events, initially with neural networks trained in a supervised strategy to investigate possible model solutions and optimization strategies that can be adapted for future use with data from real detectors.

Advances were made in mitigating crosstalk for a delimited scope, considering a single electron hitting the centroid of a cell with fixed coordinates and a fixed energy level of 50 GeV. The perspectives are to make further steps for scenarios with variability, whether in the coordinates of the hit cell, the area of the hit cell (beyond the centroid), the energy level of the incident particle, and/or the type of simulated physical event. The idea is to develop strategies in toy experiments and mature new implementations that can generalize to various conditions, such as different energy levels, different regions (η, ϕ) with different cell granularity per region, and other physics events, e.g., a $Z \rightarrow e^+e^-$ decay. Furthermore, per cell normalization during optimization returned good results on the experiments hereby discussed, but it isn't possible to retrieve clean target data from real calorimeters, as the crosstalk effects come together with the observed signal; so unsupervised training strategies should be considered in future experiments, such as unsupervised denoising strategies, for example.

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REFERENCES

- [1] The ATLAS Collaboration, "The ATLAS Experiment at the CERN Large Hadron Collider," *Journal of Instrumentation*, vol. 3, no. 08, p. S08003, Aug 2008. [Online]. Available: <https://dx.doi.org/10.1088/1748-0221/3/08/S08003>
- [2] The CMS Collaboration, "The CMS experiment at the CERN LHC," *Journal of Instrumentation*, vol. 3, no. 08, p. S08004, Aug 2008. [Online]. Available: <https://doi.org/10.1088/1748-0221/3/08/S08004>
- [3] P. Langacker, *The Standard Model and Beyond*, 2nd ed. Taylor & Francis, 2017. [Online]. Available: <https://doi.org/10.1201/b22175>
- [4] H. Kolanoski and N. Wermes, *Particle Detectors: Fundamentals and Applications*. Oxford University Press, 2020. [Online]. Available: <https://doi.org/10.1093/oso/9780198858362.001.0001>
- [5] G. Barr, R. Devenish, R. Walczak *et al.*, *Particle Physics in the LHC Era*. Oxford University Press, 2016. [Online]. Available: <https://doi.org/10.1093/acprof:oso/9780198748557.001.0001>
- [6] M. Livan and R. Wigmans, *Calorimetry for Collider Physics, an Introduction*. Springer Cham, 2019. [Online]. Available: <https://doi.org/10.1007/978-3-030-23653-3>
- [7] B. R. Martin, *Nuclear and Particle Physics: an introduction*. Wiley, 2006. [Online]. Available: <https://doi.org/10.1002/0470035471>
- [8] N. Nikiforou, "Performance of the ATLAS Liquid Argon Calorimeter after Three Years of LHC Operation and Plans for a Future Upgrade," in *2013 3rd International Conference on Advancements in Nuclear Instrumentation, Measurement Methods and their Applications (ANIMMA)*, 2013, pp. 1–12.
- [9] A. L. Solis, "Contribution à la mesure d'énergie et du temps des électrons et des photons dans l'expérience ATLAS et recherche de la production de matière noire en association avec un boson de Higgs," Ph.D. dissertation, Université Pierre et Marie Curie, 2017. [Online]. Available: <https://theses.hal.science/tel-02430126>
- [10] M. Santos, E. Simas Filho, P. Farias *et al.*, "Crosstalk mitigation in an atlas-like high energy liquid argon calorimeter using artificial neural networks," *Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment*, vol. 1087, p. 171382, 2026. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0168900226001087>
- [11] W. Cleland and E. Stern, "Signal processing considerations for liquid ionization calorimeters in a high rate environment," *Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment*, vol. 338, no. 2, pp. 467–497, 1994. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/0168900294913323>
- [12] A. P. C. Rodrigues, A. C. L. F. Júnior, E. E. P. Souza *et al.*, "Redes Neurais Convolucionais para Mitigação de Ruído Cruzado em um Sistema de Calorimetria de Altas Energias com Elevada Segmentação," in *XVII Congresso Brasileiro de Inteligência Computacional (CBIC 2025)*, Belo Horizonte, MG, 2025. [Online]. Available: <https://doi.org/10.21528/CBIC2025-1191630>
- [13] M. V. Araújo, M. Begalli, W. S. Freund *et al.*, "Lorenzetti Showers - A general-purpose framework for supporting signal reconstruction and triggering with calorimeters," *Computer Physics Communications*, vol. 286, p. 108671, 2023. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0010465523000164>
- [14] R. Wigmans, *Calorimetry: Energy Measurement in Particle Physics*, 2nd ed. Oxford University Press, 2017.
- [15] P. R. A. Silva, E. F. S. Filho, P. C. M. A. Farias, E. E. P. Souza, J. L. Marin, and J. M. Seixas, "Machine Learning for Energy Calibration in High Energy Physics Experiments Using the Lorenzetti Showers Framework," *IEEE Transactions on Nuclear Science*, vol. 73, no. 5, pp. 1853–1875, 2026.
- [16] J. Labbé and R. Ishmukhametov, "Crosstalk Measurements in the Electromagnetic Calorimeter during ATLAS Final Installation," CERN, Geneva, Tech. Rep., 2008. [Online]. Available: <https://cds.cern.ch/record/1143373>
- [17] D. P. Kingma and J. L. Ba, "Adam: A Method for Stochastic Optimization," *3rd International Conference for Learning Representations*, 2014.