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ENERGY ESTIMATION CONSIDERATIONS FOR A HIGH-ENERGY CALORIMETER OPERATING AT HIGH PILE-UP CONDITIONS

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Abstract. The high-luminosity LHC program brings new challenges to the calorimeter energy reconstruction task. Due to the increase of interactions per collision, the calorimeter readout signal may be distorted by the consequent signal pile-up effects, which introduce nonlinearities to the readout channel noise, degrading the efficiency of standard energy estimation algorithms. This work evaluates the performance from two promising methods that have recently been proposed to deal with the signal pile-up effect for high-energy calorimetry. The first one is based on a signal deconvolution technique, while the other makes use of a linear approach combined with a neural network which performs a fine adjustment on the linear estimation. The methods are developed for the ATLAS Tile Calorimeter, which is currently under operation at LHC. A simulation data set was produced covering a wide range of pile-up scenarios expected for high-luminosity LHC. The results show that the energy estimation efficiency can be significantly improved.

Keywords: Energy Estimation, Signal Pile-up, Neural Networks, High-Energy Physics.

1. INTRODUCTION

Particle colliders are complex facilities used in experimental high-energy physics (Livingston and Blewett (1969)). They are built to accelerate particles and perform collisions at very high energy levels (order of Tera-electron Volts). The LHC (Large Hadronic Collider) (Evans & Bryant (2008)) is the largest particle collider ever built and it is designed to cover a large physics research program. The scientists are interested in explaining some of the fundamental building blocks that have shaped the universe.

At LHC, two beams of protons are accelerated at approximately the speed of light in opposite directions along a 27 km circular tunnel. The beams are made to collide at specific points

every 25 ns, where experiments are placed to collect information from each proton-proton (p-p) collision. ATLAS (The ATLAS Collaboration (2008)) is the largest LHC experiment and it is designed as a general-purpose detector that explores the full potential of LHC. During its operation from 2010 and 2012, ATLAS confirmed the existence of the Higgs boson (The ATLAS Collaboration (2012)), a particle that is foreseen by the Standard Model (Cottingham & Greenwood (1998)) but never observed until then.

Since the physics of interest is rare, a massive amount of data is needed. Therefore, the LHC is consistently increasing its beam luminosity, aiming at increasing the probability of discovering new phenomena. The luminosity is proportional to the number of p-p interactions per collision (Ruggiero (2004)). In high-luminosity LHC (HL-LHC) conditions the beam becomes denser, producing more events from each p-p collision. The problem arises due to the time window that is needed for the calorimeter system to respond to each collision. While the LHC high event rate is fixed at 40 MHz (collisions are spaced 25 ns from each other) the calorimeter response takes approximately 150 ns to produce its response. As a result, more than a single event may be present within a same readout window in a given channel. As a result, the received signal becomes distorted due to the signal pile-up, degrading the performance of typical energy estimator algorithms.

This work presents an evaluation of the performance from two promising methods that are being considered to operate in the ATLAS Tile Calorimeter (TileCal) at HL-LHC. The first one, called Multi-Amplitude Estimator (MAE) (Filho et al. (2015)) is based on a linear signal deconvolution technique. The second one makes use of a nonlinear computational intelligence solution combined with a linear approach (Peralva et al. (2017)) to reconstruct the readout signals. A wide range of pile-up conditions is investigated and the efficiency from both methods is also compared to the current algorithm used in TileCal for offline energy reconstruction, which is based on a linear combination of the incoming time samples (Bertuccio et al. (1992)).

The text is organized as follows. In the next section, the TileCal and its energy reconstruction algorithm are briefly introduced. Both MAE and the combined method are described in Section 3. The designs of the methods and the simulation results, considering different signal pile-up conditions, are shown in Section 4. Finally, the conclusions are outlined in Section 5.

2. THE ATLAS TILECAL

The Tile Calorimeter (TileCal) is the main hadronic calorimeter of the ATLAS experiment. In total, TileCal has approximately 10,000 readout channels that provide precise measures of the energies from particles that interact with the calorimeter. The particles that are produced at the interaction point of the ATLAS experiment cross the TileCal cells and their energy are sampled by plastic scintillating tiles. The resulting light produced by the tiles are transmitted to photo-multiplier tubes (PMT) which produce the electric signals. Figure 1 illustrate the TileCal detection principle.

The analog pulse from the PMT output is conditioned in such a way that its amplitude is proportional to the deposited energy. Therefore, by estimating the pulse amplitude, the energy can be recovered. The pulse is sampled at 40 MHz and a readout window of seven samples (150 ns) represents the entire pulse (Anderson et al. (1998)). In Fig. 2, the TileCal pulse is displayed. The seven time samples are represented by the dots along the pulse.

The seven signal samples are sent to Read-Out-Drivers, where the online digital processing is carried out.

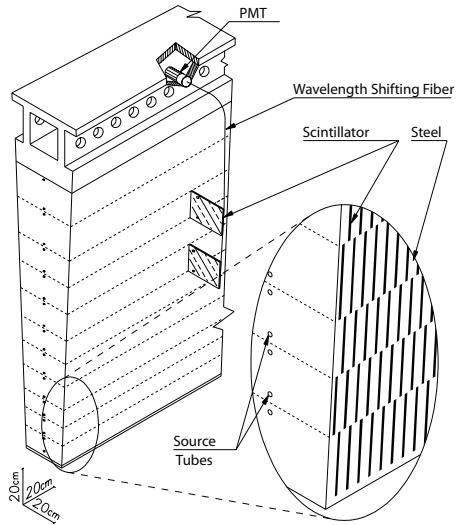


Figure 1- Schematic view of TileCal cell segmentation for an LB and an EB module.

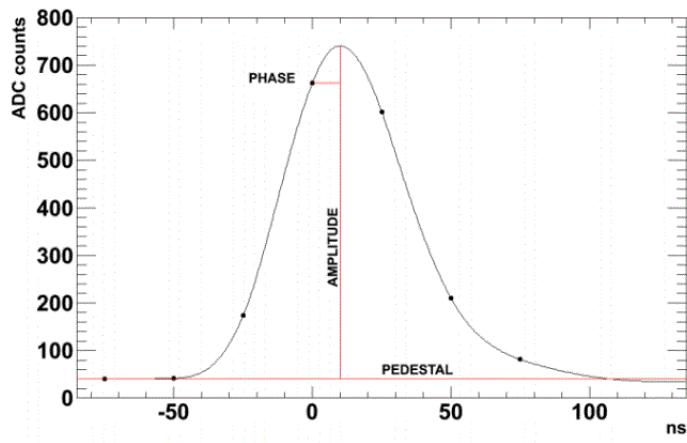


Figure 2- The TileCal pulse shape and its magnitudes.

2.1 Current TileCal Energy Reconstruction Algorithm

The current energy reconstruction algorithm used in TileCal is called Optimal Filter (OF) (Ful-lana et al. (2006)). It estimates the signal amplitude and reconstructs the energy from signal that are validated by the ATLAS trigger system (Kordas and Abolins (2007)). The method is based on a weighted sum of the seven incoming time samples $s[k]$ that belong to a given readout window to compute the amplitude as follows:

$$\hat{A}_{OF} = \sum_{k=0}^6 c[k]s[k], \quad (1)$$

where the coefficients $c[k]$ are obtained from the TileCal pulse shape and the noise covariance matrix. The procedure aims at minimizing the estimation variance. Therefore, the method is optimum for signals corrupted from Gaussian noise. The coefficients are obtained through the minimization of the noise effect in the reconstruction of the amplitude using Lagrange multipliers.

ers (Bertuccio et al. (1992)).

However, signals coming from adjacent collisions may be observed within a same readout window, causing signal pile-up. Since such effect introduces a nonlinear component to the noise, the OF efficiency decreases as OF does not take into account the signal pile-up statistics in its design. Figure 3 illustrates a signal pile-up occurrence in a TileCal readout window where the signal of interest has its peak at 0 ns and an additional out-of-time signal, which the peak is located at 50 ns, is superimposed, distorting the resultant signal (pulse with a double peak).

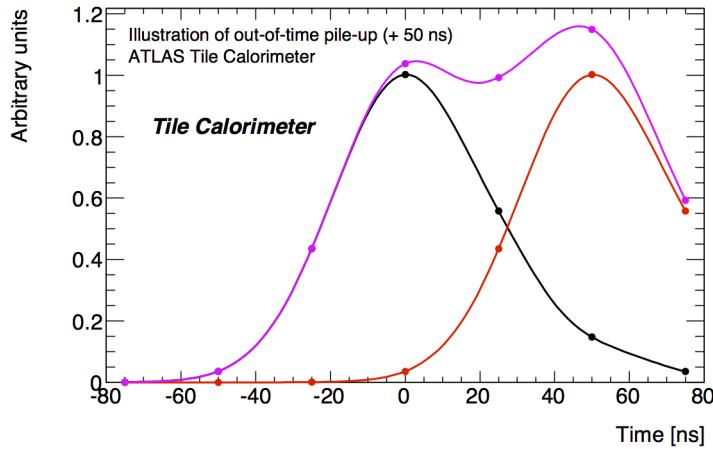


Figure 3- The signal pile-up effect observed in a TileCal readout window.

3. ALTERNATIVE TILECAL ENERGY RECONSTRUCTION METHODS

Due to the LHC high-event rate operation, a severe pile-up conditions is expected to be observed in the TileCal readout channels. Therefore, alternative methods have been proposed in order to mitigate the pile-up in such harsh conditions. In this work, two promising approaches are described and their performance are presented in Section 4.4.

3.1 The multi-amplitude estimator (MAE)

The LHC is a synchronous machine where each collision takes place every 25 ns during data taking. Since the TileCal pulse shape is known (see Fig.2), the vector of time samples \mathbf{s}_{7x1} from a given readout window can be approximated as:

$$\mathbf{s}_{7x1} = \mathbf{H}_{7x7}\mathbf{a}_{7x1} + \mathbf{w}_{7x1}, \quad (2)$$

where the \mathbf{H}_{7x7} is a matrix that comprises shifted versions (spaced 25 ns) of the TileCal pulse shape whose amplitudes \mathbf{a}_{7x1} must be estimated. The \mathbf{w}_{7x1} is an uncorrelated zero-mean Gaussian noise, which corresponds to the electronic noise. As a result, \mathbf{y} becomes

$$E\{\mathbf{s}_{7x1}\} = E\{\mathbf{H}_{7x7}\mathbf{a}_{7x1} + \mathbf{w}_{7x1}\} = \mathbf{H}_{7x7}\mathbf{a}_{7x1}, \quad (3)$$

where $E\{\cdot\}$ is the expected value of a random variable. A sub-optimal deconvolution matrix \mathbf{G}_{7x7} can be computed in such way that

$$\mathbf{G}_{7x7}^{-1}\mathbf{H}_{7x7} = \mathbf{I}_{7x7}. \quad (4)$$

As a result, the amplitude vector \mathbf{a}_{7x1} can be found by applying the following expression:

$$\hat{\mathbf{a}}_{7x1} = \mathbf{G}_{7x7}^{-1} \mathbf{s}_{7x1}. \quad (5)$$

which the $\hat{\mathbf{a}}_{7x1}$ estimates are the amplitudes for each shifted version of the TileCal pulse shape, assuming that a signal was read out in every seven collisions associated to a given TileCal readout window.

However, this may be not the case for every readout window acquired, and only some of the shifted signals may be present within a window. Therefore, a simple threshold is applied on the $\hat{\mathbf{a}}_{7x1}$ vector, in order to select only the p shifted signals that have significant information. Hence, both matrices \mathbf{H}_{px7} and \mathbf{G}_{px7} are redesigned taking into account only such shifted signals, following the vectorial closed formula:

$$\mathbf{G}_{px7} = \mathbf{H}_{px7} (\mathbf{H}_{px7}^T \mathbf{H}_{px7})^{-1}, \quad (6)$$

where \mathbf{H}_{px7}^T is transpose of \mathbf{H}_{px7} .

Equation (6) performs the approximation of the deconvolution process for the p selected components.

3.2 Computational intelligence approach

The linear method currently used in TileCal does not fully handle the nonlinearities introduced in the received signal by signal pile-up. Therefore, a computational intelligence approach may be used in order to assist the reconstruction of the energy performed by the OF method. A nonlinear corrector may be designed to provide a fine tuning to the linear estimate according to the pile-up condition (Peralva et al. (2017)), aiming at estimating a function to map the input to the correct output (Sarajedini et al. (1999)). For this, the OF approach can be combined with an artificial neural network (ANN) (Haykin (1998)) as shown in Fig. 4.

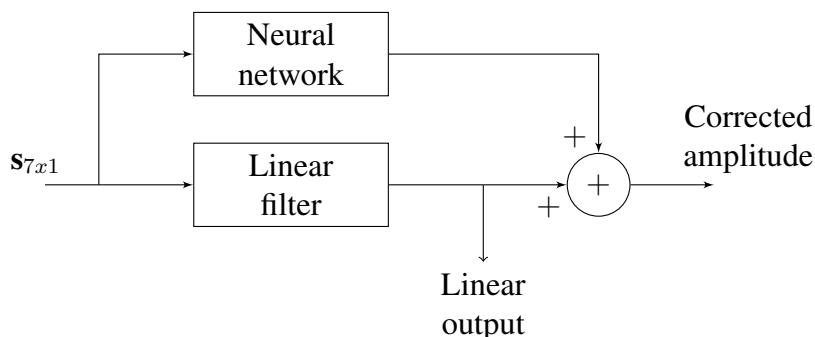


Figure 4- Block diagram illustrating the combined system to perform the energy estimation under severe signal pile-up conditions. A linear estimator is combined with a nonlinear corrector that performs an adjustment for the final estimate.

The goal of the nonlinear processing is to correct for the linear model. That is, the nonlinear corrector does not estimate the signal energy itself, but it provides an adjustment to the linear estimate already available. For the case where the noise comes mainly from electronic noise, the nonlinear contribution should be minimal, and the estimate is dominated by the linear method. Additionally, the estimation from the OF method is always available for use, and the correction is applied upon the user decision.

4. SIMULATION RESULTS

This section presents the data set used and the results achieved by the considered methods. A comparison with the OF technique, which is currently being used in TileCal, is also provided.

4.1 Data set

The pile-up conditions can be expressed by the signal occupancy level. A occupancy of 0% means that only the signal of interest is present within the TileCal readout window, which comprises seven bunch crossings (LHC collisions). In the other hand, in an occupancy of 100%, TileCal would read a signal for every bunch crossing, leading to a severe pile-up condition. In order to cover a wide range of pile-up conditions, the scenarios of 10%, 30%, 50%, 70% and 90% of occupancy were considered. It should be stressed that the pile-up may differ according to the physical location of the readout channel. For example, channels closer to the collision beam are likely to present higher activity. Therefore, these conditions describe the activity for different cases that TileCal will face during the HL-LHC operation.

For each occupancy level, a data set was produced comprising two sets, the training set and the test set containing 80,000 and 20,000 events, respectively. The training set was used to train the ANN while the test set was used for performance evaluation. The signal amplitudes for the signals of interest and the pile-up were generated following an exponential distribution having a mean value of 100 and 30 ADC counts, respectively. All signals were corrupted with a zero-mean white Gaussian noise with $\sigma=1$ ADC count, simulating the TileCal electronic noise. Additionally, the signal phase is also considered through the inclusion of a zero-mean Gaussian random variable ($\sigma=1$ ns). Another zero-mean Gaussian distributed variable ($\sigma=0.05$ ADC counts) emulates the pulse deformation due to electronics aging and precision. The results are presented in energy units where, in TileCal, 1 ADC count corresponds to approximately 12 MeV (Mega-Electron Volt).

4.2 Neural network design

The neural network topology was based on the configuration previously designed for the same purpose (Peralva et al. (2015)), where the number of neurons was chosen according to the estimation error performance. The input nodes correspond to the seven time samples received. A Multi-Layer Perceptron (MLP) was used with one hidden layer (4 neurons), and a 1 output layer with a single neuron. For the neurons in the hidden layer, the hyperbolic tangent was used, while a linear function was employed for the output neuron. The Levenberg-Marquardt (Hagan & Menhaj (1994)) was chosen as the training algorithm.

The training strategy chosen is shown in Fig.5. To this end, the training data sets for each occupancy level were used where the neural network target corresponds to the absolute difference between the reference value (known from the simulation) and the OF output. A test data set was used to test the designed methods and evaluate their performances (see Section 4.4).

4.3 Noise characteristics

In conditions where the signal pile-up is not present, the noise can be described by a Gaussian distribution, which is a typical description for the electronic noise. As the occupancy increases, the signal pile-up introduces another component to the noise, and the Gaussian characteristics changes in function of the occupancy level.

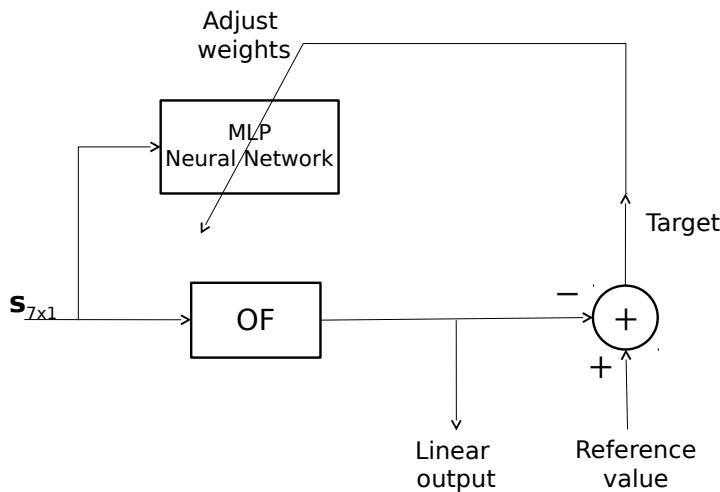


Figure 5- ANN training strategy used for the combined method.

In order to analyze the behavior of the symmetry parameters in the noise as a function of the occupancy, Table 1 shows the skewness and kurtosis from the noise distribution of each occupancy level. These parameters are a measure of asymmetry for a given distribution. The value for both skewness and kurtosis for an ideal Gaussian function is zero.

Table 1- Asymmetry parameters from the noise distributions for difference occupancy levels.

	Occupancy level				
	10%	30%	50%	70%	90%
Skewness	2.56	1.78	1.56	1.39	1.32
Kurtosis	6.40	3.25	2.92	2.57	2.64

It can be noticed that the higher the occupancy level is, the more symmetric the noise distribution is likely to become. This may be explained by the increase of the signal pile-up in the noise, where more signals are convolved leading to a more symmetric distribution.

4.4 Estimation error performance

The estimation error was used for performance evaluation. This quantity is measured by computing the absolute difference between the estimated energy value and the reference value (taken from simulation). Figure 6 and 7 show the estimation error distributions using the 30% and 90% of occupancy data sets, respectively. As it can be noted, the combined method (OF+ANN) presents the best efficiency when compared to the MAE and OF methods.

The standard deviation from the estimation error distributions can be used to analyze the performance from each of the methods. Figure 8 shows the evolution of the estimation error in function of the occupancy level. The values are summarized in the Table 2.

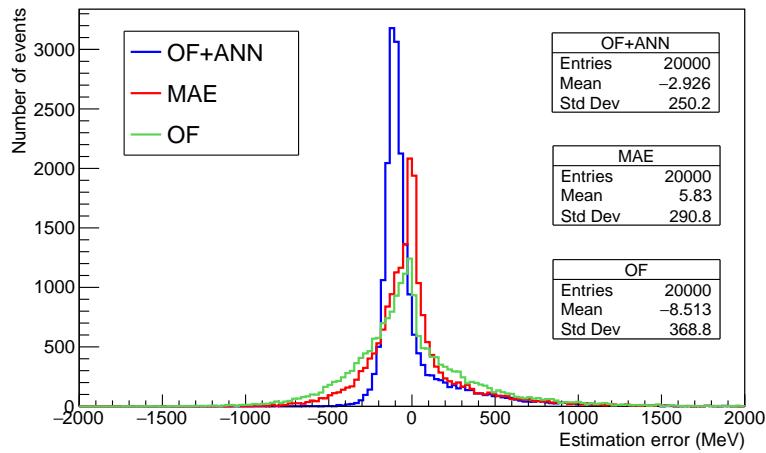


Figure 6- Estimation error for 30% of occupancy.

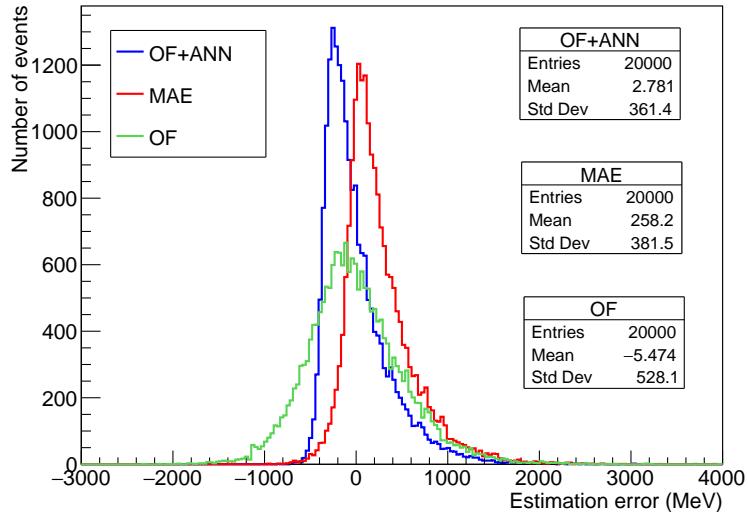


Figure 7- Estimation error for 90% of occupancy.

Table 2- Estimation error (in MeV) from each of the considered methods considering different occupancy levels.

	Occupancy level				
	10%	30%	50%	70%	90%
OF+ANN	159.4	250.2	521.6	349.7	361.4
MAE	213.4	290.8	353.1	374.0	381.5
OF	229.7	368.8	460.6	503.9	528.1

As the OF method does not take into account the pile-up information, its efficiency is significantly degraded in severe pile-up conditions. Also, although the MAE method presents a better efficiency than the OF technique, it is designed for signals within the acquisition window. Therefore, its noise comprises also the pile-up outside the readout window, leading to sub-

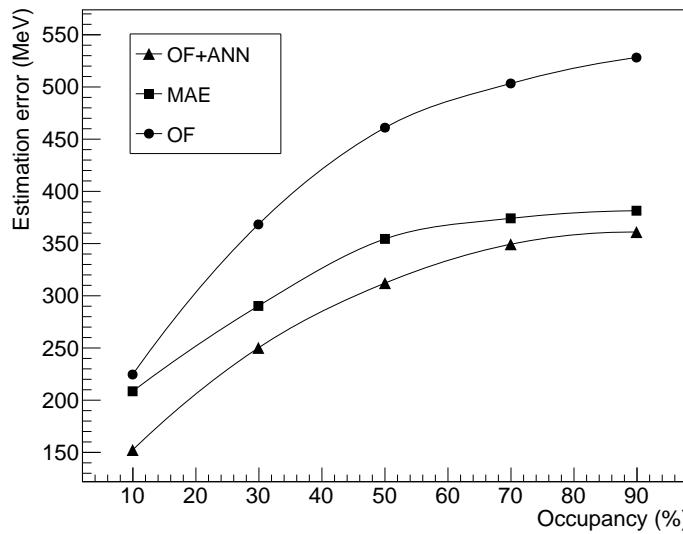


Figure 8- Estimation error as a function of the occupancy level.

optimal operation. Finally, it can be noticed that the combined method outperforms the OF and the MAE methods, showing that the nonlinear correction provided by the ANN considerably improves the linear estimation performed by OF.

5. CONCLUSIONS

This work described different signal processing options to be considered as TileCal energy estimation algorithm for the high-luminosity LHC. The noise in TileCal readout channels changes its description as a function of the signal pile-up intensity (also refers as occupancy), which introduces a nonlinear component to the noise. The current algorithm for energy reconstruction in TileCal, called OF, is based on a variance minimization procedure. As the channel occupancy increases due to the high-luminosity LHC operation, the nongaussian characteristics degrade its efficiency.

Two alternative methods were considered in this work. The Multi-Amplitude Estimator (MAE) estimates the amplitude of the signals within a readout window through an linear deconvolution approach. Although the MAE design is independent from the luminosity value, the signals outside the readout window introduces a pile-up noise in the noise that degrades its performance. The other approach tested in this work uses the current algorithm that is used in TileCal combined with an artificial neural network (OF+ANN) that applies an adjustment to the OF estimate to correct for the nonlinear introduced by the signal pile-up.

The results show that the efficiency of the OF technique is considerably degraded due to the signal pile-up, as expected. In other hand, both alternative methods tested in this work (MAE and OF+ANN) outperformed the OF technique. Compared to the OF method, the improved achieved from the MAE is approximately 30% along the occupancy range while MAE introduces a maximum of 27% of improvement (at 90% of occupancy). Therefore, these results indicate that these promising algorithms are to be considered to operate in TileCal in high-luminosity LHC. The next steps will be focused on evaluating the energy estimation efficiency on real data acquired from the LHC collisions.

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