

LHCF- RECONSTRUCTION OF MULTIPLE CALORIMETRIC CLUSTERS



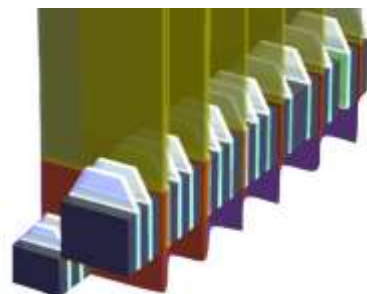
Giuseppe Piparo^{1,2}

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2. Università degli studi di Catania

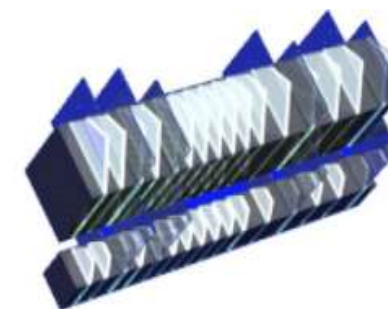
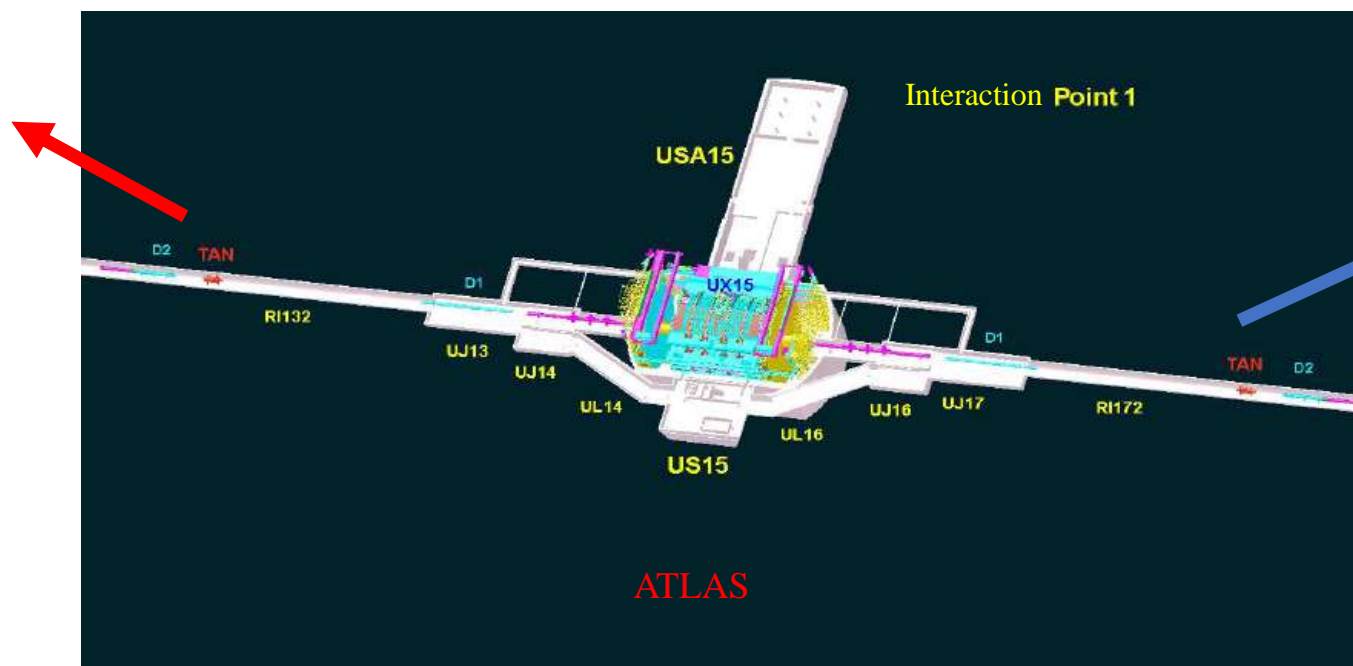


THE LHCf EXPERIMENT

- A **unique experiment** designed to measure neutral particle production in the **forward pseudorapidity region**.
- Composed by two **sampling** and calorimeters (**ARM1** & **ARM2**), located at about ± 141 m from the LHC Interaction Point 1 (IP1).
- The aim of LHCf is to provide experimental data needful to tune and calibrate **hadronic interaction models** widely used by ground-based cosmic ray experiments.



LHCf-ARM2



LHCf-ARM1

THE LHCf DETECTORS

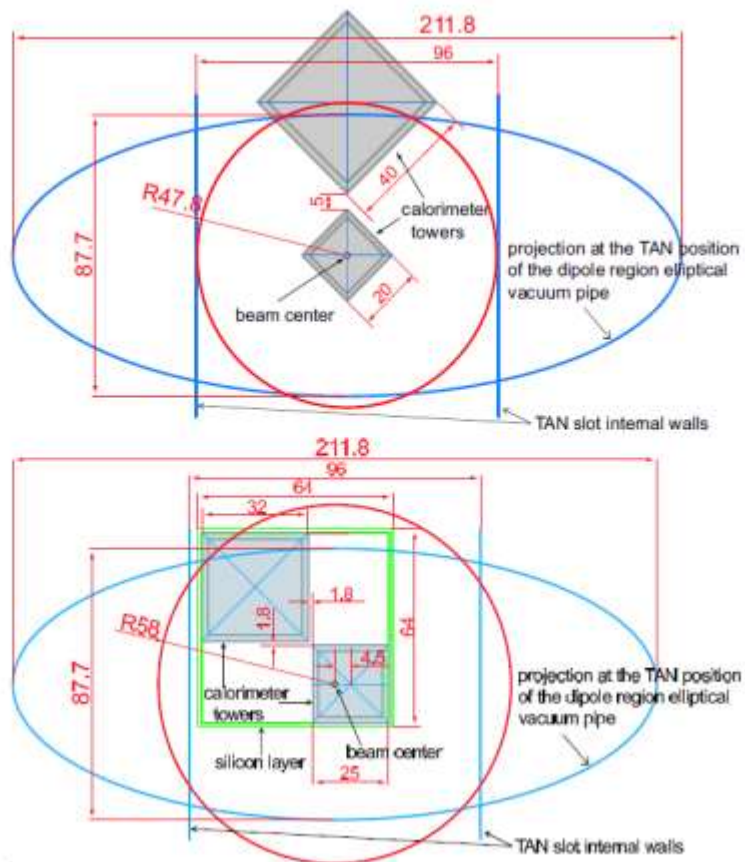
ARM1

- **Energy resolution** <5% for photons and 35-40% for neutrons.
- Tracking with 4 GSO scintilating layers.
- **Position resolution** $\approx 200 \mu\text{m}$.

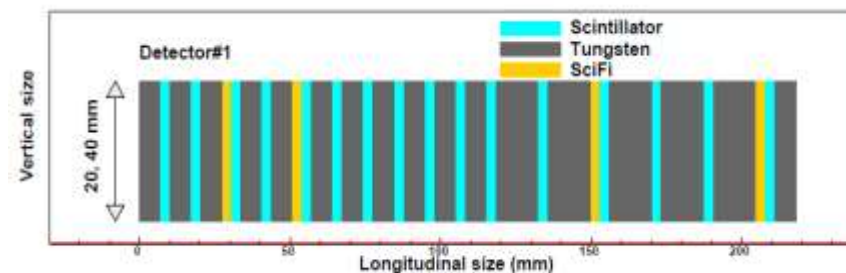
ARM2

- Same Energy resolution as ARM1.
- Tracking with 4 XY **silicon microstrips** layers.
- **Position resolution** $\approx 40 \mu\text{m}$.

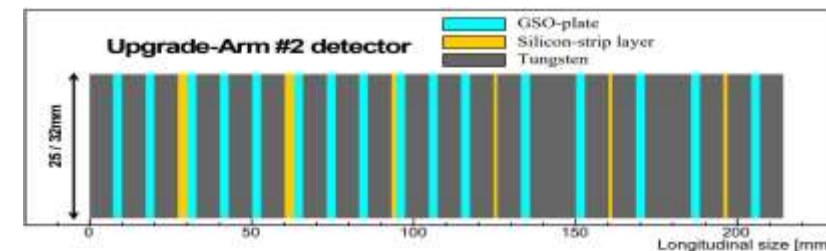
Transversal view



Longitudinal view



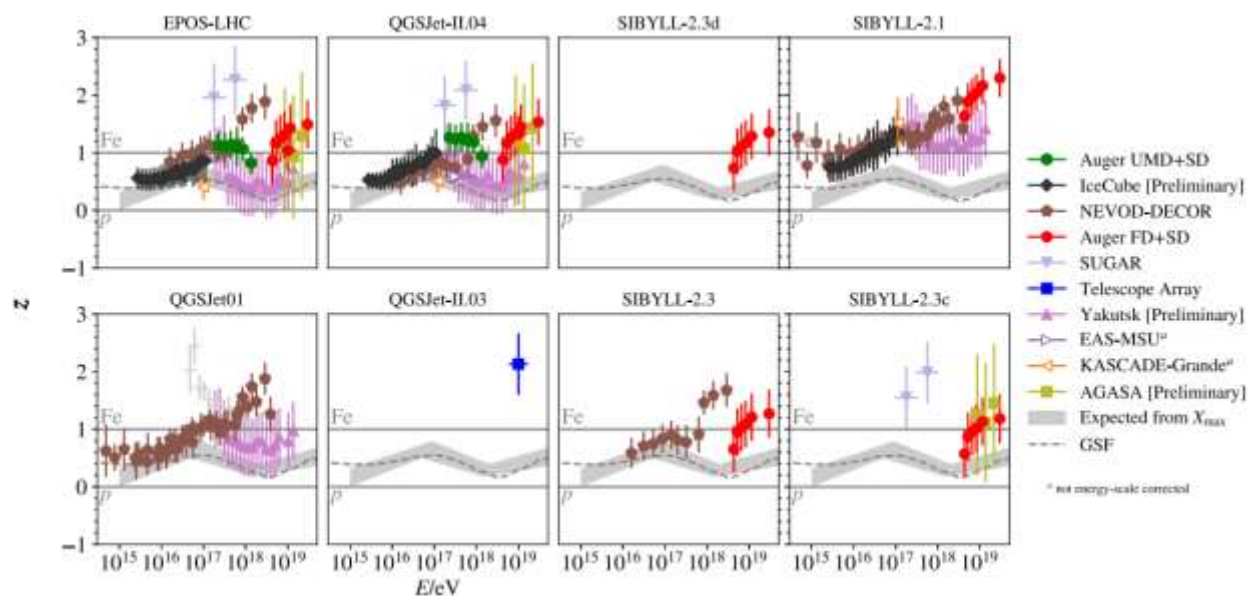
44 X_0 and $1.6 \lambda_I$ deep



EXPERIMENTAL PURPOSE

- The main **hadronic interaction models** (HIM) (like QGSJET, SIBYLL or EPOS) suffer of large discrepancy due to limited understanding of the **soft QCD processes**.
- This is reflected on **large uncertainties** induced in the results of the ground-based cosmic rays experiments, due to the dependency of **air shower modelling** on HIM.
- LHCf provides neutral particles' energy and momentum distributions in the **forward region** to test and calibrate the models.

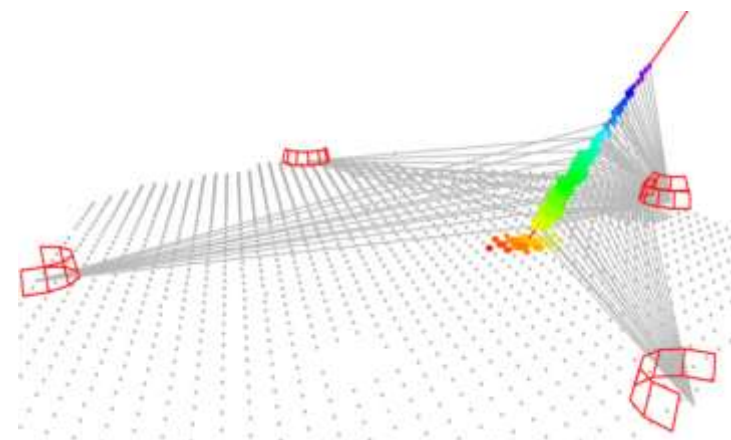
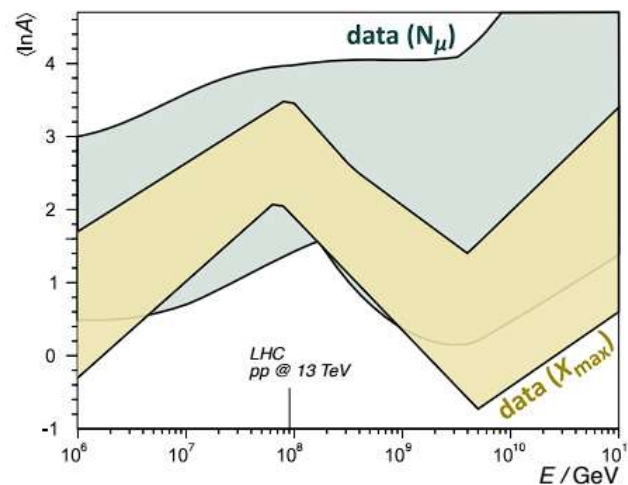
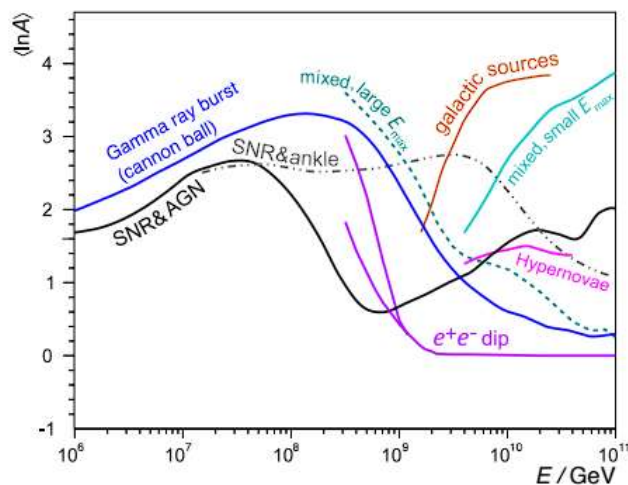
ASS 367, 1 (2022)



EXPERIMENTAL PURPOSE

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- **These informations are essential, since these large uncertainties affect most of the astroparticle experiments!!**

ULTRA-HIGH ENERGY COSMIC RAYS



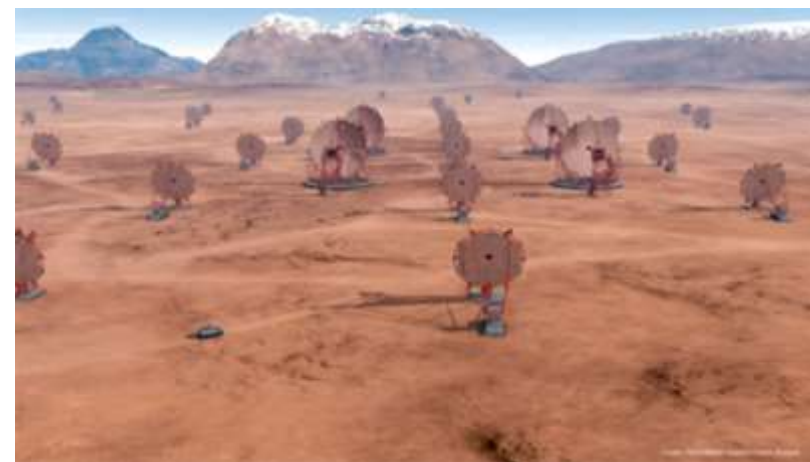
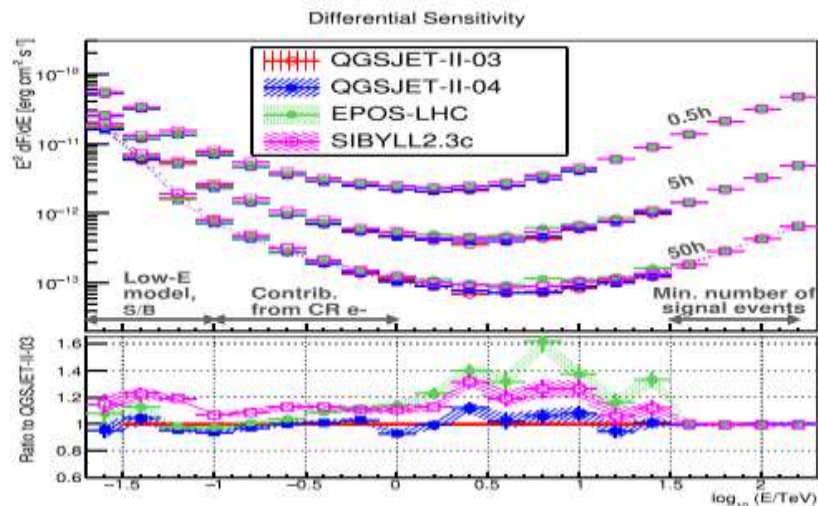
ASS 367, 1 (2022)

EXPERIMENTAL PURPOSE

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HIGH ENERGY GAMMA RAYS

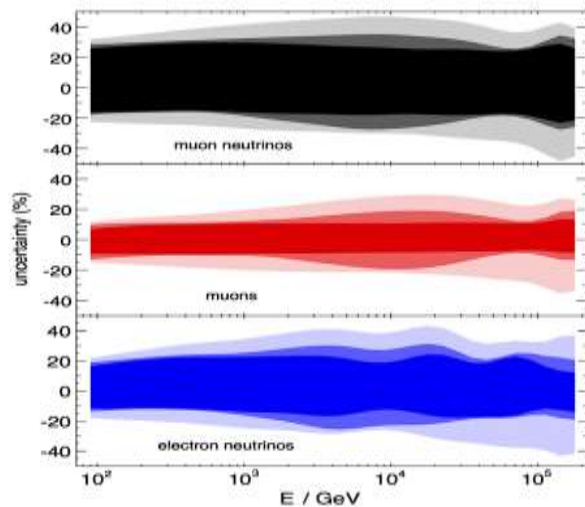
NIMPR Section A: 553,
268 (2005)



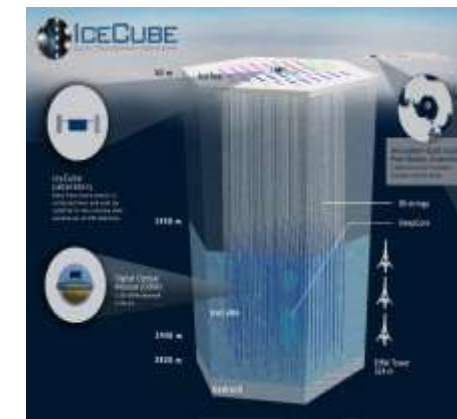
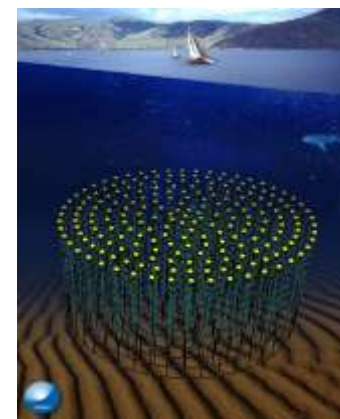
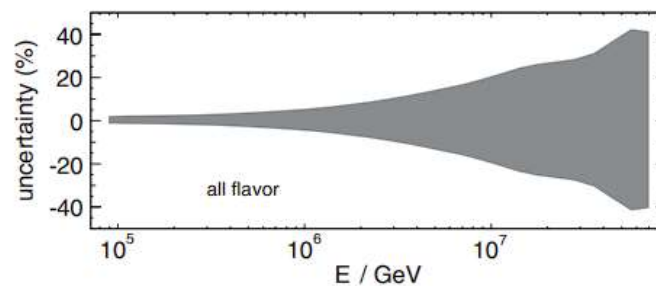
EXPERIMENTAL PURPOSE

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PR D 86, 114024 (2012)



HIGH ENERGY NEUTRINOS





LHCf PUBLICATION TABLE

	γ	neutron	π^0	η^0
Detector Calibration	NIM A, 671, 129 (2012) JINST 12 P03023 (2017)	JINST 9 P03016 (2014)		
p+p 510 GeV (RHICf)	...submitted to PLB		Phys. Rev. Lett. 124, 252501 (2021)	
p+p 900 GeV	Phys. Lett. B 715, 298 (2012)			
p+p 7 TeV	Phys. Lett. B 703, 128 (2011)	Phys. Lett. B 750 (2015) 360-366	Phys. Rev. D 86, 092001 (2012) Phys. Rev. D 94 032007 (2016)	
p+p 2.76 TeV			Phys. Rev. C 89, 065209 (2014)	
p+Pb 5.02TeV			Phys. Rev. D 94 032007 (2016)	
p+p 13 TeV	PLB 780 (2018) 233-239	JHEP 11 (2018) 073 JHEP 07 (2020) 16	Analysis ongoing	Almost complete
p+Pb 8.1TeV	Analysis ongoing			

JHEP 2023, 169 (2023)

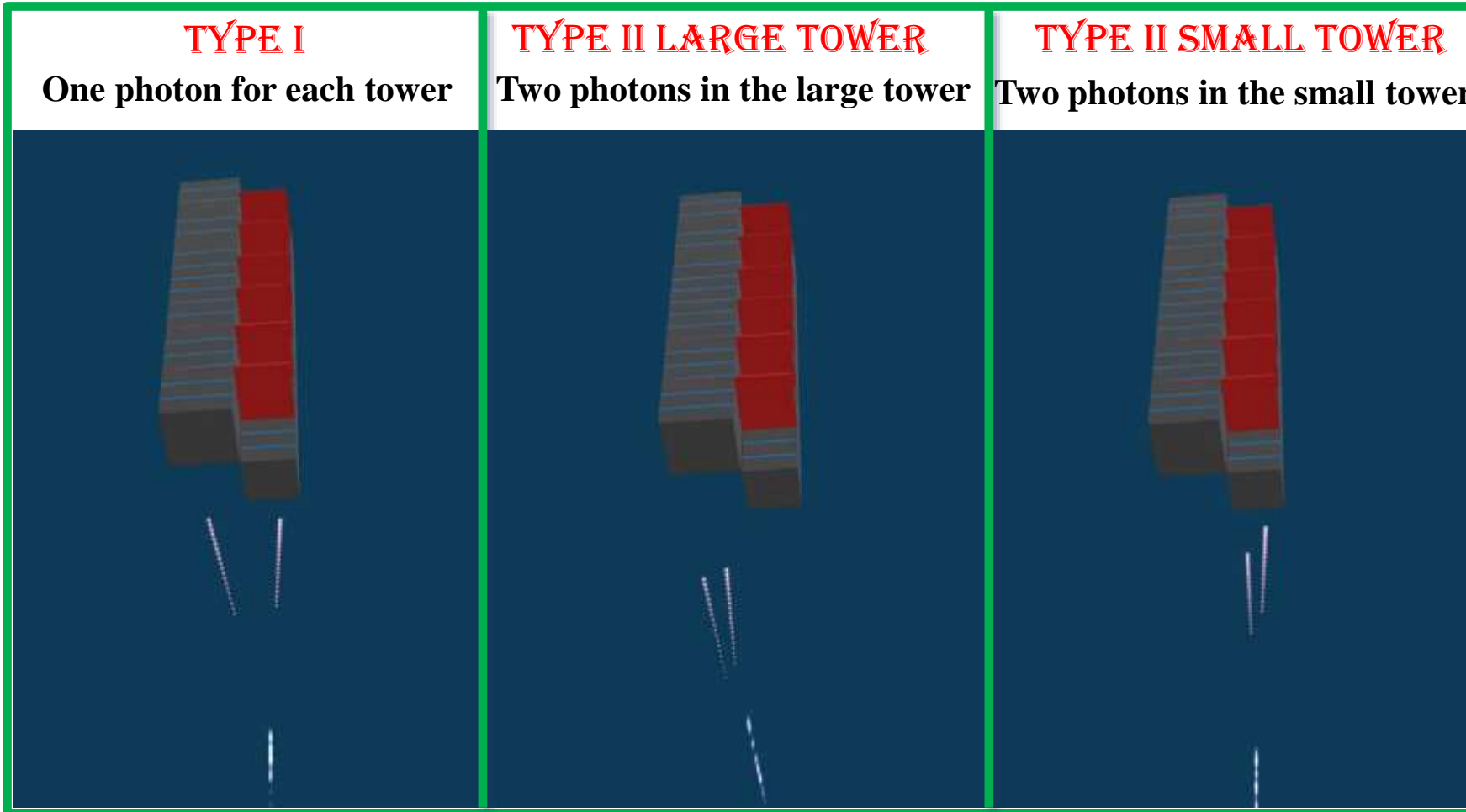


PURPOSE OF THE USE CASE

- In LHCf energy and position are reconstructed using the information of calorimetric and tracking detectors, respectively.
- Performances are good in the case of a single particle hitting the detectors (or better, at least one for each tower).
- **But there is a decrease in performances in the case of two or more particles hitting the calorimetric towers!**
- **The purpose of this Use Case is to develop an ML-based method to improve the reconstruction algorithm of LHCf for multiple calorimetric clusters.**

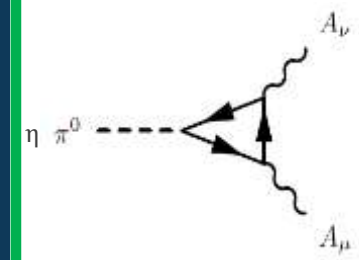
MOTIVATION I: π^0 AND η ANALYSIS

 Scintillator
 Tungsten
 Silicon



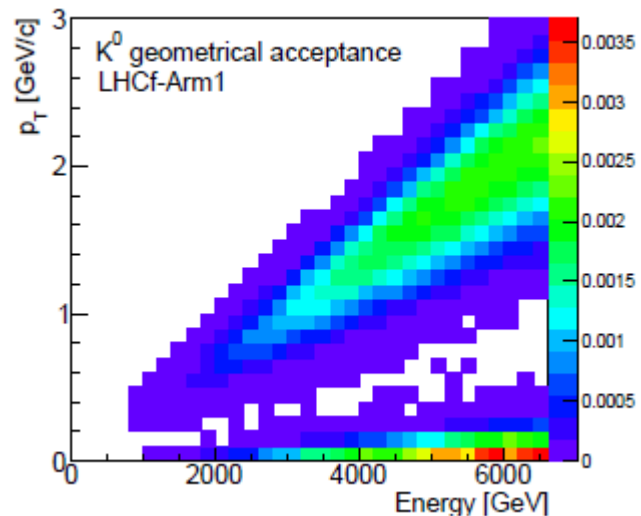
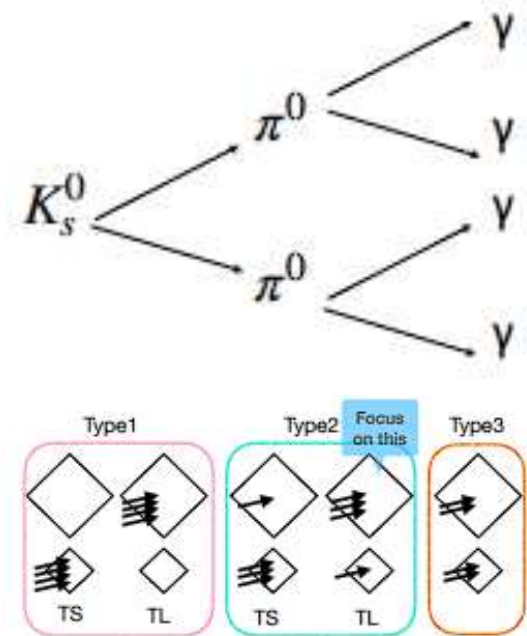
π^0 AND η DECAY

- Both particles decay mainly into **two photons**.
 $\eta/\pi^0 \rightarrow \gamma\gamma$
- Branching ratio in the case of π^0 is about **98.82%**.
- In the case of η is about **39.36%**.

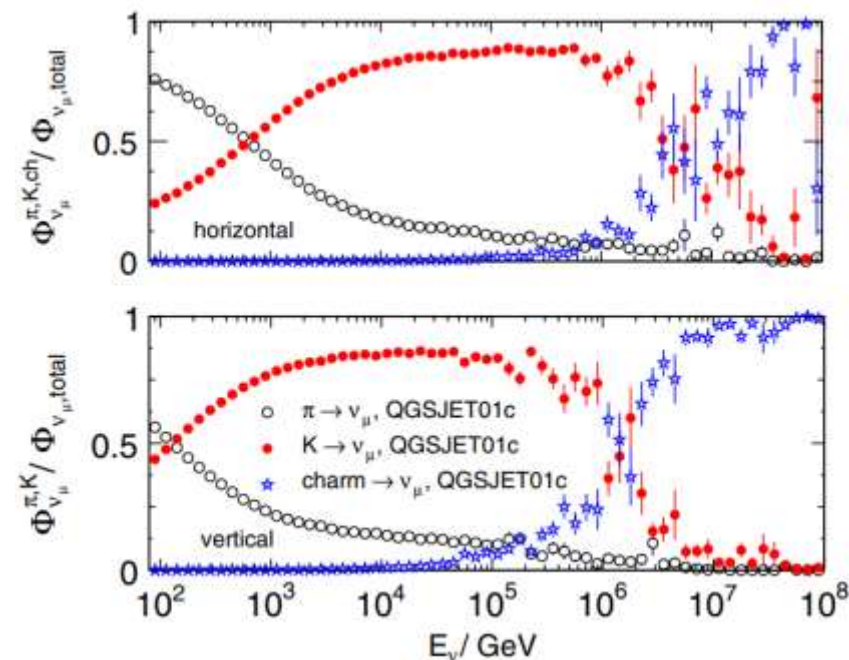


MOTIVATION II: K^0 ANALYSIS

K^0 detection in LHCf



K mesons as main source of TeV-PeV atmospheric neutrinos



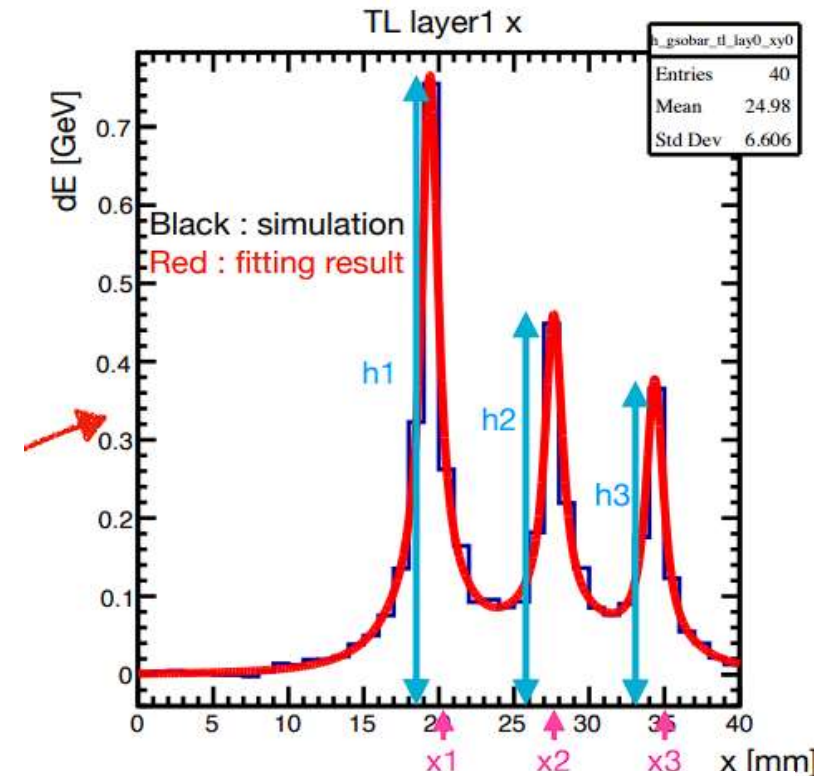
In this case, it's necessary to reconstruct at least three calorimetric hits!

NEW ENERGY SHARING METHOD FOR MULTI-HIT EVENTS



- To reconstruct the position of hitting particles, we use the transversal profile of tracking detectors, by finding the peaks using TSpectrum and fitting them with a 3-component Lorentzian function for each peak.
- The current energy-sharing method uses the ratio of peak heights for each particle to share the energy.
- this work aims to find an **alternative method** to share the energy between multi-hit particles. This will be performed using **Machine Learning techniques**.
- For the moment, two methods were tested based on **Boosted Decision Trees (BDT)** and **Deep Neural Networks (DNN)**, using 2 and 3 hit test datasets based on QGSJET II-04 full simulation of Arm2 events.
- To evaluate the performances, we used the metric **root mean squared error (rmse)** between true and predicted results.

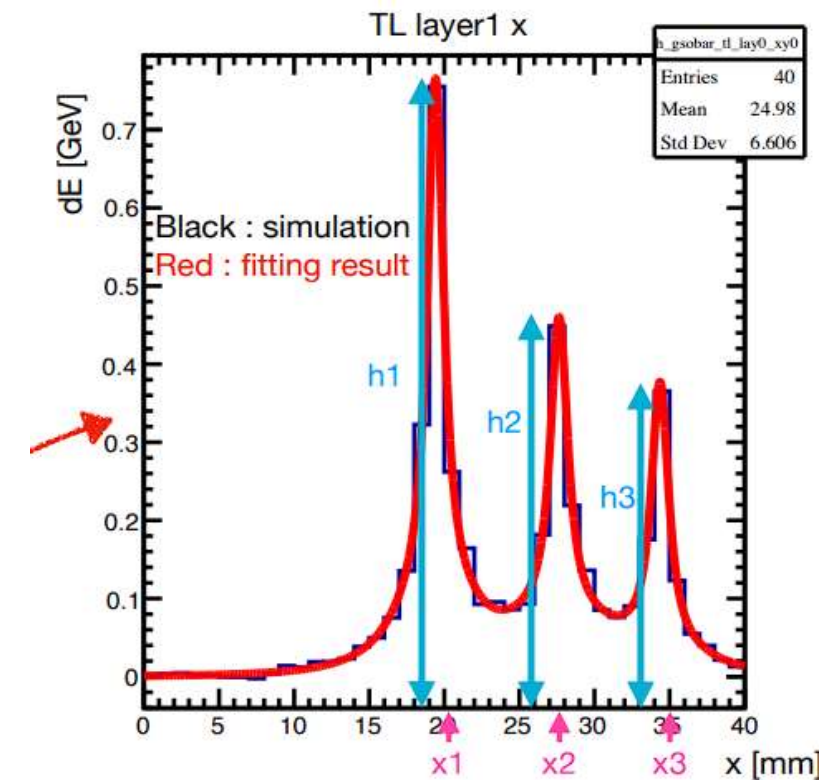
An example of transverse profile with 3 clusters



$$f(x) = p_0 \left[\frac{p_2}{\frac{(x-p_1)^2}{p_3} + p_3} + \frac{p_4}{\frac{(x-p_1)^2}{p_5} + p_5} + \frac{1-p_2-p_4}{\frac{(x-p_1)^2}{p_6} + p_6} \right]$$

3-components Lorentzian function

An example of transverse profile with 3 clusters



$$f(x) = p_0 \left[\frac{p_2}{\frac{(x-p_1)^2}{p_3} + p_3} + \frac{p_4}{\frac{(x-p_1)^2}{p_5} + p_5} + \frac{1 - p_2 - p_4}{\frac{(x-p_1)^2}{p_6} + p_6} \right]$$

3-components Lorentzian function

- To make inferences on energies of multi-hit events (2 and 3 hit for each tower) we used as input for the BDTs and DNN **the fit results of the silicon transverse profile**.
- Currently, the analysis has been carried out using **only photons** for simplicity. Two separate analyses were carried out for 2- and 3-hit events
- In particular, the fit parameters for **each particle** (2 or 3) for **each view** (x and y) for the first two **silicon plane pairs** were used as input variables (56 and 84 inputs for 2 and 3 particles, respectively).
- Different models were constructed and trained for **each tower**.

GRADIENT BOOSTING DECISION TREES (XGBOOST)

- The inference of single photon energies was performed using **2 (3) separated XGBoost models**, one for each particle of the event.
- Predicted energies were corrected to consider the constraint $E_1 + E_2(+ E_3) = E_{tot}$. Each energy is multiplied for the ratio between the sum of predicted energies and the total energy.
- **It is not the most orthodox method but gives good results**
- Hyper-parameters of the 2 (3) models are optimized by using the **Optuna library**, a package based on the **Bayesian optimization** (less effective, but also less resource/time-consuming with respect to grid-search)

DEEP NEURAL NETWORK (TENSORFLOW+KERAS)

- In this case, a single model was developed, **able to predict the 2 (3) energies at the same time.**
- Using the **softmax output layer** it was possible to obtain a prediction that respect the $E_1 + E_2(+ E_3) = E_{tot}$ constraint by default. In this case, the model directly predict the **percentage of energy** for each particle.
- **It is an orthodox method but actually gives worst results.**
- Hyper-parameters of the model are not currently optimized. A first test was performed by using a 5 hidden layer model with 256-128-64-32-16 neurons.
- To limit the overfitting a **dropout rate of 10%** for each layer was considered.


```
def objective_E1(trial):  
    # Definizione dello spazio dei parametri per E1_tow1_mc  
    param = {  
        'lambda': trial.suggest_loguniform('lambda', 1e-8, 10.0),  
        'alpha': trial.suggest_loguniform('alpha', 1e-8, 10.0),  
        'colsample_bytree': trial.suggest_float('colsample_bytree', 0.1, 1),  
        'subsample': trial.suggest_float('subsample', 0.1, 1),  
        'learning_rate': trial.suggest_float('learning_rate', 0.01, 0.3),  
        'n_estimators': trial.suggest_int('n_estimators', 100, 10000),  
        'max_depth': trial.suggest_int('max_depth', 3, 20),  
        'min_child_weight': trial.suggest_int('min_child_weight', 0, 10),  
        'objective': 'reg:squarederror'  
    }  
    model = xgb.XGBRegressor(**param, missing=np.inf)  
    model.fit(X_train, Y_train.iloc[:, 0]) # E1_tow1_mc  
    preds = model.predict(X_test)  
    rmse = np.sqrt(mean_squared_error(Y_test.iloc[:, 0], preds))  
    return rmse
```

Typical values of the number of weak learners are always very high and near to the maximum limit



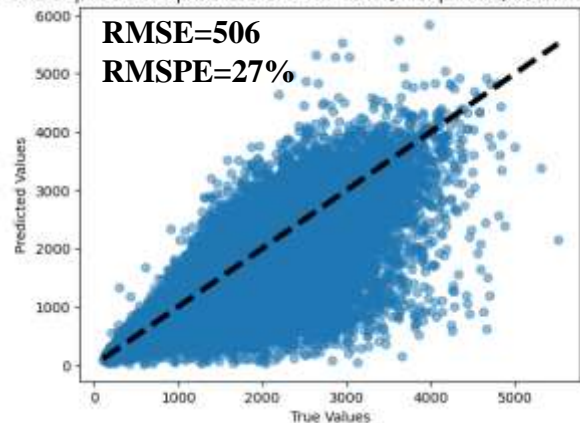
RESULTS FOR TWO PHOTONS ON SMALL TOWER

$N_{train}=66547$

$N_{test}=66547$

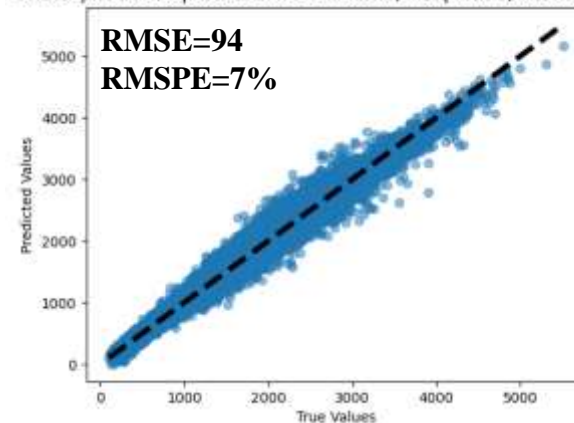
BASELINE

Scatter plot true vs predicted for Small Tower, first particle, Baseline Method



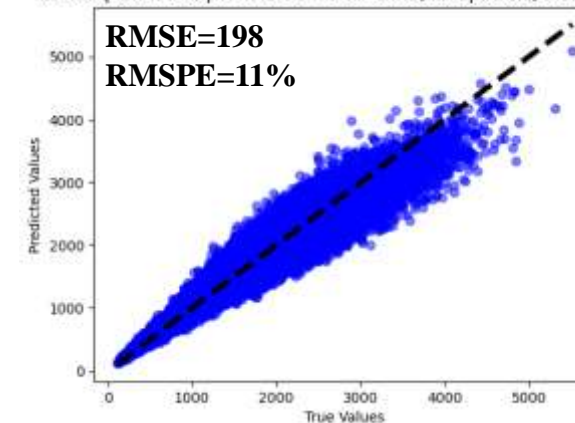
XGBOOST

Scatter plot true vs predicted for Small Tower, first particle, XGBoost Method



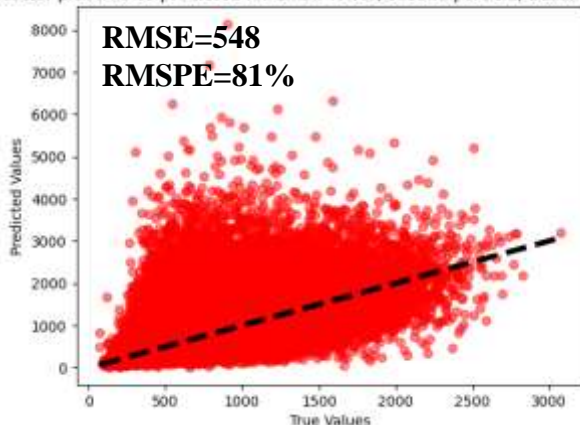
DNN

Scatter plot true vs predicted for Small Tower, first particle, DNN Method

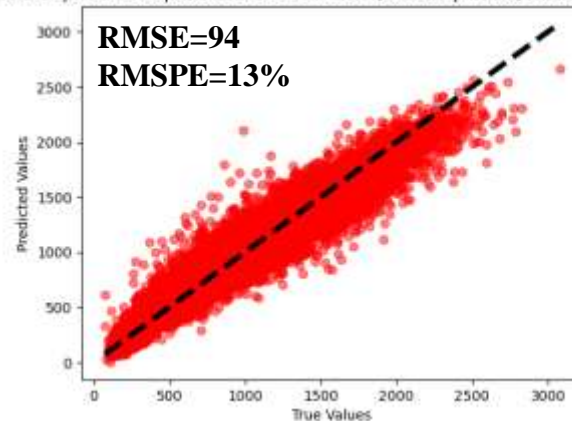


1° PHOTON

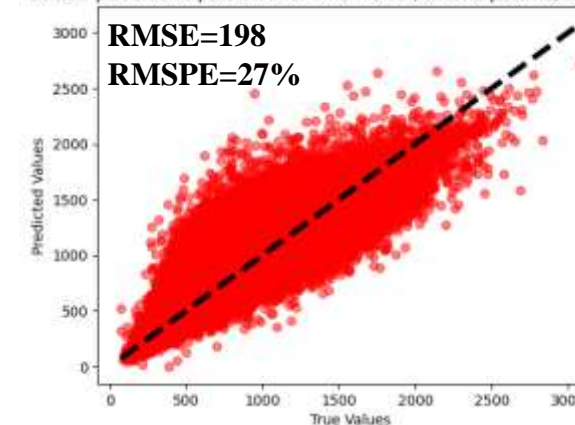
Scatter plot true vs predicted for Small Tower, second particle, Baseline Method



Scatter plot true vs predicted for Small Tower, second particle, XGBoost Method



Scatter plot true vs predicted for Small Tower, second particle, DNN Method



2° PHOTON

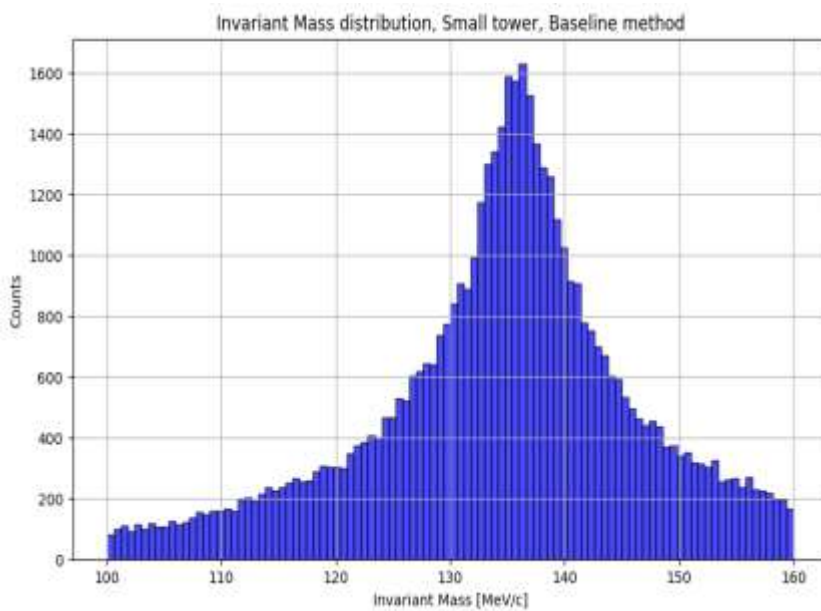


RESULTS FOR TWO PHOTONS ON SMALL TOWER

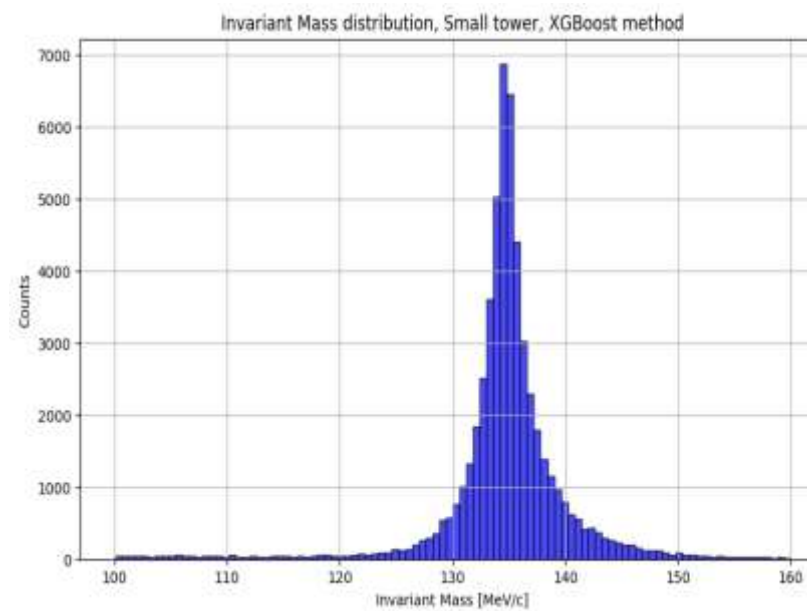
$N_{train}=66547$

$N_{test}=66547$

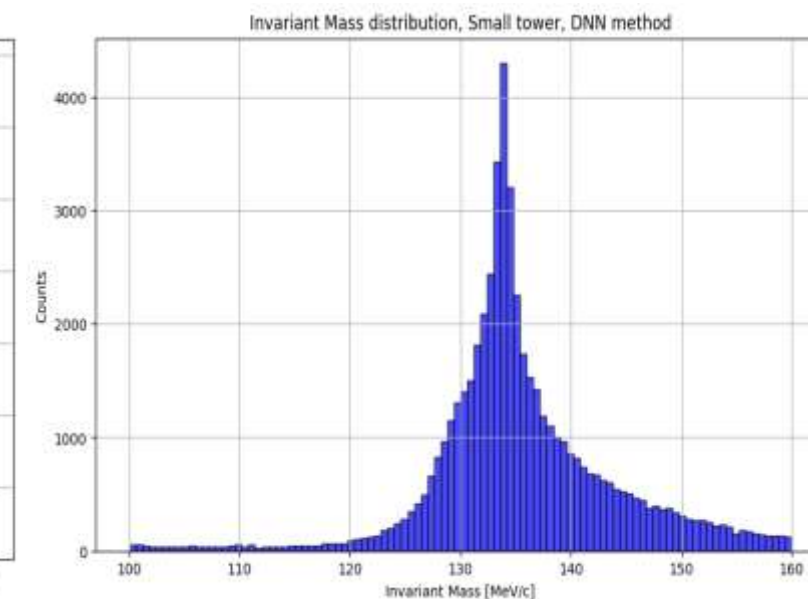
BASELINE



XGBOOST



DNN





RESULTS FOR TWO PHOTONS ON LARGE TOWER

$N_{train}=29992$

$N_{test}=29992$

BASELINE

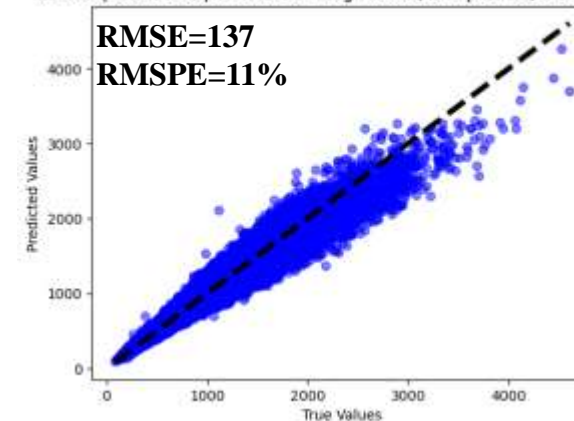
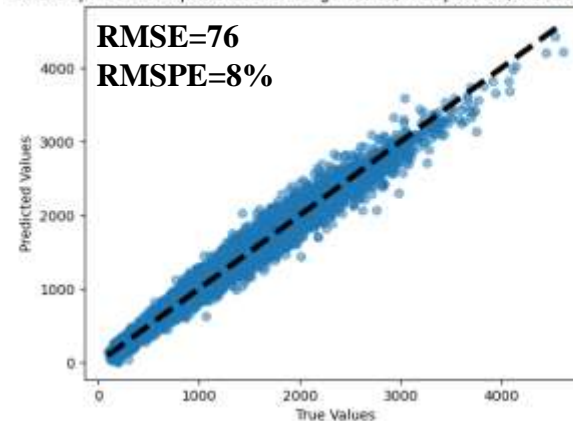
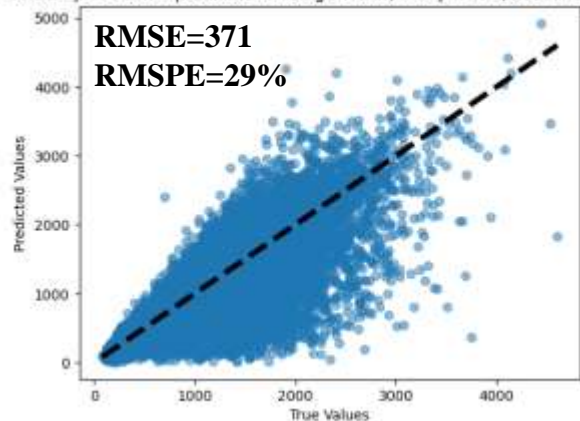
XGBOOST

DNN

Scatter plot true vs predicted for Large Tower, first particle, Baseline Method

Scatter plot true vs predicted for Large Tower, first particle, XGBoost Method

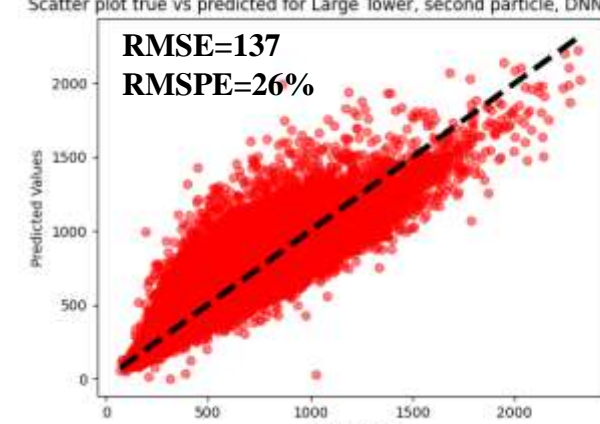
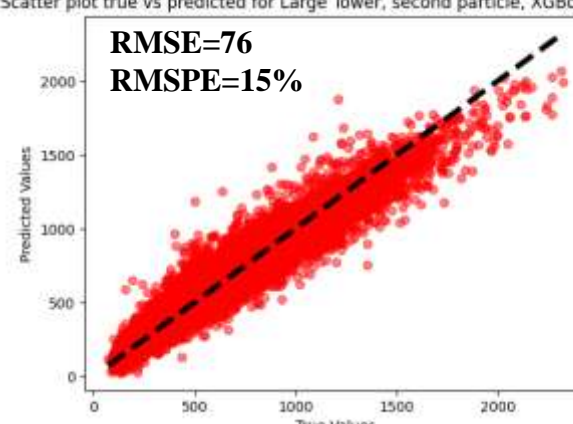
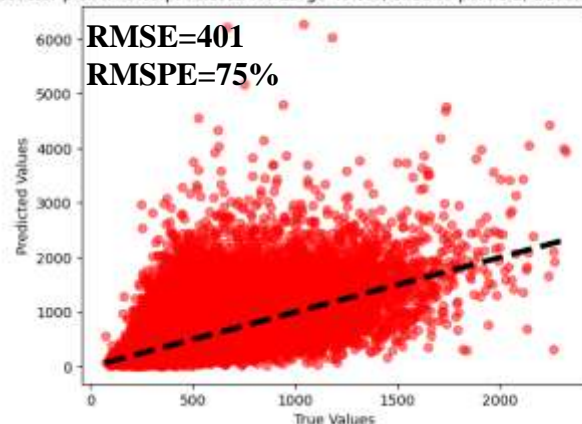
Scatter plot true vs predicted for Large Tower, first particle, DNN Method



Scatter plot true vs predicted for Large Tower, second particle, Baseline Method

Scatter plot true vs predicted for Large Tower, second particle, XGBoost Method

Scatter plot true vs predicted for Large Tower, second particle, DNN Method



1° PHOTON

2° PHOTON



RESULTS FOR TWO PHOTONS ON LARGE TOWER

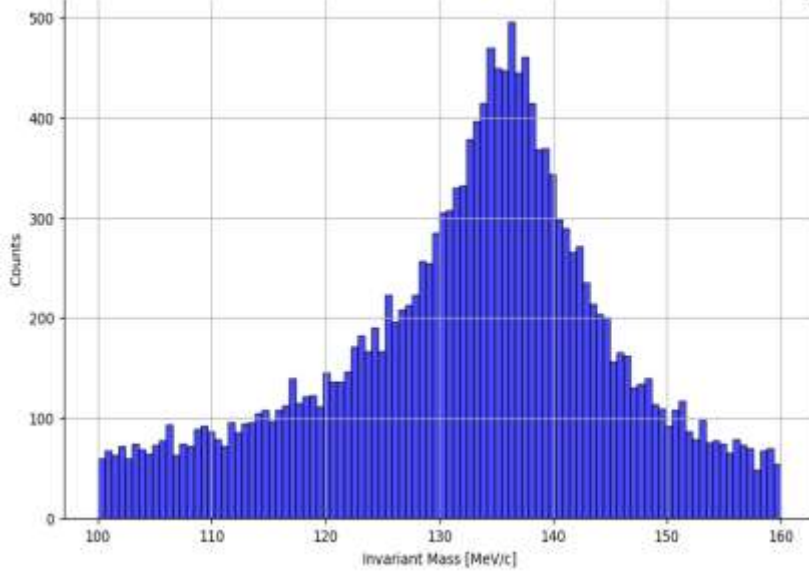
$N_{train}=29992$
 $N_{test}=29992$

BASELINE

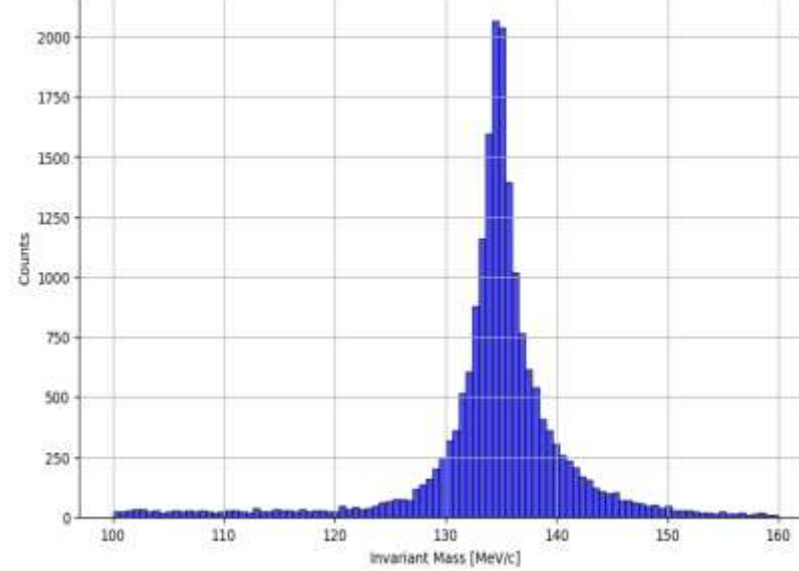
XGBOOST

DNN

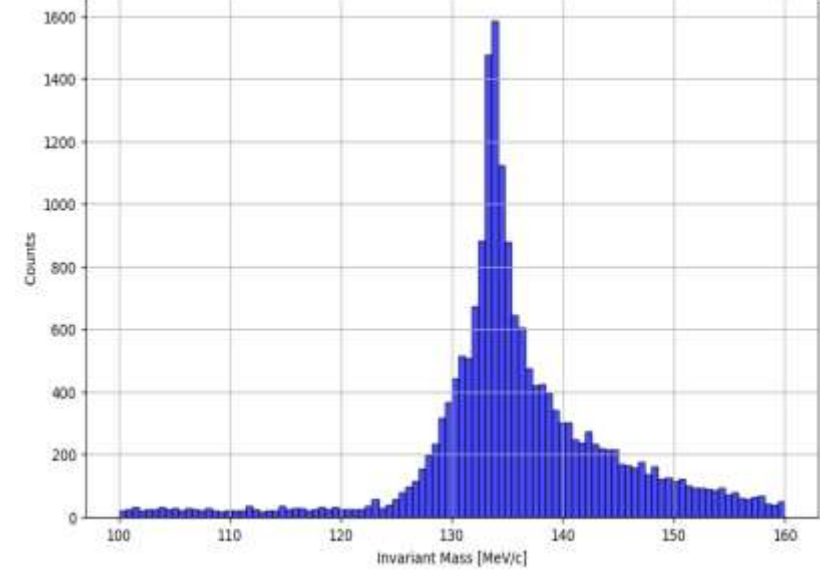
Invariant Mass distribution, Large tower, Baseline method



Invariant Mass distribution, Large tower, XGBoost method



Invariant Mass distribution, Large tower, DNN method





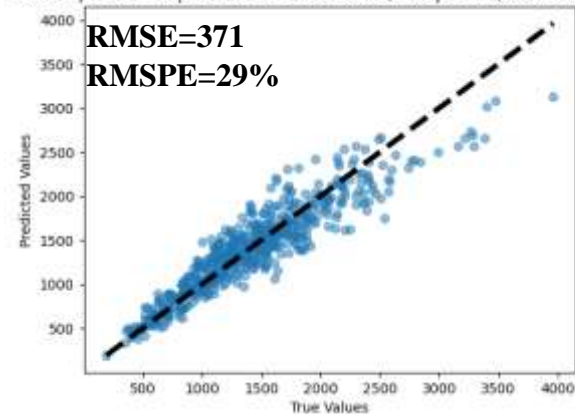
RESULTS FOR THREE PHOTONS ON SMALL TOWER

$N_{train}=567$

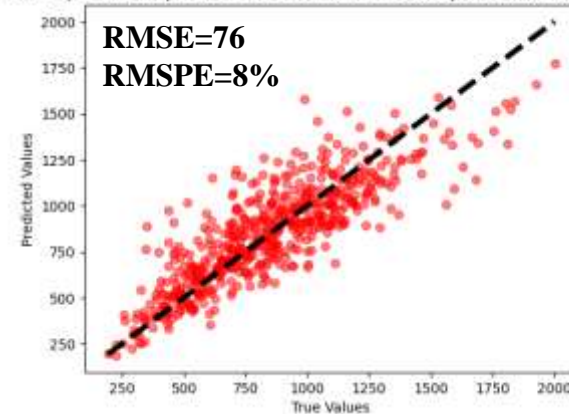
$N_{test}=567$

XGBOOST

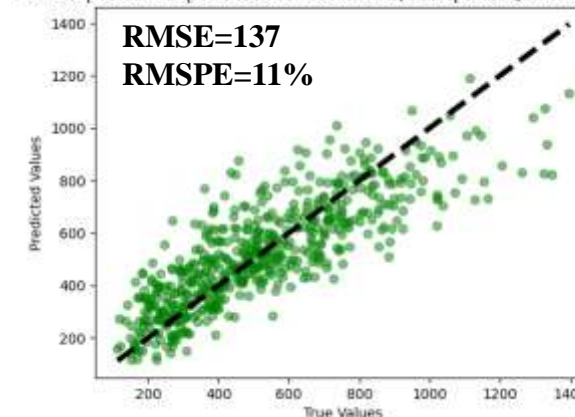
Scatter plot true vs predicted for Small Tower, first particle, XGBoost Method



Scatter plot true vs predicted for Small Tower, second particle, XGBoost Method

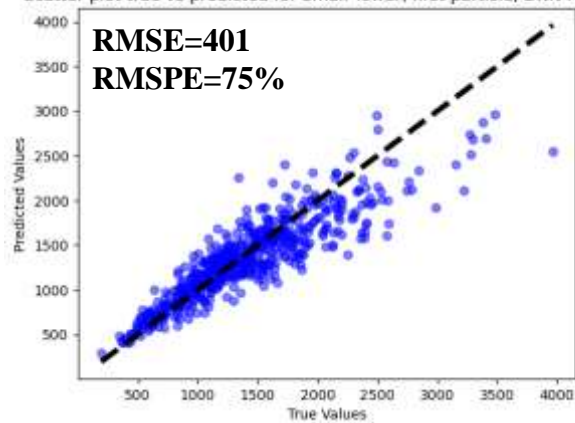


Scatter plot true vs predicted for Small Tower, third particle, XGBoost Method

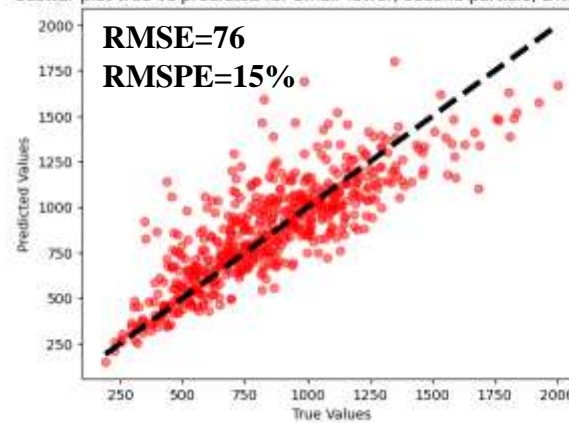


DNN

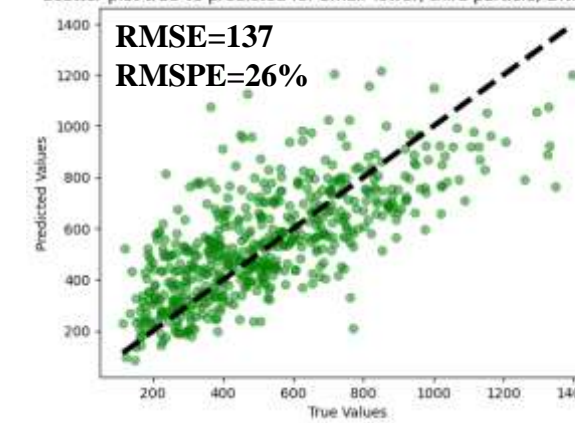
Scatter plot true vs predicted for Small Tower, first particle, DNN Method



Scatter plot true vs predicted for Small Tower, second particle, DNN Method



Scatter plot true vs predicted for Small Tower, third particle, DNN Method





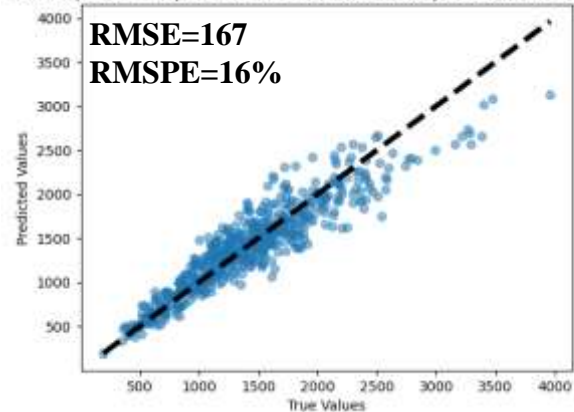
RESULTS FOR THREE PHOTONS ON LARGE TOWER

$N_{train}=381$

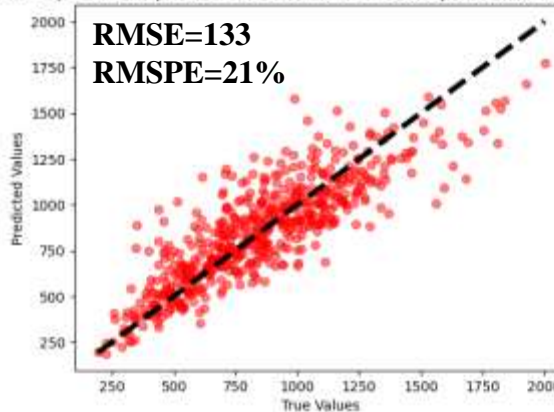
$N_{test}=381$

XGBOOST

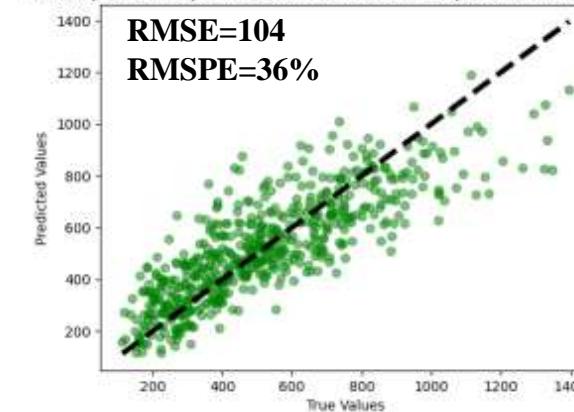
Scatter plot true vs predicted for Small Tower, first particle, XGBoost Method



Scatter plot true vs predicted for Small Tower, second particle, XGBoost Method

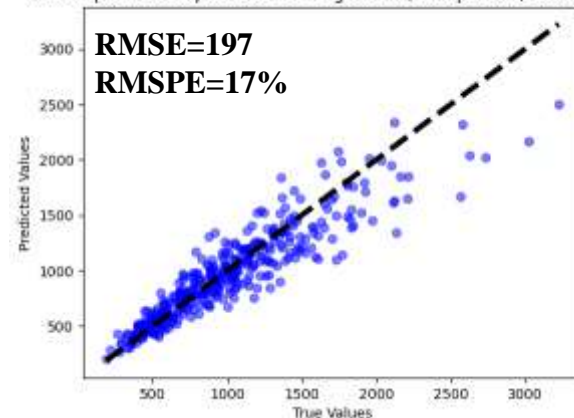


Scatter plot true vs predicted for Small Tower, third particle, XGBoost Method

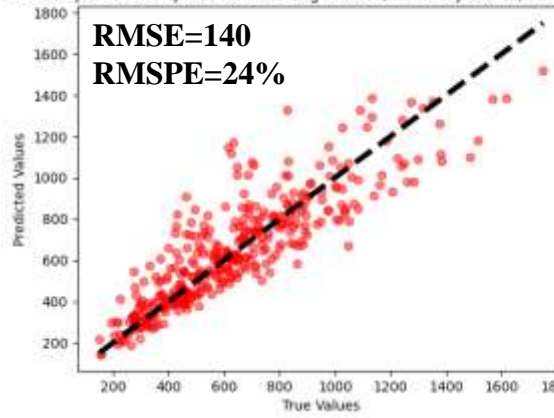


DNN

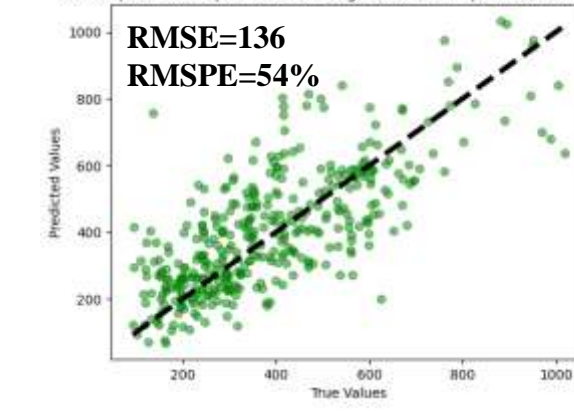
Scatter plot true vs predicted for Large Tower, first particle, DNN Method



Scatter plot true vs predicted for Large Tower, second particle, DNN Method



Scatter plot true vs predicted for Large Tower, third particle, DNN Method



NEXT STEPS

- A first step forward should be the **increase of the statistics, especially for 3-hit events**. This will permit us to obtain better results and to validate them better (k-Folding).
- It could be a good idea to test new input features, such as the **energy deposits** in the calorimetric layers.
- Also, a **better understanding of the methodology and possible improvements could be required** (Suggestions by all of you are very welcome!).
- A **deeper optimization phase** could be helpful to improve the performances of the models.
- Finally, it will be necessary **to validate the future official results with other datasets**, for example, based on other models, like the one already simulated with EPOS-LHC as the generator.

THANK YOU FOR THE ATTENTION

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2. Università degli studi di Catania