

Unsupervised Learning for Calorimeter Response Correction: A WGAN-Based Method

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Abstract. The long-term stability of calorimeters is crucial in high-energy physics experiments, where precise energy measurements are essential for accurate particle reconstruction. This study introduces a Wasserstein GAN (WGAN)-based machine learning approach for calibrating calorimeter responses affected by aging and other systematic shifts. Our methodology is applied to realistic, high-granularity calorimeter data that more accurately mimic physical detector conditions. The dataset reflects energy deposition across all calorimeter cells, following an exponential energy spectrum and eliminating artificial peaks in the distribution. By leveraging Wasserstein distance minimization, our model estimates aging coefficients of cells, realigning degraded detector responses with their undamaged counterparts. The results highlight the potential of a data-driven approach for calorimeter calibration, demonstrating correcting energy measurement discrepancies with a reduced number of required events, making it a valuable tool for future detector calibration strategies.

Keywords: Calorimeter · Calibration · Generative Adversarial Networks · Wasserstein GAN

1 Introduction

1.1 Calorimeter

A calorimeter is an essential component in high-energy physics, designed to measure the energy of incoming particles by absorbing their energy and converting it into detectable signals [2,10,13]. These detectors play a crucial role in experiments conducted at facilities like the Large Hadron Collider (LHC) [2] and other major research infrastructures worldwide. By analyzing the energy deposited by particles, calorimeters provide critical insights into particle interactions and properties. Their applications extend beyond high-energy physics to fields such as nuclear reactor monitoring and medical imaging techniques, including radiation therapy [10,13]. Ensuring the accuracy and stability of calorimeter measurements over time is a significant challenge, as detector responses can degrade

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due to radiation exposure, material aging, and environmental effects. Calibration techniques are essential for maintaining precision in energy measurements, compensating for variations across different detector regions, and correcting shifts in response due to operational wear [2,10,13].

1.2 Machine Learning in High-Energy Physics

The integration of machine learning (ML) techniques into high-energy physics (HEP) has significantly advanced our ability to analyze complex particle interactions and fundamental processes [6]. With modern experiments, such as the Large Hadron Collider (LHC) and its upcoming high-luminosity upgrade (HL-LHC), generating vast amounts of data, traditional analysis methods are often insufficient for efficient processing. ML algorithms provide powerful tools for reducing data complexity, identifying patterns, and optimizing event reconstruction and particle classification [7].

Among the ML approaches that are used in HEP are Boosted Decision Trees (BDTs) [8] and Neural Networks (NNs), which have proven to be highly effective in classifying particles and distinguishing between different event types. These methods offer superior performance over conventional techniques by improving classification accuracy and increasing computational efficiency [12].

Another application of ML in HEP is realistic event simulation, which is essential for comparing experimental results with theoretical models. Deep learning architectures, such as Generative Adversarial Networks (GANs) [5] and Variational AutoEncoders (VAEs), have demonstrated their capabilities in generating synthetic particle interactions and modeling detector responses. These generative models not only enhance the precision of simulations but also significantly reduce the computational burden associated with Monte Carlo methods, making large-scale data processing more feasible.

Given the enormous data rates produced in modern experiments, real-time data processing is critical. HEP detectors operate at extreme acquisition speeds, often generating information that exceeds traditional storage capacities. To manage this, ML-powered techniques facilitate data compression, filtering, and zero suppression, allowing for more efficient processing at the hardware level. Integrating edge computing and ML-driven analytics into data center architectures ensures faster decision-making and improved storage efficiency [11].

Another challenge in particle physics is signal-background separation, particularly in environments with high event overlap, a phenomenon known as pile-up. Advanced ML algorithms, such as graph neural networks (GNNs) and adaptive filtering techniques, are now used for pile-up suppression, significantly improving signal clarity and background rejection [9]. These approaches enhance event reconstruction precision, enabling physicists to extract valuable insights from rare physical processes.

We want to expand the role of ML in HEP, by offering data-driven solutions for calorimeter calibration.

1.3 Calorimeter Calibration

Calibrating calorimeters is essential for ensuring the accuracy and reliability of energy measurements. Ideally, all sections of a calorimeter should respond identically when exposed to the same type and energy of particles. However, due to manufacturing differences, construction misalignments, and aging effects, detector responses can vary across different calorimeter cells [10,13]. Ensuring accurate energy measurements in calorimeters requires periodic calibration. Various calibration techniques exist to align responses across detector cells and compensate for systematic deviations. The main approaches include:

1. **Hardware-Based Calibration:** This includes methods like electronic pulse injection to verify response uniformity [10] or the use of radioactive sources and laser signals to establish reference energy levels [13].
2. **Test Beam Calibration:** Dedicated particle beams with known energy levels are directed at the calorimeter to measure and standardize responses [10, 13]
3. **In Situ Calibration:** During active experiments, well-characterized particle interactions, such as decays of W and Z bosons, are used to fine-tune calibration parameters [6,10,13].

Despite these calibration procedures, calorimeters degrade over time due to radiation exposure and other environmental factors. Periodic recalibration is necessary to counteract these effects and maintain accurate energy measurements [10]. The traditional approach to recalibration requires significant experimental resources and can be labor-intensive.

To address these challenges, we developed a machine learning technique that offers a promising alternative. By leveraging deep learning models, it is possible to automate the calibration process, reducing manual intervention and optimizing detector performance [6,12]. Specifically, generative models, such as Wasserstein GANs [3], learn to correct energy misalignment by predicting aging effects.

2 Experimental Data and Simulation Setup

In this study, we employ Monte Carlo simulations using the Geant4 framework [1] to model hadronic showers in a calorimeter. Specifically, we simulate 100,000 single-pion events, each with an energy of 10 GeV. The detector geometry follows a high-granularity configuration, representative of next-generation collider experiments [4]. The simulated calorimeter features a layered sampling structure, where the absorber consists of 20 mm-thick copper plates, while the active detection elements are polystyrene scintillator tiles. These tiles are organized in a 24×24 matrix with a thickness of 5 mm. This setup provides a high level of spatial resolution, allowing precise analysis of energy deposition patterns.

To investigate the impact of detector aging, we introduce synthetic degradation effects into the simulation. This degradation is modeled by assigning a cell-specific aging coefficient A_i, which depends on the cumulative energy absorbed

by each readout channel over the entire dataset. This approach mimics real-world radiation damage, where prolonged exposure leads to a decline in detector sensitivity.

2.1 Defining the Aging Coefficients

The aging coefficient A_i quantifies the extent of response deterioration in each calorimeter cell over time. It represents the discrepancy between the original signal (before damage) and the altered signal (after exposure to aging effects). For a given calorimeter cell i, we define its coefficient as follows:

$$A_i = \frac{E_{\text{undamaged}_i}}{E_{\text{damaged}_i}} \tag{1}$$

where:

1. $E_{\text{undamaged}_i}$ is the reference energy measurement from an unaffected calorimeter.
2. E_{damaged_i} is the recorded energy from the same cell after simulated aging.

An ideal cell, unaffected by aging, will have $A_i = 1$, meaning its response remains unchanged. Conversely, values $A_i < 1$ indicate signal attenuation due to degradation, which necessitates corrective calibration. By estimating these coefficients across all readout channels, our methodology compensates for aging-induced distortions, thereby restoring the accuracy of energy measurements.

2.2 Dataset Structure and Unsupervised Learning Approach

The dataset consists of two distinct groups:

1. Undamaged dataset: Represents energy measurements from a pristine calorimeter.
2. Damaged dataset: Contains data from the same detector after simulated degradation effects have been applied.

Unlike traditional supervised learning tasks, where models learn from labeled inputs, our approach follows an unsupervised paradigm. Since the ground truth aging coefficients are not explicitly provided, the model must infer them directly from the data. This eliminates the need for separate training and testing subsets—both datasets are utilized in full to optimize calibration parameters.

The histograms in Fig. 1 illustrate the changes in energy sum distributions between the undamaged and aged calorimeters. A noticeable shift in these distributions confirms the impact of synthetic degradation effects, emphasizing the need for robust calibration techniques.

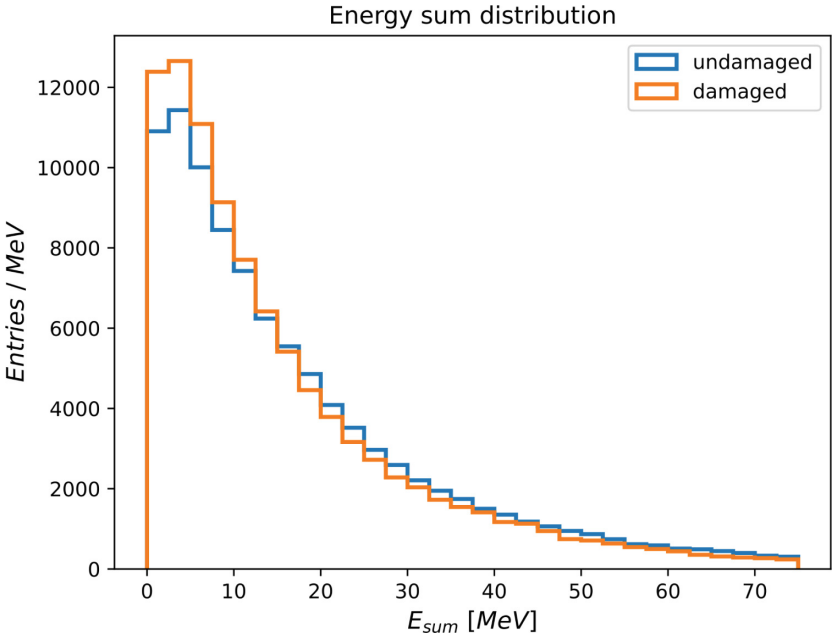


Fig. 1. Comparison of energy sum distributions for undamaged and degraded calorimeters.

2.3 Addressing Radiation Damage in Detector Performance

Over time, prolonged exposure to radiation gradually weakens the detector's response, reducing signal amplitudes in affected regions. This work focuses on correcting signal loss at the individual cell level by leveraging deep learning techniques. By developing a data-driven calibration framework, we aim to extend the operational lifespan of calorimeters, ensuring their long-term reliability in high-energy physics experiments.

3 Generative Adversarial Networks for Calorimeter Calibration

The Wasserstein GAN (WGAN) [3] framework is designed to minimize the Earth Mover's distance (Wasserstein distance) between two data distributions, ensuring a stable and effective learning process. Leveraging this principle, we developed a WGAN-inspired calibration model to predict aging-induced distortions in calorimeter measurements. Instead of generating new data, our approach focuses on distribution alignment, transforming degraded calorimeter readings to match their undamaged counterparts.

In this setup, the Generator learns a mapping function that predicts the aging coefficients for each calorimeter cell. These coefficients, once applied, adjust

the damaged calorimeter's response to restore its original accuracy. The Critic, rather than performing binary classification as in traditional GANs, evaluates the Wasserstein distance between the corrected (synthetic) and undamaged (real) data distributions. The Generator iteratively refines its predictions by minimizing this distance, progressively improving the calibration process.

A detailed schematic of our WGAN-based calibration architecture, including the Generator and Critic components, is depicted in Fig. 2. This framework demonstrates how adversarial learning can be adapted to detector recalibration, improving long-term performance in high-energy physics experiments.

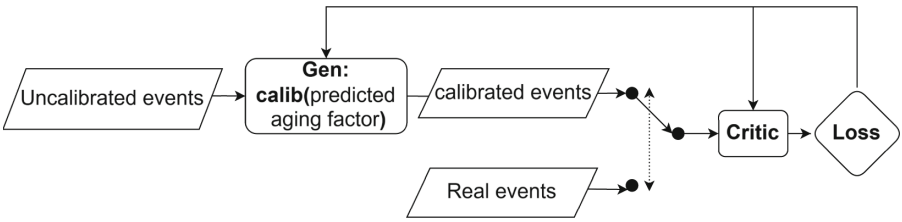


Fig. 2. Architecture of the WGAN-Based calibration model for correcting aging effects in calorimeter data.

4 Results and Discussion

The effectiveness of our WGAN-based calibration approach is demonstrated by the model's ability to estimate aging coefficients and align the damaged calorimeter's response with its undamaged counterpart. Figure 3 presents a scatter plot comparing the predicted and true aging coefficients. The strong correlation between the two, with data points clustering along the diagonal y=x line, confirms the model's capability to learn and approximate the degradation patterns.The overall trend suggests that the model successfully captures the underlying distribution of energy shifts in the calorimeter. The Root Mean Squared Error (RMSE) trend through learning aging coefficients process, shown in Fig. 4, highlights the progressive improvement in prediction accuracy as training progresses. Initially, the RMSE starts above 0.08, but as the number of training epochs increases, the error steadily declines, stabilizing around 0.02 after approximately 60 epochs, with R^2 value of 0.88. This consistent reduction indicates that the model minimizes discrepancies between calibrated data and the undamaged data by tuning aging coefficients parameters that are getting closer to actual aging coefficients, reinforcing its ability to generalize well across different calorimeter regions.

The decreasing RMSE trend underscores the stability of the training process, demonstrating that the WGAN-inspired model refines its predictions. The smooth and monotonic decline in error suggests that the Wasserstein loss function provides reliable gradient updates, leading to aging coefficients estimations.

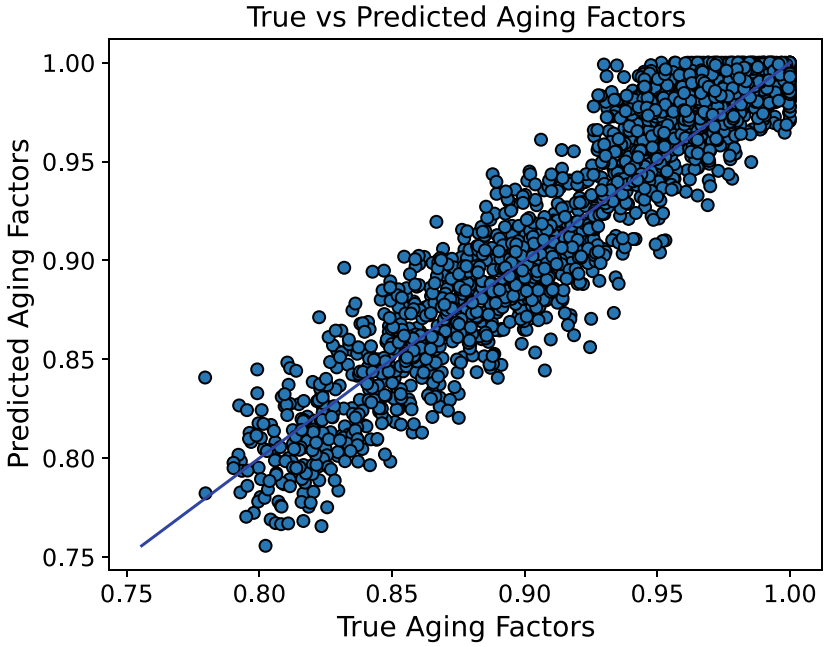


Fig. 3. Scatter plot of true vs. predicted aging coefficients, demonstrating the model's calibration ability.

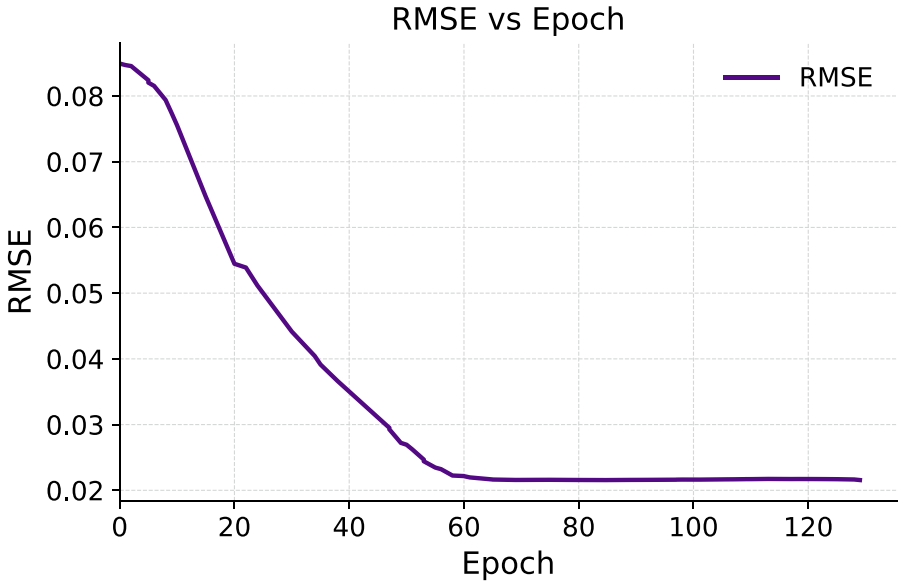


Fig. 4. RMSE versus epochs showing convergence of the model during aging coefficient estimation.

Figure 5 demonstrates the impact of Calibration on Energy Distributions By applying the predicted aging coefficients, the calibrated calorimeter data exhibits improved alignment with the undamaged dataset.

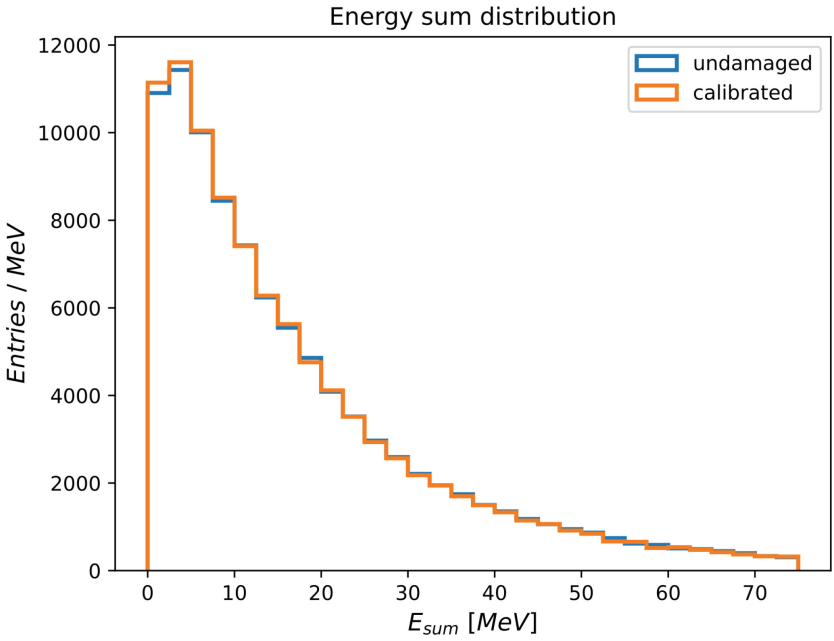


Fig. 5. Energy sum distribution before and after calibration, showing alignment with undamaged data.

5 Conclusion

In this work, we presented a Wasserstein GAN (WGAN)-based approach for calibrating calorimeter responses affected by aging effects. Traditional calibration methods, while effective, require significant manual intervention, computational resources, and repeated experimental procedures. By leveraging deep learning techniques, particularly generative models, we demonstrated a potential data-driven approach that can autonomously learn the aging coefficients to correct energy misalignment in calorimeters.

Our experimental results validate the potential of the proposed model in predicting aging coefficients and realigning energy distributions. The correlation between predicted and true aging factors, as shown in scatter plots Fig. 3, confirms that the model captures detector degradation patterns. Furthermore, the steady decline in Root Mean Squared Error (RMSE) during the learning process highlights the stability of the process. The improved alignment between

calibrated and undamaged calorimeter data further reinforces the model's capability to restore detector accuracy.

This study showcases how machine learning can revolutionize detector calibration in high-energy physics (HEP), offering a scalable and automated alternative to conventional recalibration techniques. By integrating ML-driven solutions, we can enhance the longevity and precision of calorimeters, ensuring that future HEP experiments maintain high-quality data acquisition while minimizing the operational burden of detector maintenance.

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