Angular Conditioning of Generative Models for Fast Calorimeter Shower Simulation

Erik Buhmann, Sascha Diefenbacher, Engin Eren, Frank Gaede, Daniel Hundhausen, Gregor Kasieczka, William Korcari, Anatolii Korol, Katja Krüger, **Peter McKeown[1]**, Lennart Rustige

[1] Deutsches Elektronen-Synchrotron

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peter.mckeown@desy.de

Outline

1 **The ILD detector at the ILC**

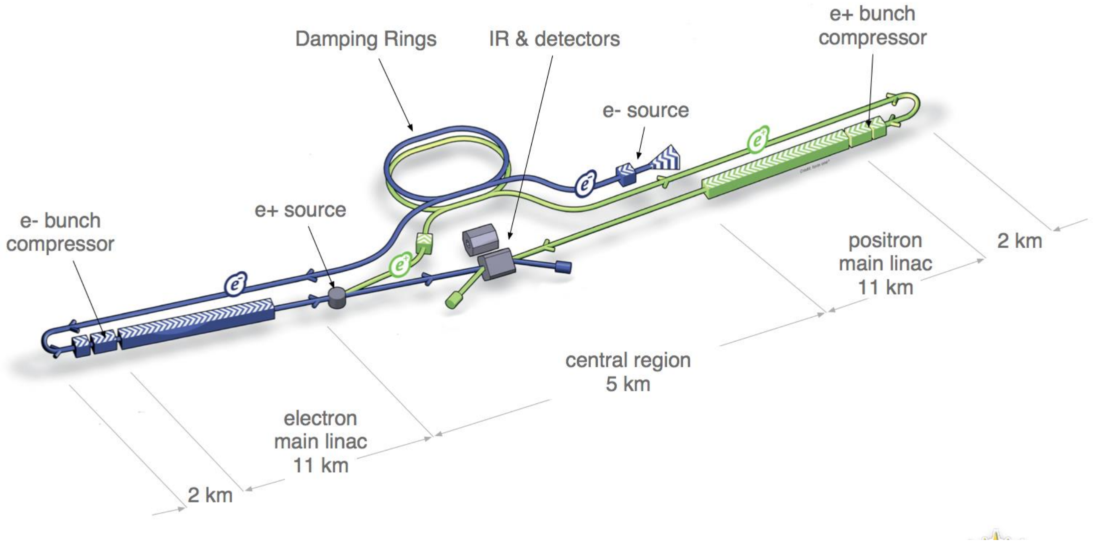
2 **Generative Models**
- Conditioning Generative Models
- Bounded-Information Bottleneck Autoencoder

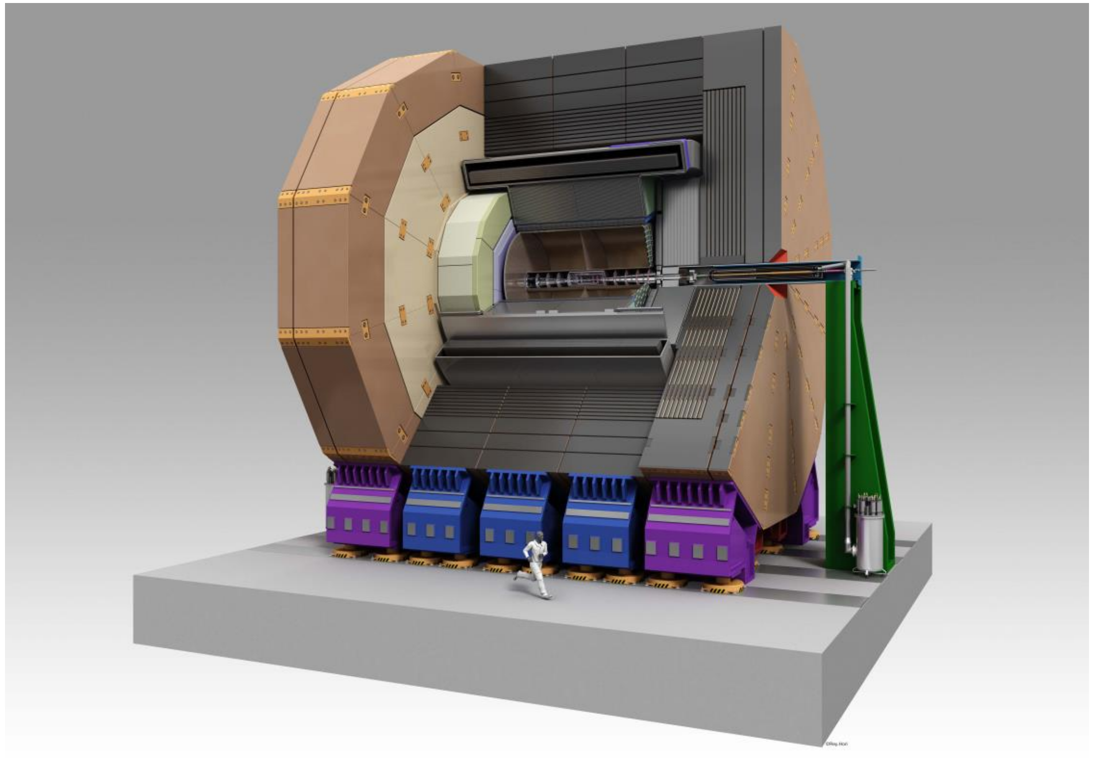
3 **Training and Validation Data**

4 **Angular and Energy Conditioning Efforts**
- Intermediate results

The ILD Concept

- International Large Detector (ILD) concept for the International Linear Collider (ILC)
  - Higgs Factory (initial 250 GeV stage)
  - High energy e^+e^- linear collider
- Optimized for Particle Flow
  - Reconstruct each individual particle in subdetector
  - Obtain optimal detector resolution
- Key features:
  - Precise tracking and vertexing
  - Excellent hermeticity
  - **High granularity calorimeters**





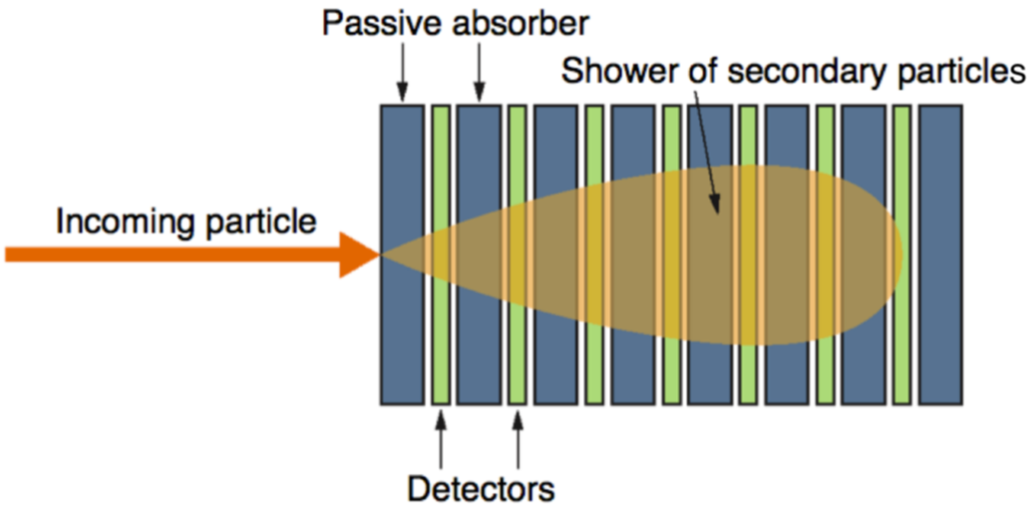
The ILD Electromagnetic Calorimeter

- Destructively measure particle's energy
  - Produce shower of secondary particles until totally absorbed

- Sampling calorimeter- measure fraction of energy

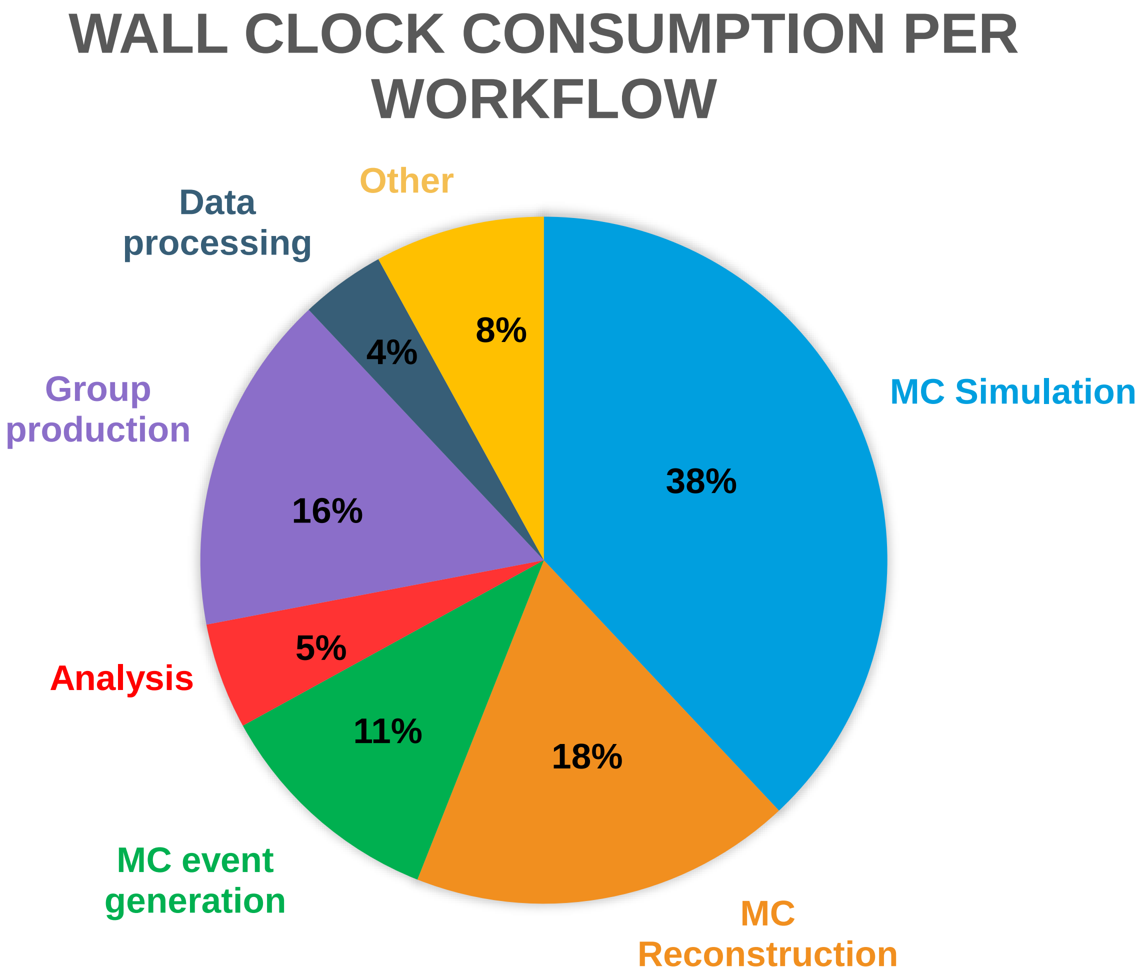
- ILD proposal: Si-W ECAL
  - 30 layers of alternating active (Si) and passive (W) material
  - 20 layers: 2.1 mm thick absorber
  - 10 layers 4.2 mm thick absorber
  - 5x5 mm^2 silicon cells
  - ~ 80 million channels for barrel

- High granularity → **High fidelity**



The Strain on HEP Computing Resources

- Ever increasing demand for computing resources
  - MC simulation largest fraction
  - Calorimeters most intensive part of detector simulation
- Projected computing resources required far outstrip what will be available
  - E.g HL-LHC
- Future lepton colliders also benefit from much faster MC
- **Generative models** potentially offer orders of magnitude speed up



D. Costanzo, J. Catmore, ATLAS Computing update, LHCC meeting , 2019

Generative Models

- Approach to fast simulation- **amplify statistics**
- Promising solution: **generative models**
  - Generate new samples following the distribution of original data
  - Map random noise to data
  - Highly parallelizable
  - **Conditioning**

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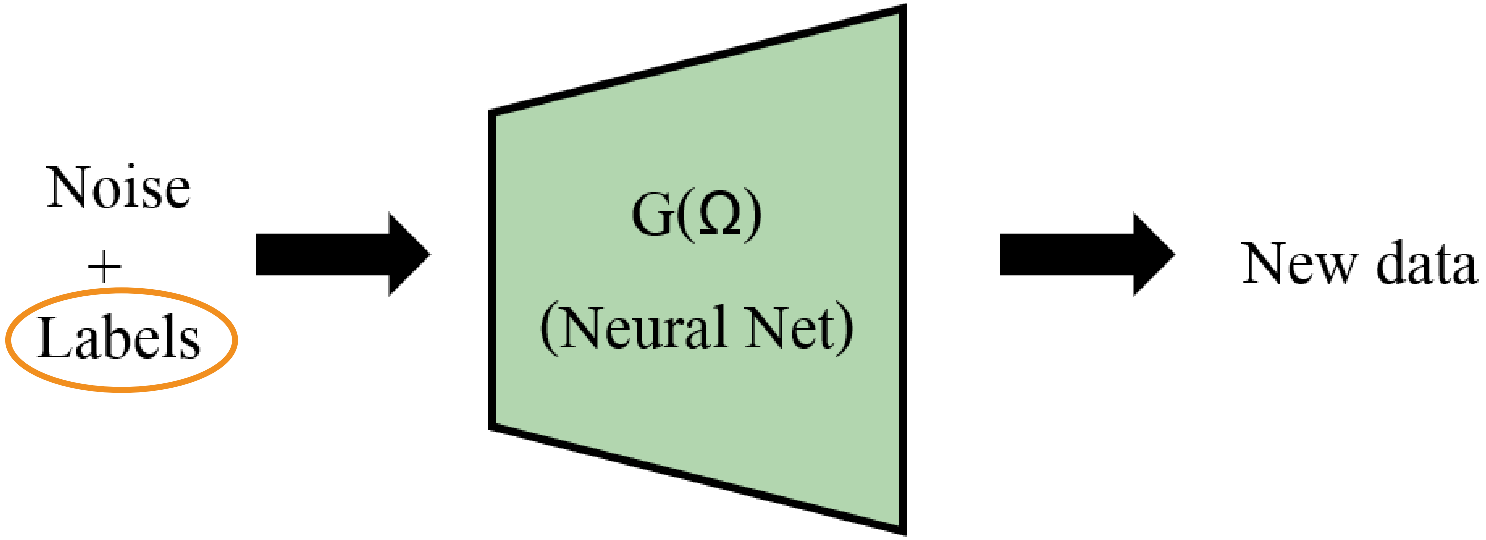
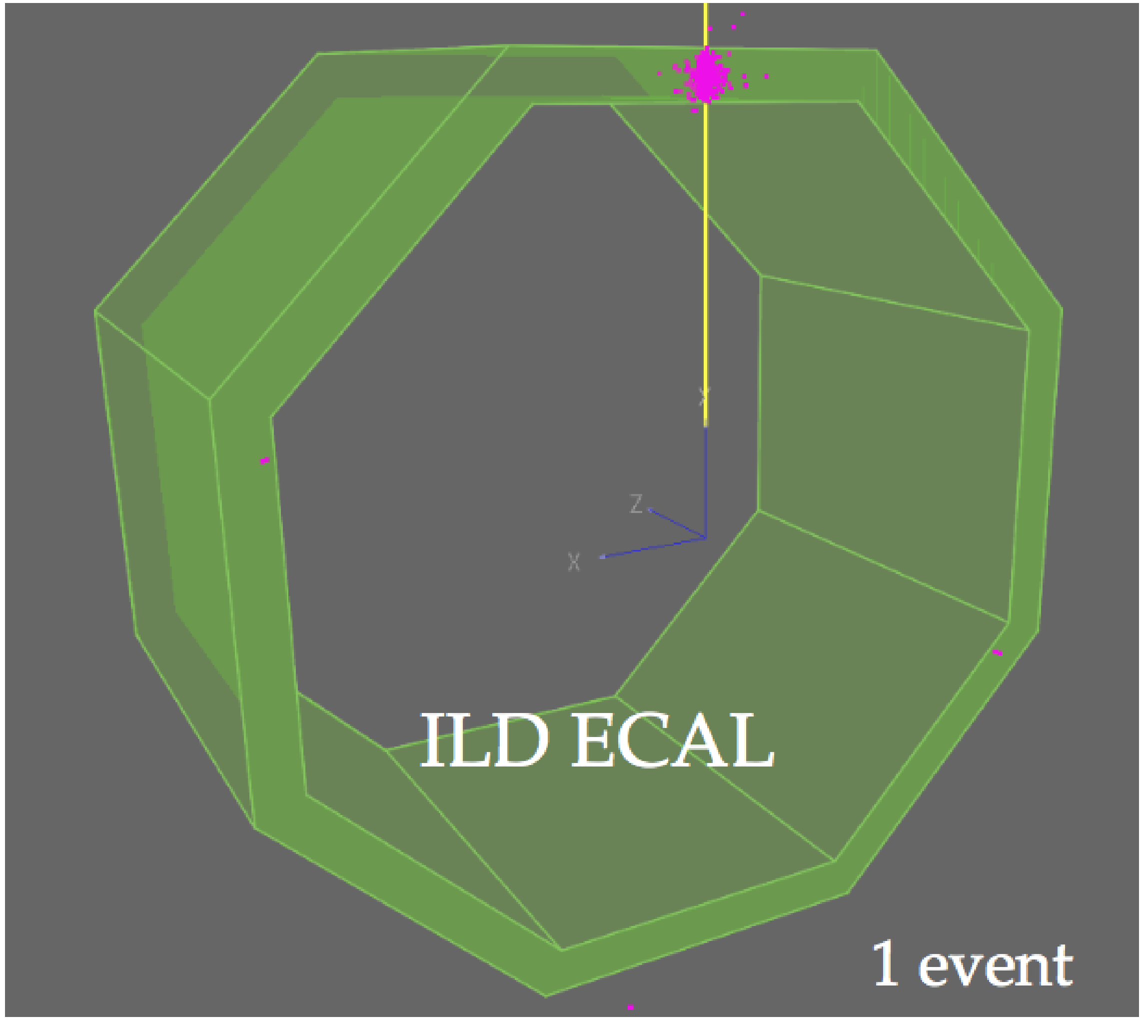
doi:10.21468/SciPostPhys.10.6.139



Conditioning Requirements for a General Simulation

- Conditioning for a general calorimeter simulation:
  - Energy
  - Incidence point
  - Two angles
    - Polar angle: θ
    - Azimuthal angle: ϕ



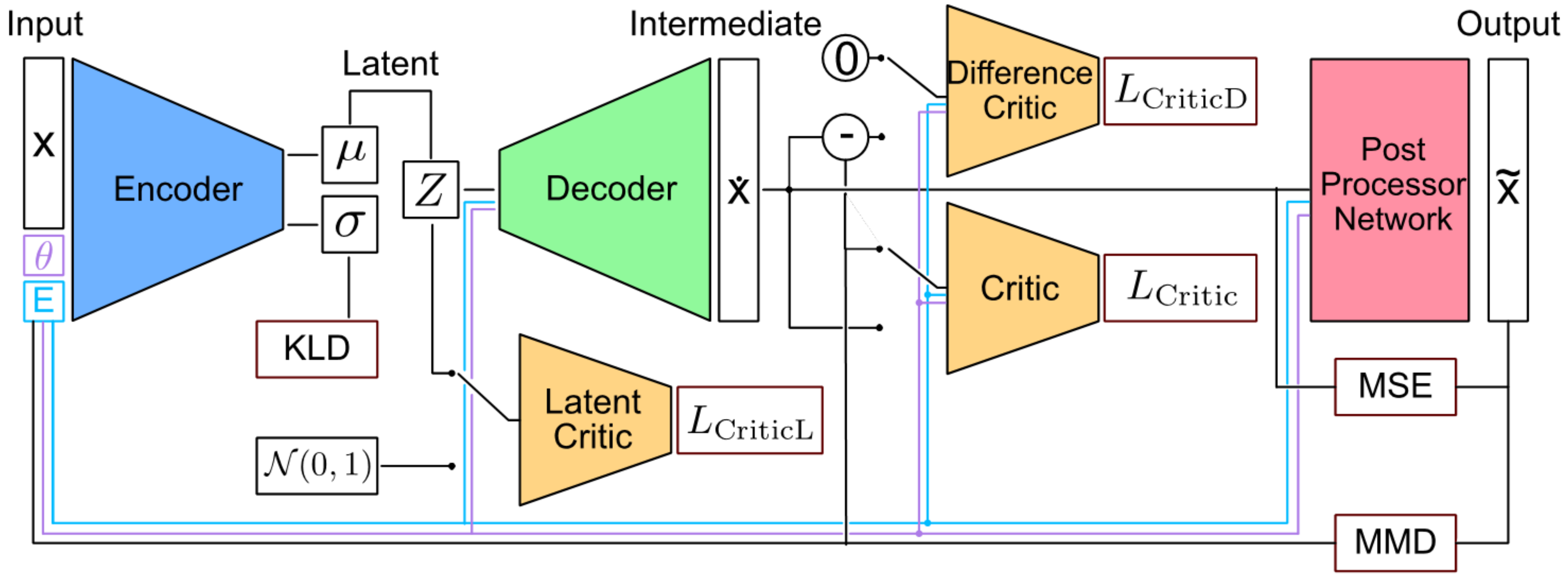
Generative Model: BIB-AE

Bounded-Information Bottleneck Autoencoder

- Unifies features of both GANs and VAEs
- Post-Processor network: Improve per-pixel energies; second training
- Use second generative model to generate latent space during inference

Voloshynovskiy et. al: **Information bottleneck through variational glasses**, arXiv:1912.00830

Buhmann et. al: **Getting High: High Fidelity Simulation of High Granularity Calorimeters with High Speed**, CSBS 5, 13 (2021)



$L_{\mathrm{BIB-AE}} = \mathrm{KLD} + L_{\mathrm{CriticL}} + L_{\mathrm{Critic}} + L_{\mathrm{CriticD}}$

$L_{\mathrm{Post}} = \mathrm{MMD} + \mathrm{MSE}$

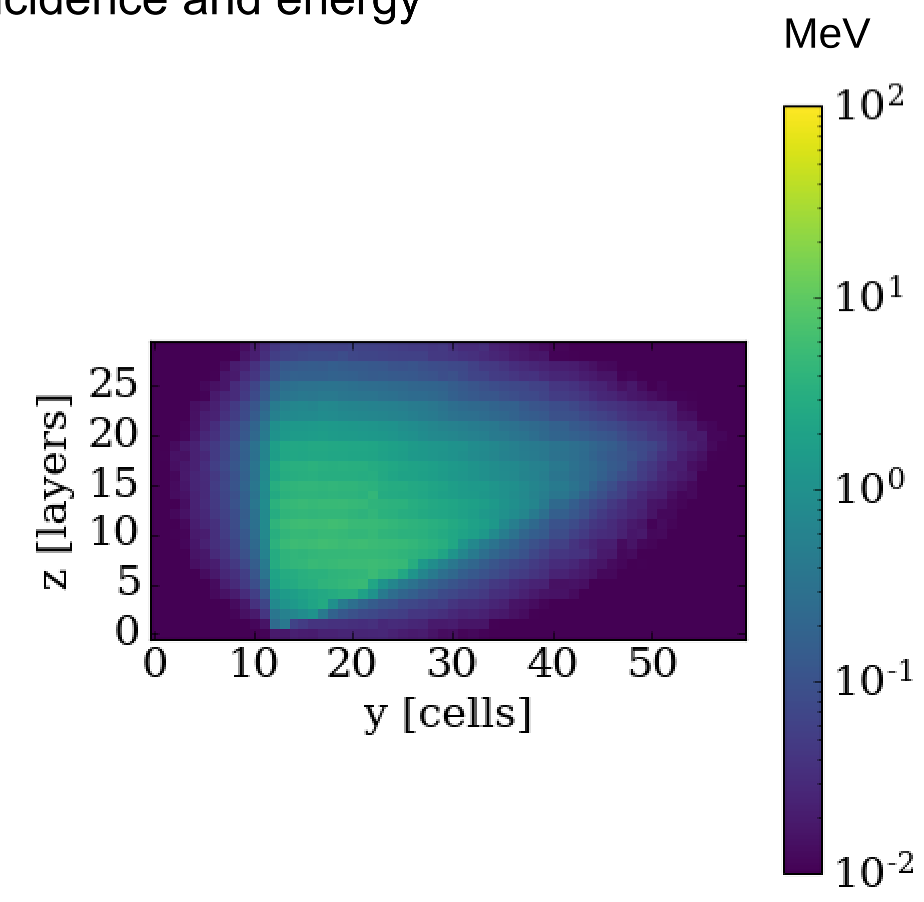
Angular and Energy conditioning- Training data

- In Progress: condition generative networks on particle's angle of incidence and energy

- Vary energy: 10-100 GeV
- Only vary polar angle in one direction: from 90°-30°
- Fixed particle type: photons

- Problem: How to make sure the full shower is contained?
  - Extend the selected grid in y: shape (30,30,60) (z,x,y)
  - Shift gun position

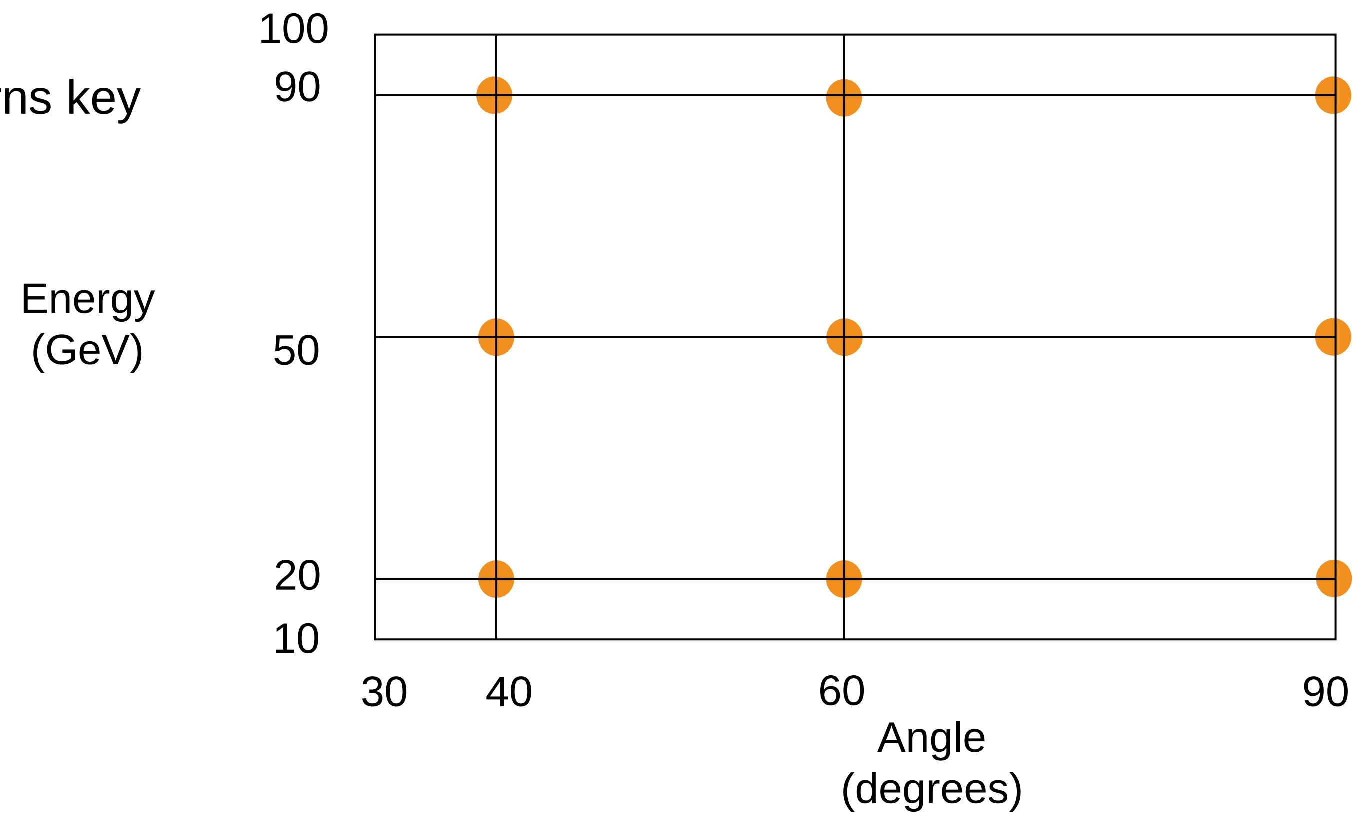
- 136,500 showers for training base BIBAE
- 500,000 for Post Processing



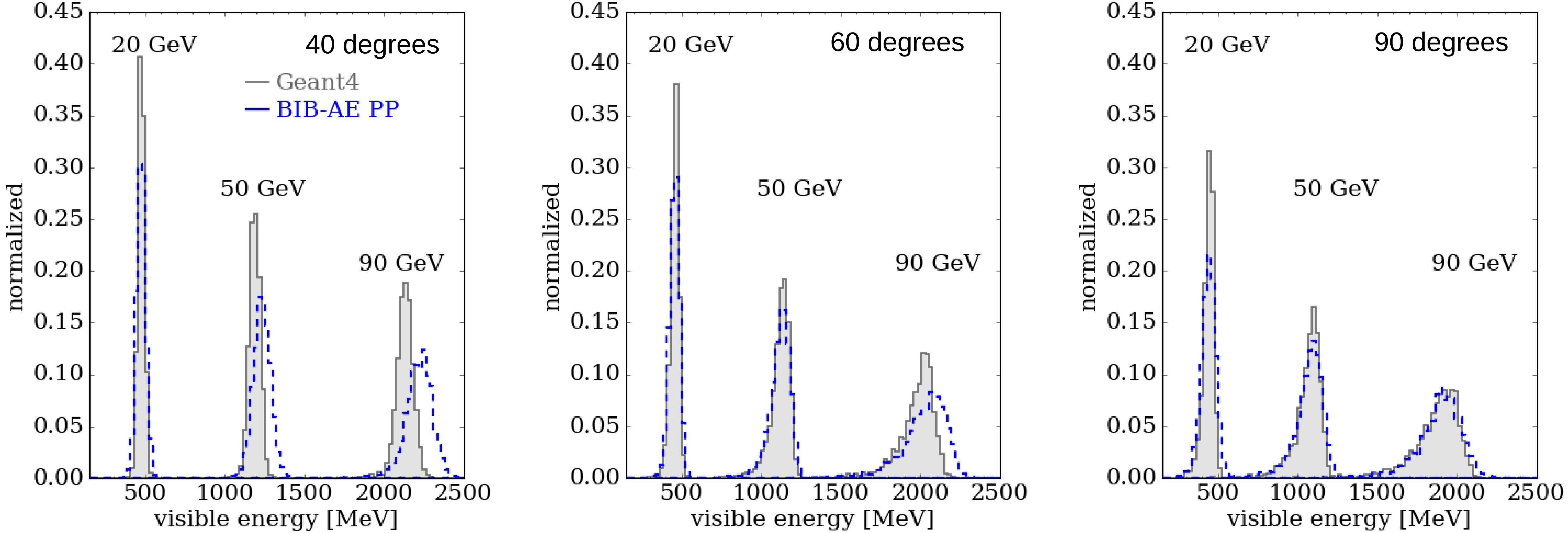
Angular and Energy conditioning- Validation data

- Choose fixed combinations of energies and angles
- 9 points in the phase space in total

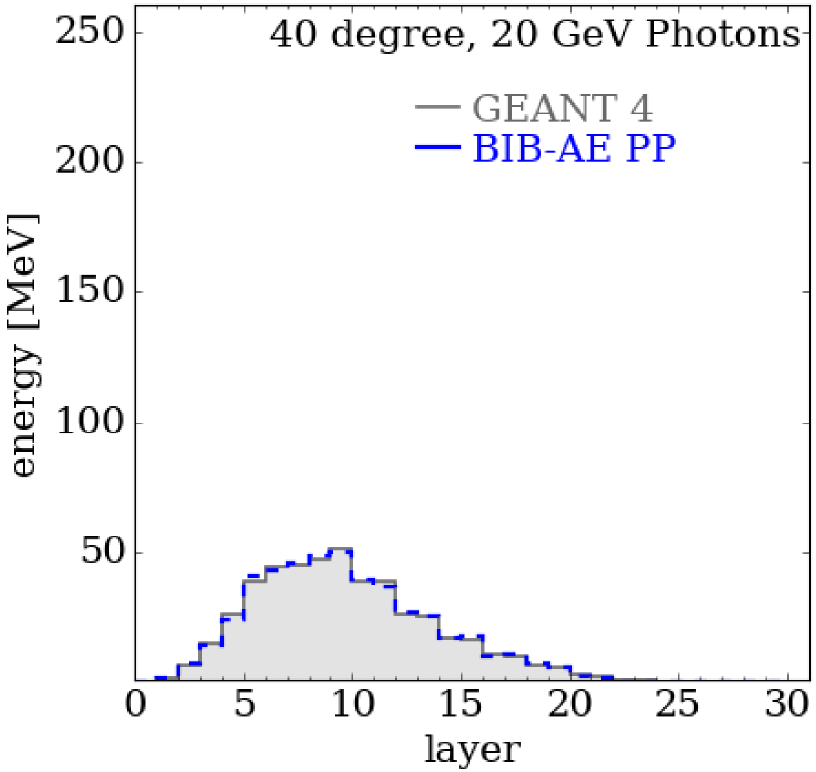
- Investigate how well generative model learns key physics properties of showers:
  - Visible energy sum
  - Number of hits and Hit energy spectrum
  - Shower profiles
  - Angular response

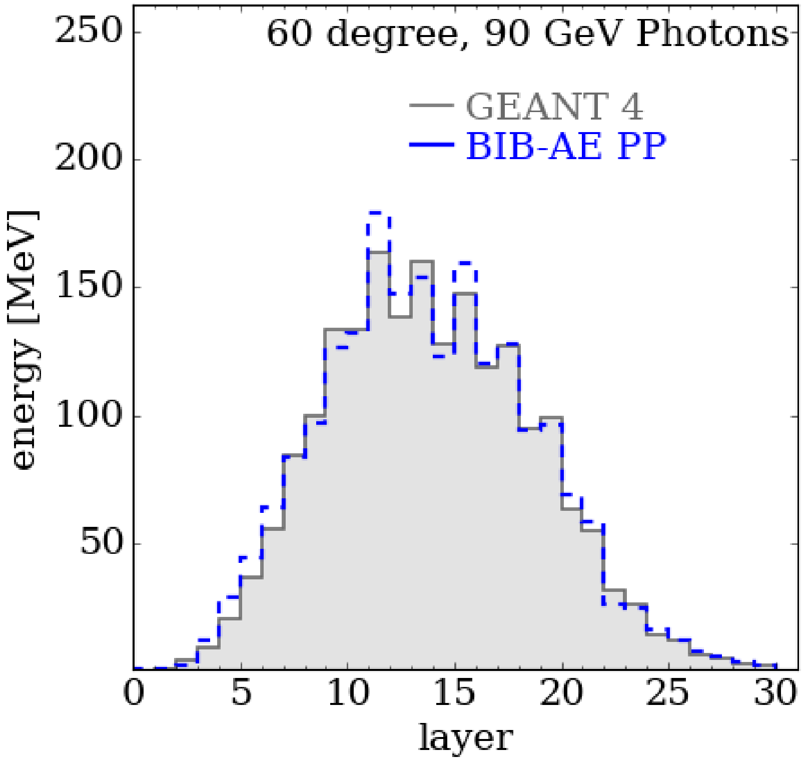


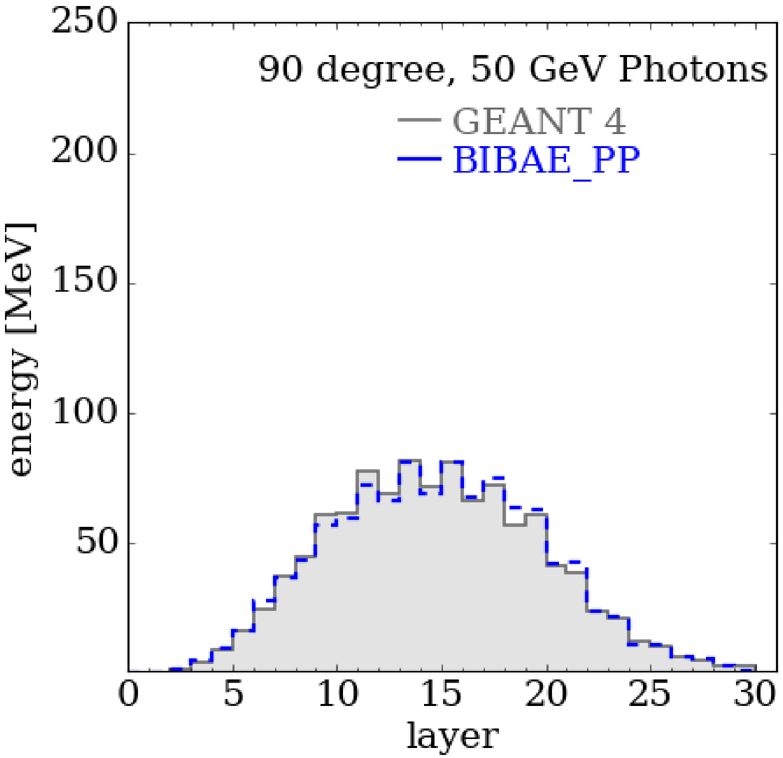
Results: Visible Energy Sum



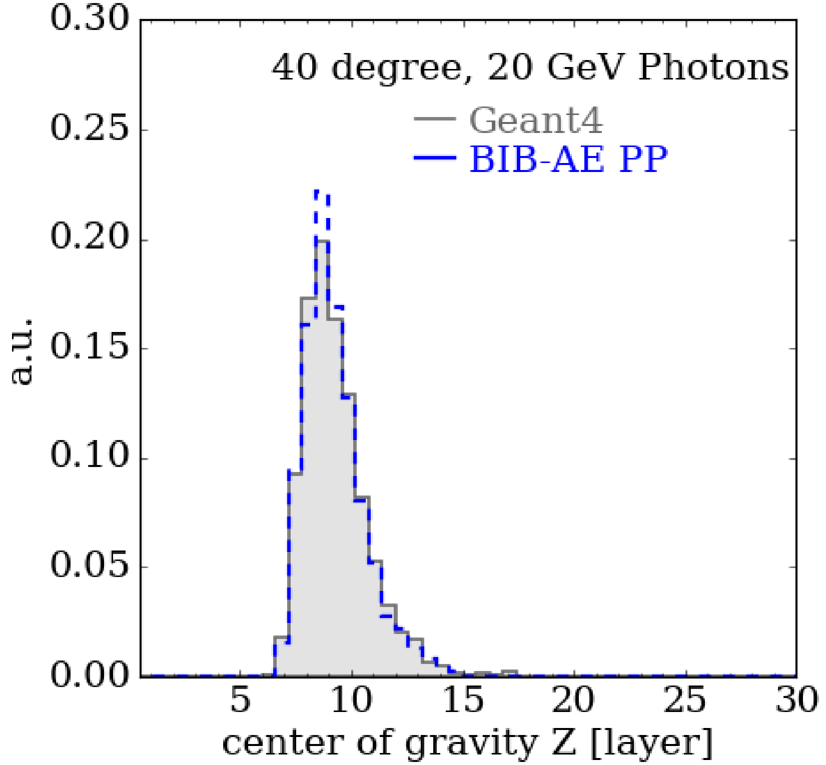
Results: Longitudinal Profile

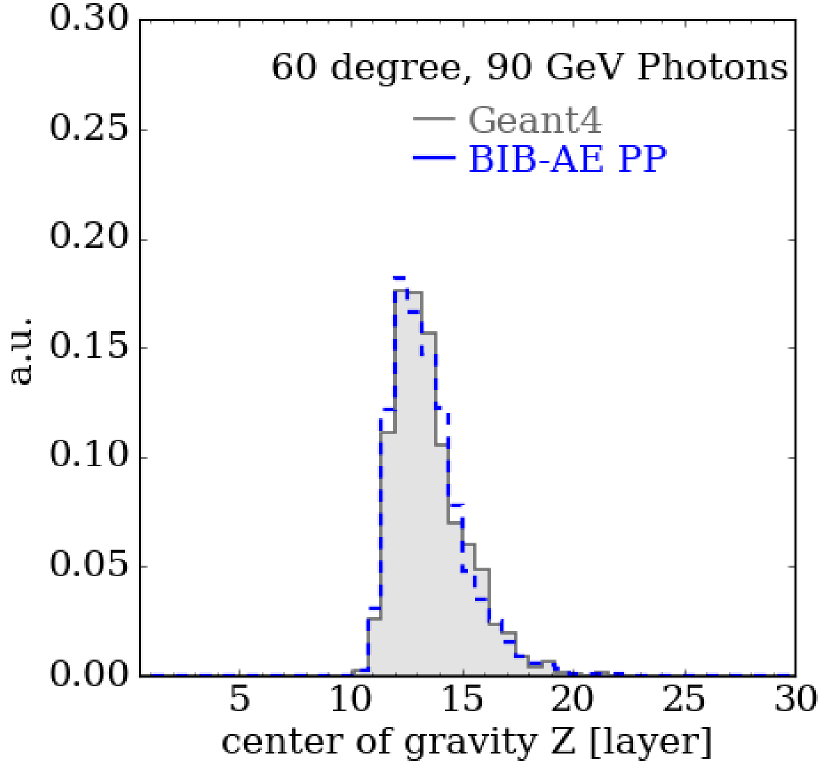


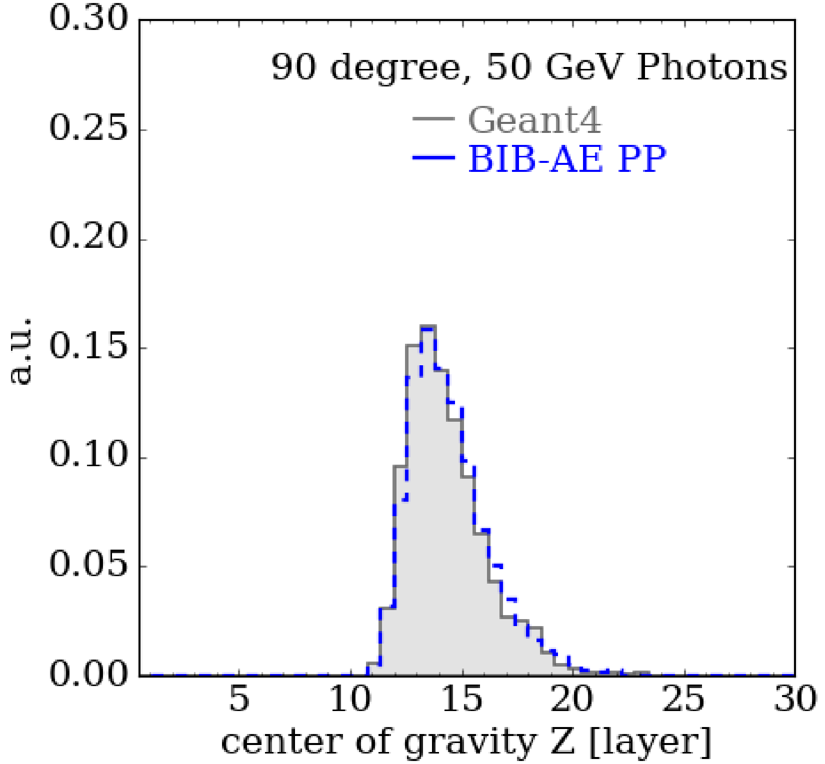




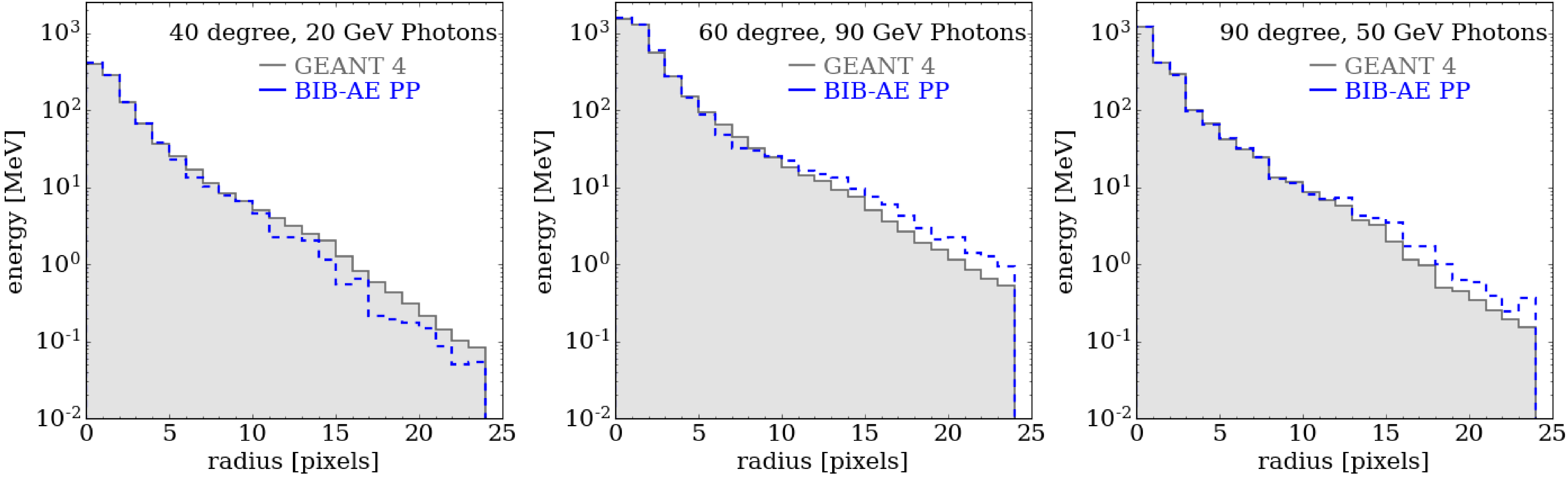
Results: Center of Gravity



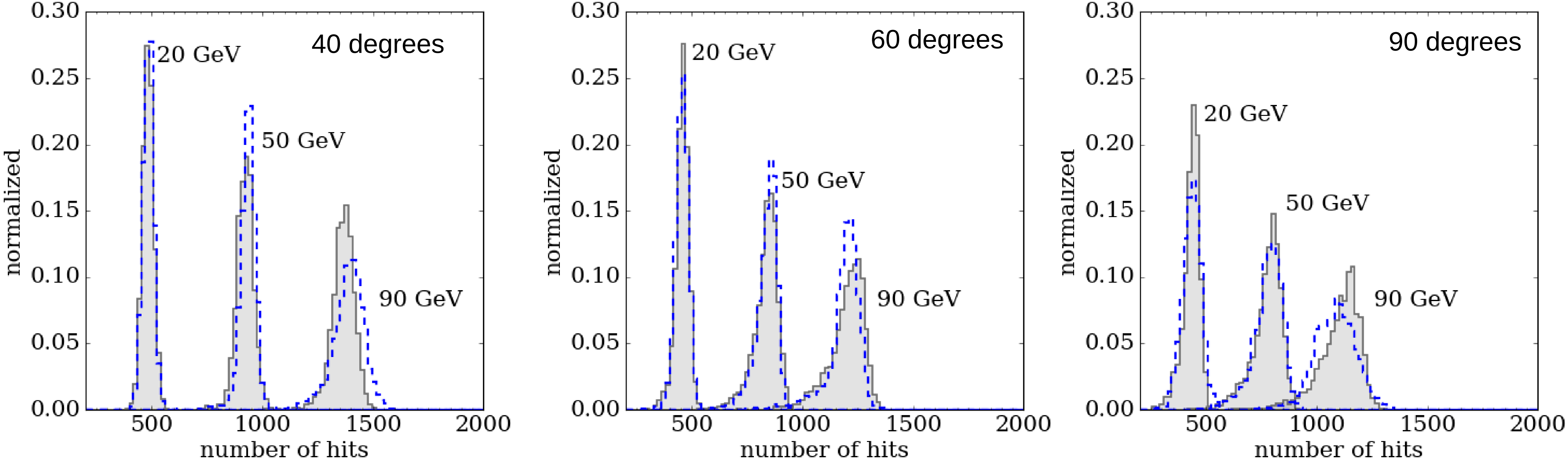




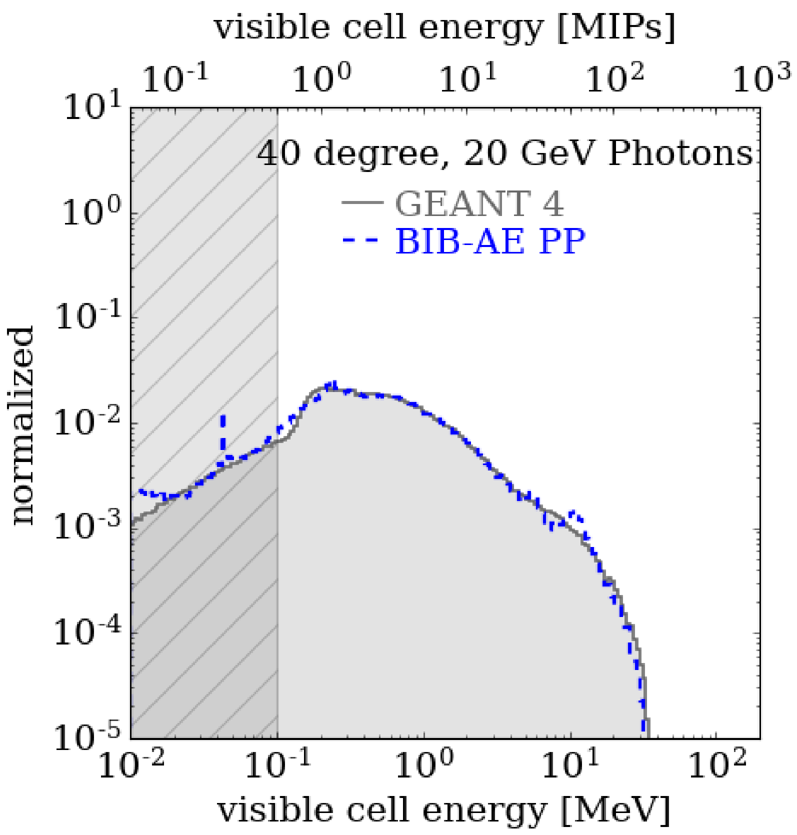
Results: Radial Profile

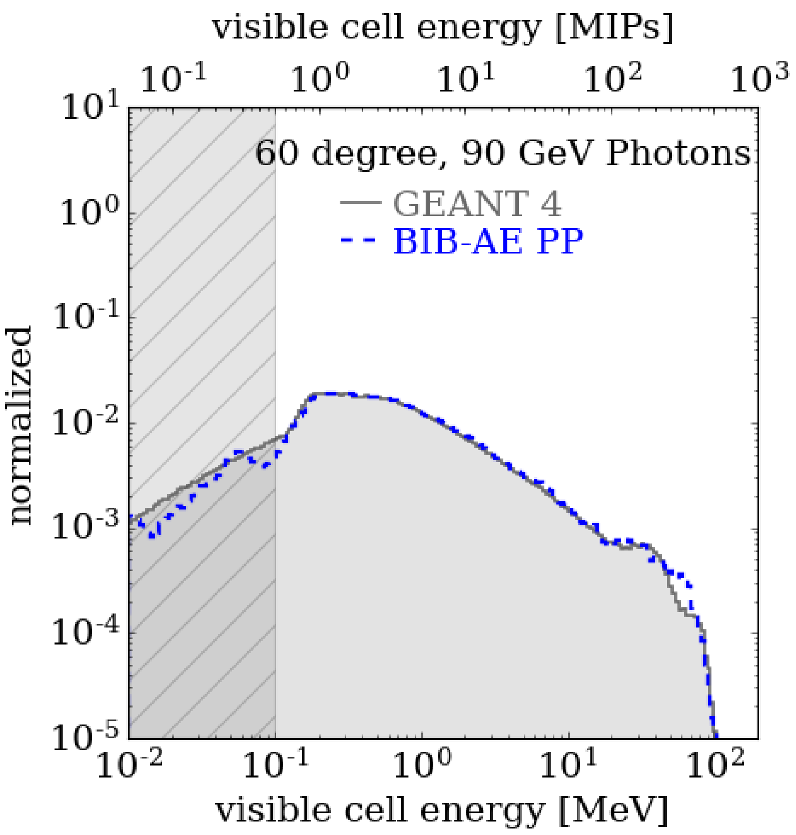


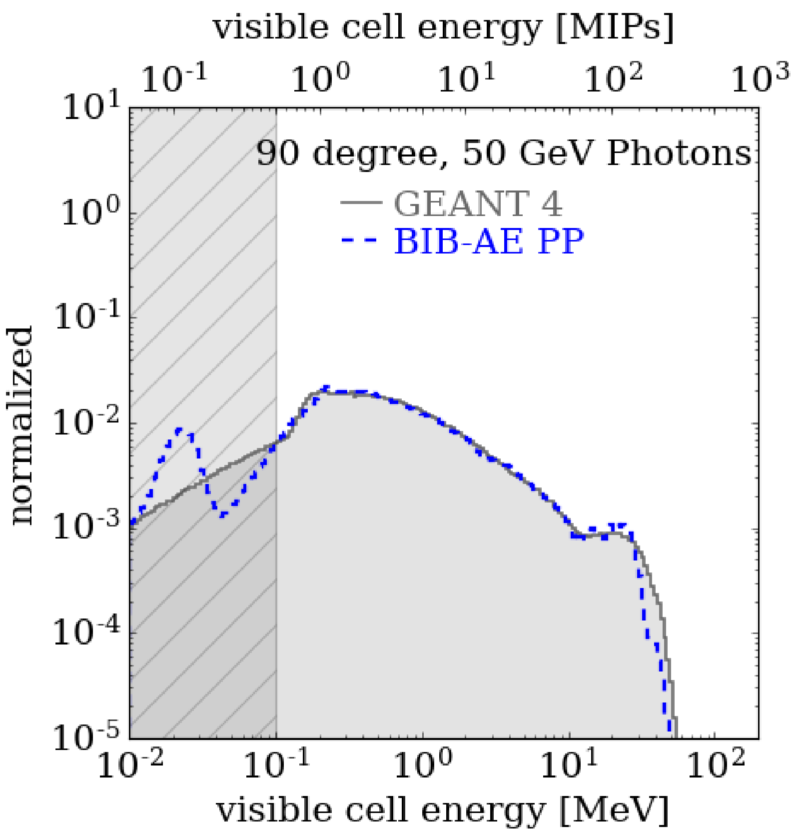
Results: Number of Hits



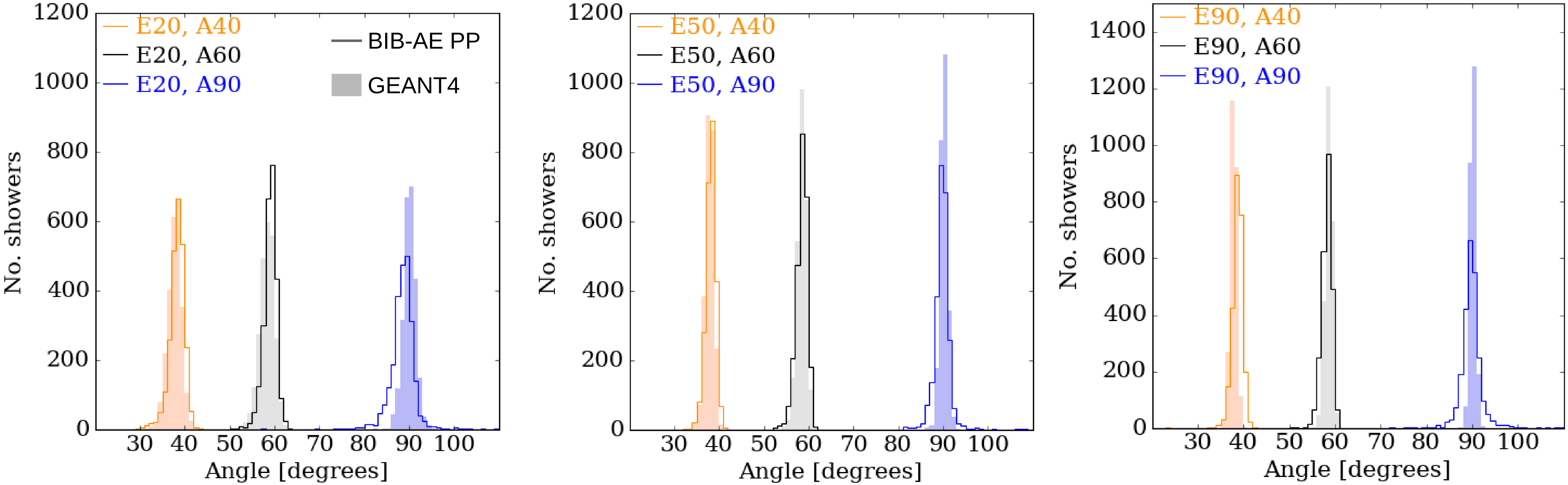
Results: Cell Energy Spectrum







Results: Angular Reconstruction Distributions



Conclusion

Achieved

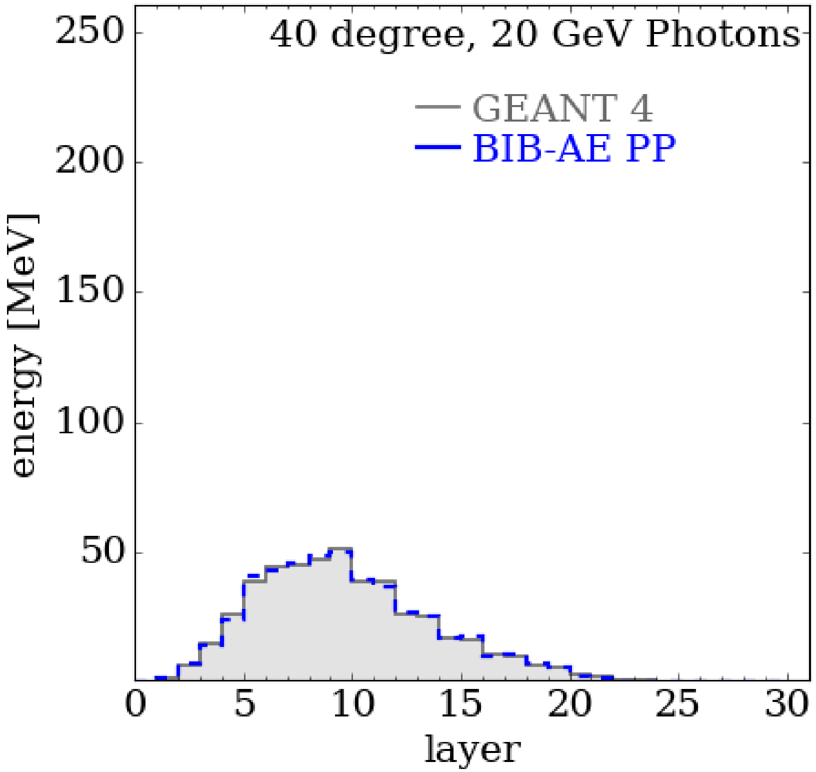
- Generative models hold promise for fast simulation of calorimeter showers with high fidelity
- Demonstrated angular and energy conditioning using BIB-AE network architecture

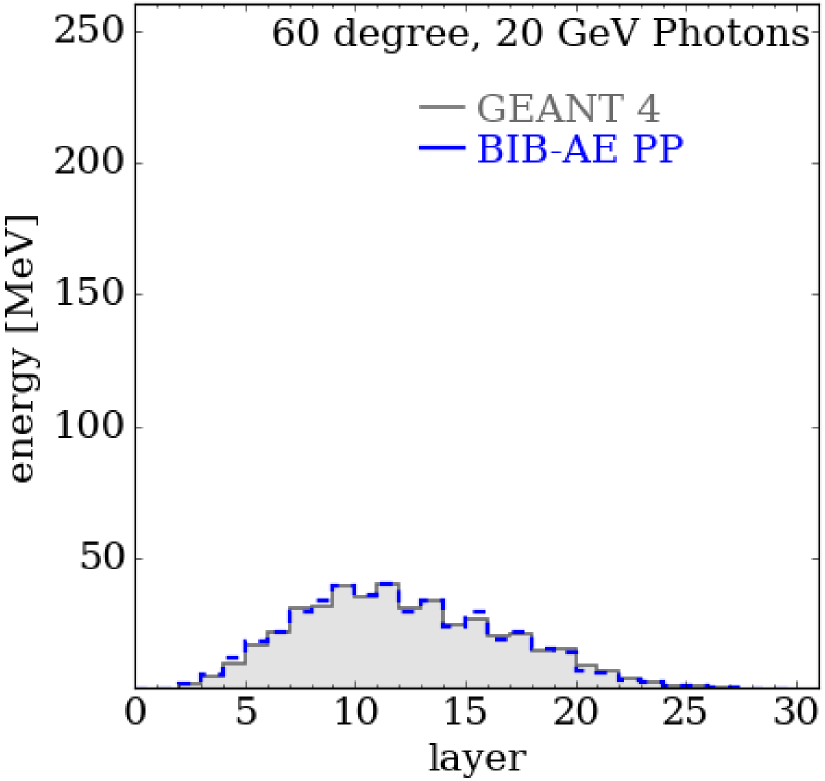
Next Steps

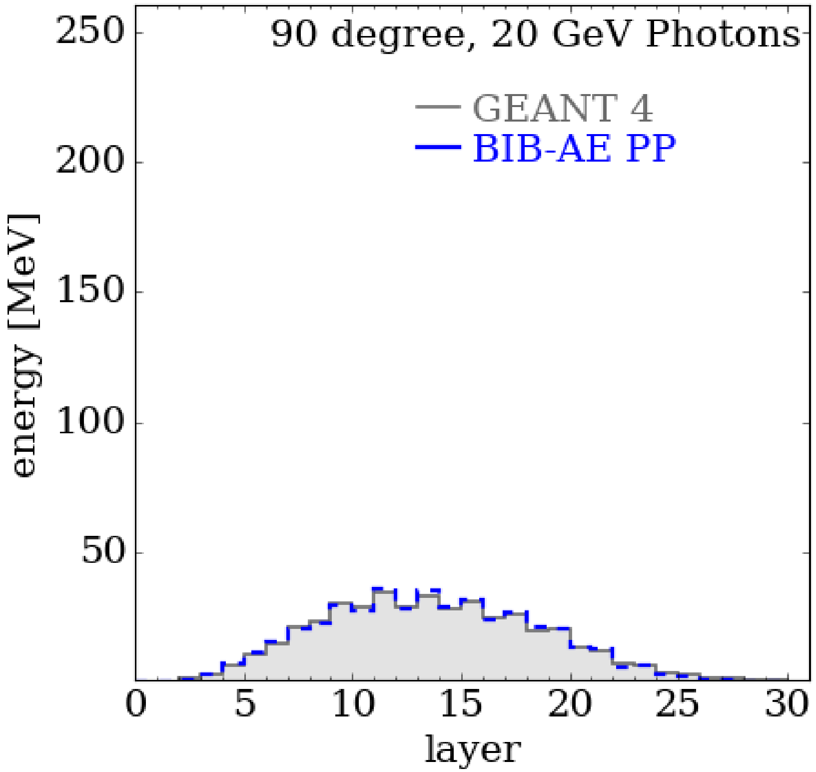
- Train the base BIB-AE with the complete data set
- Improve visible energy sum performance of the network
- Improve current Post-Processing setup
- Start considering incidence point

Backup

Results: Longitudinal Profile







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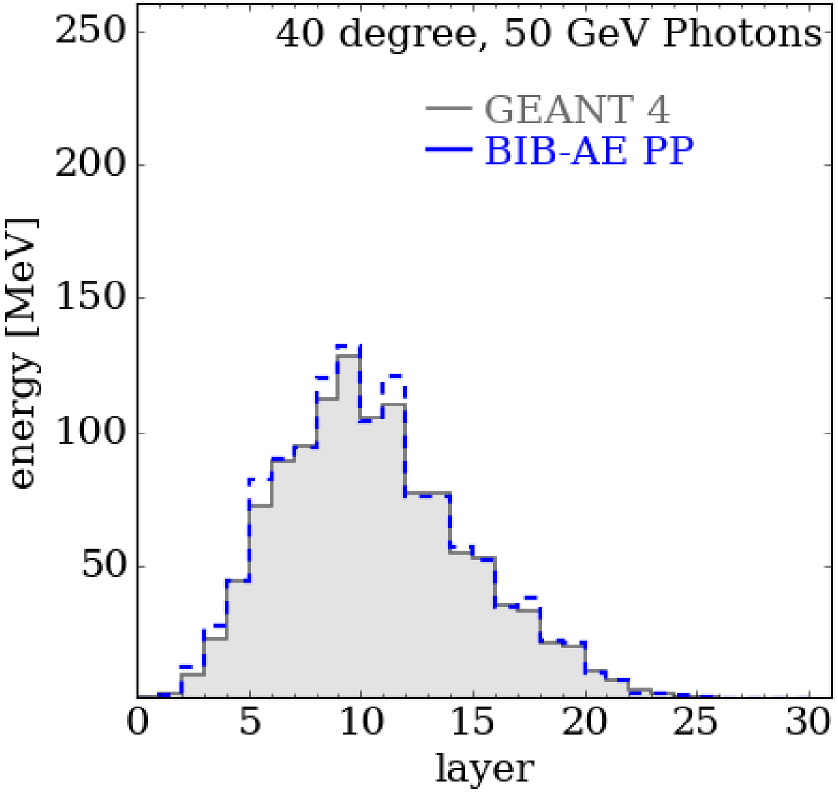

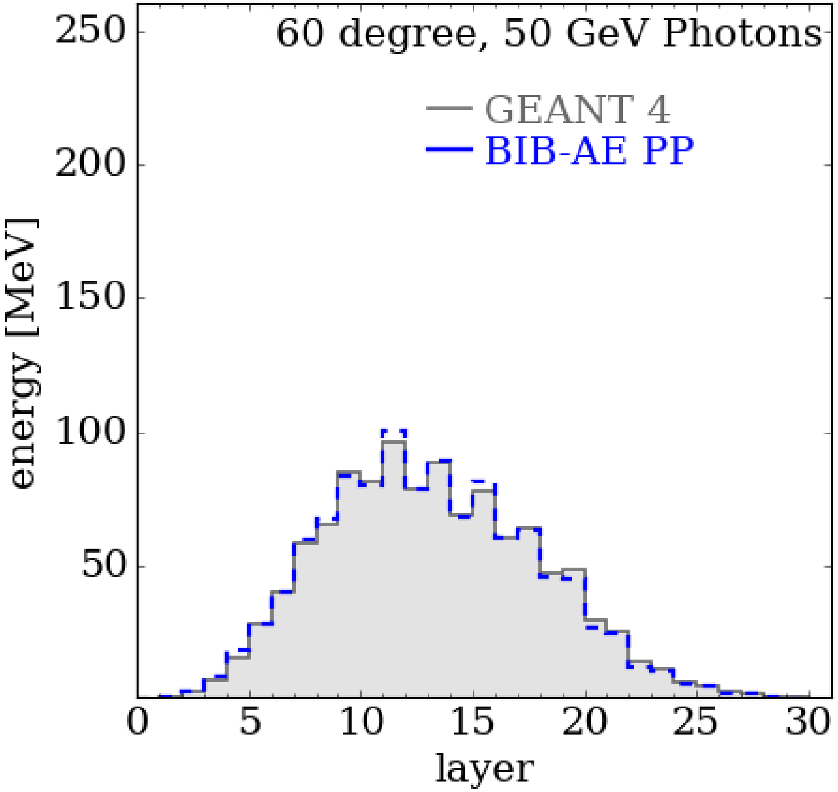

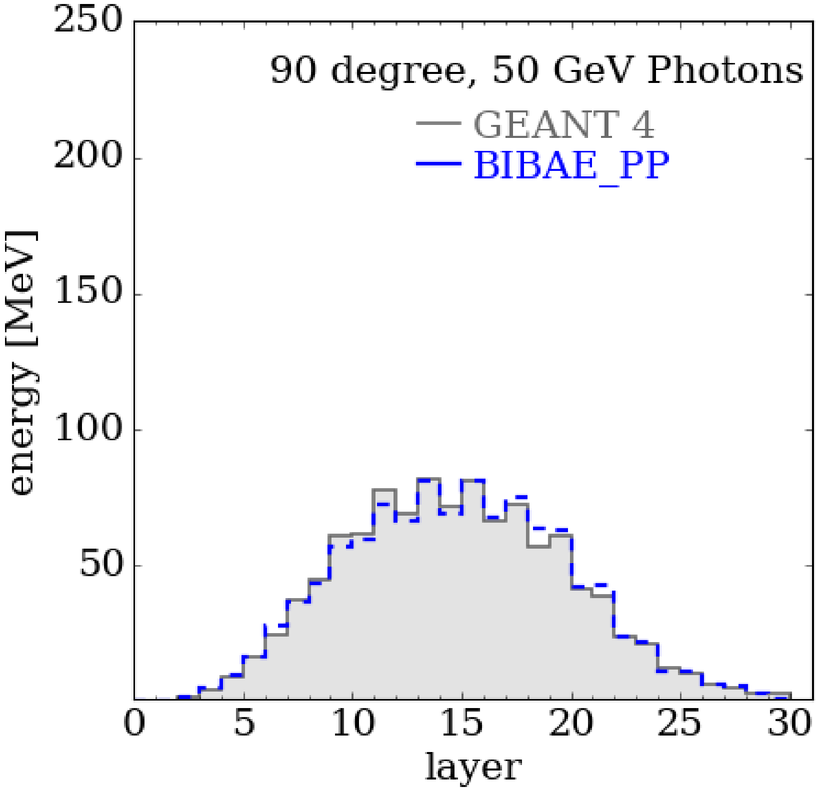

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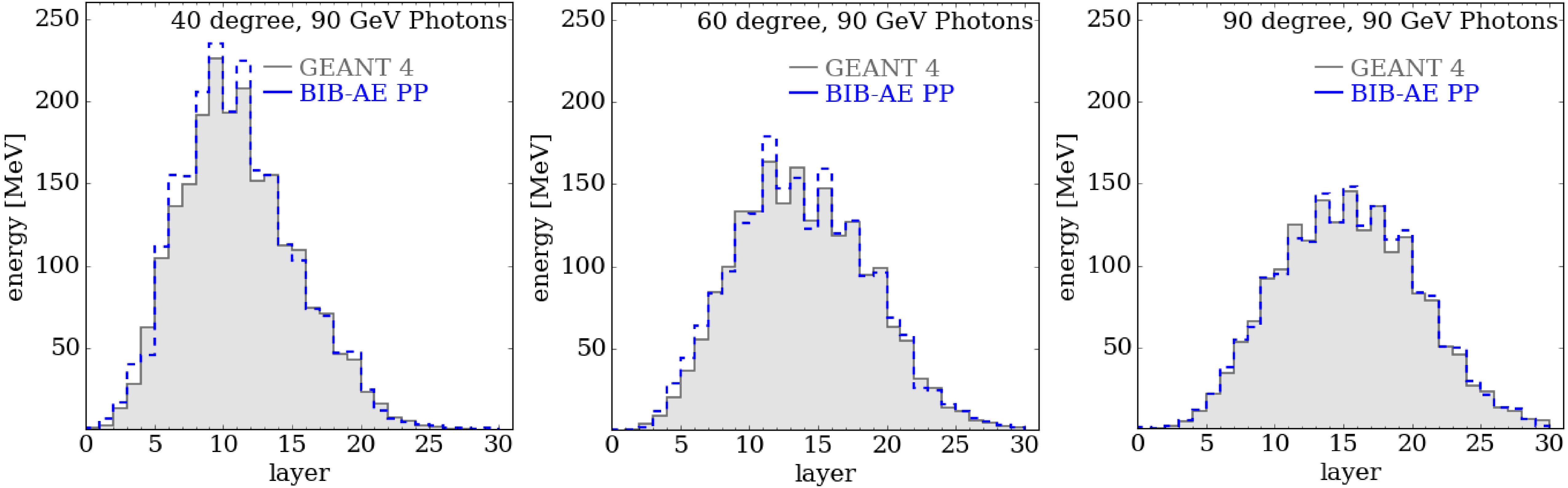
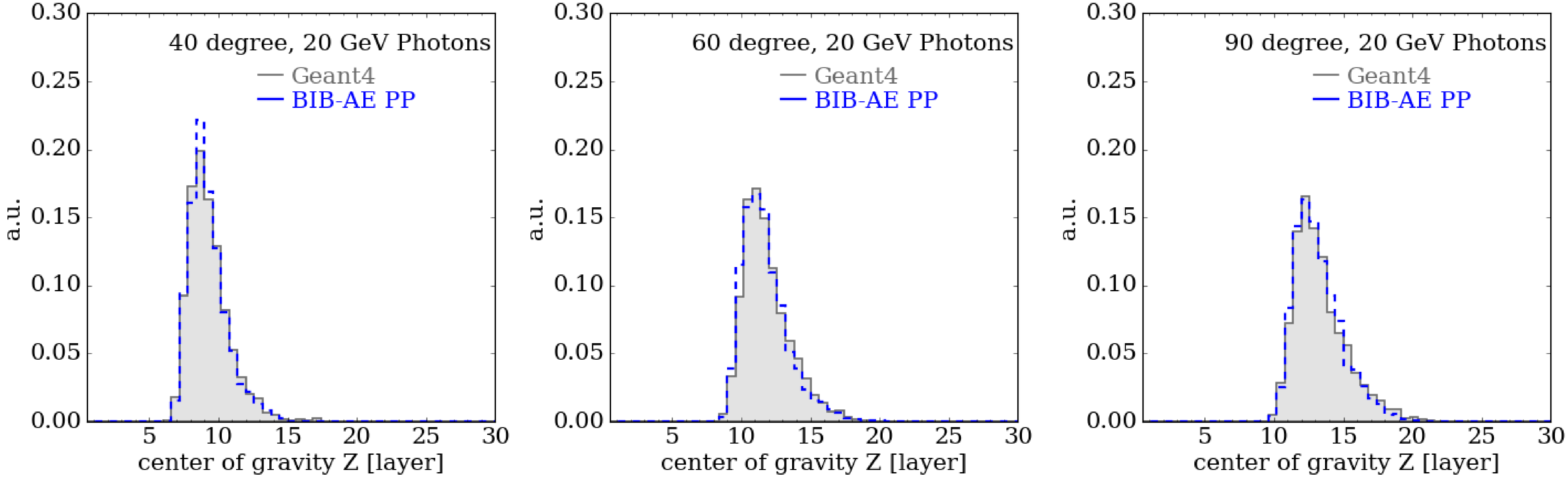


Results: Center of Gravity



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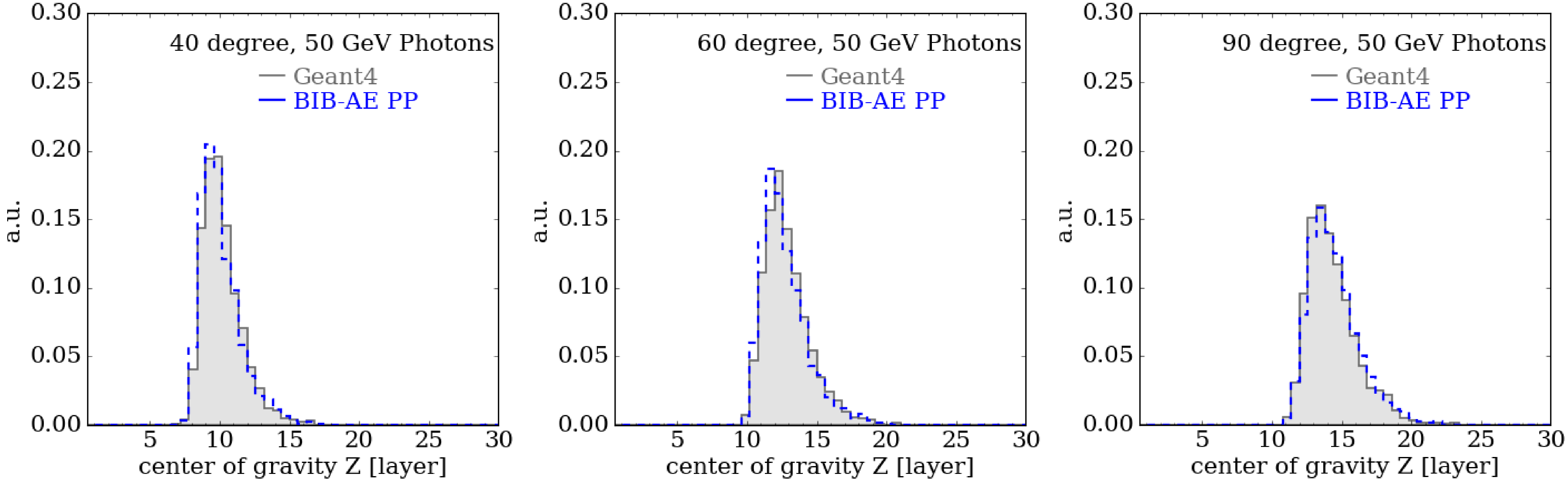

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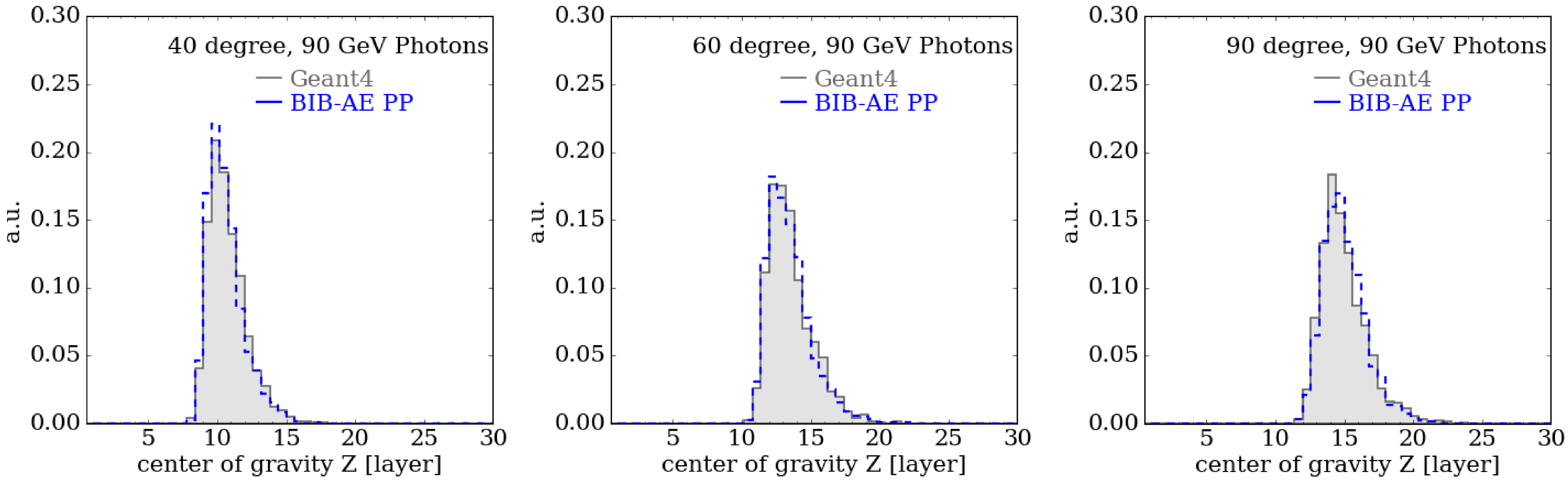
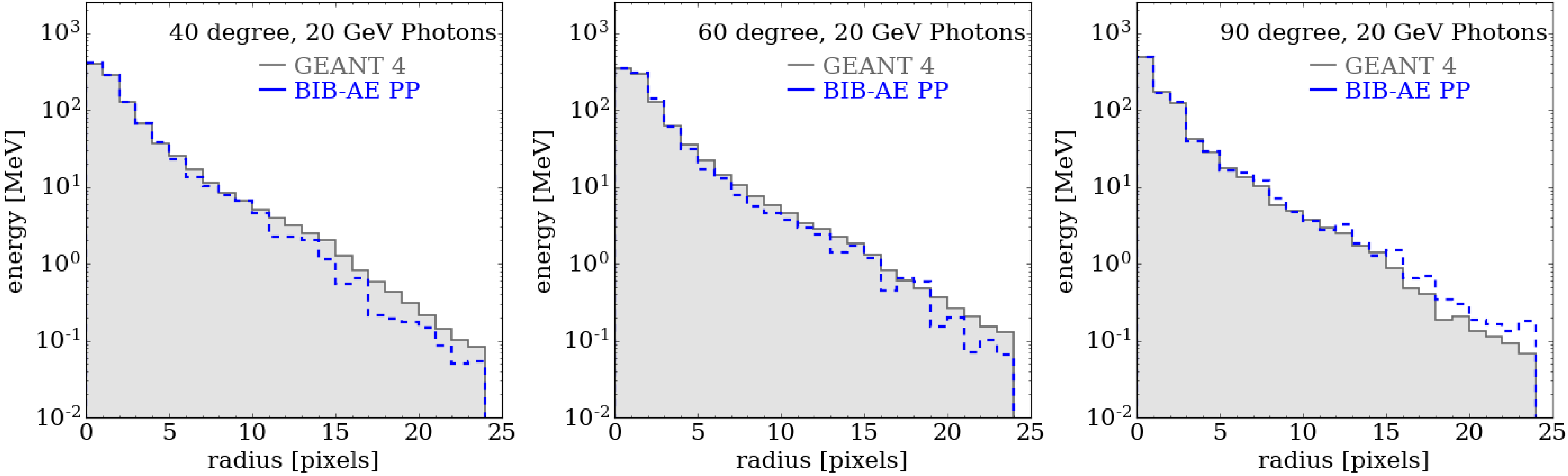
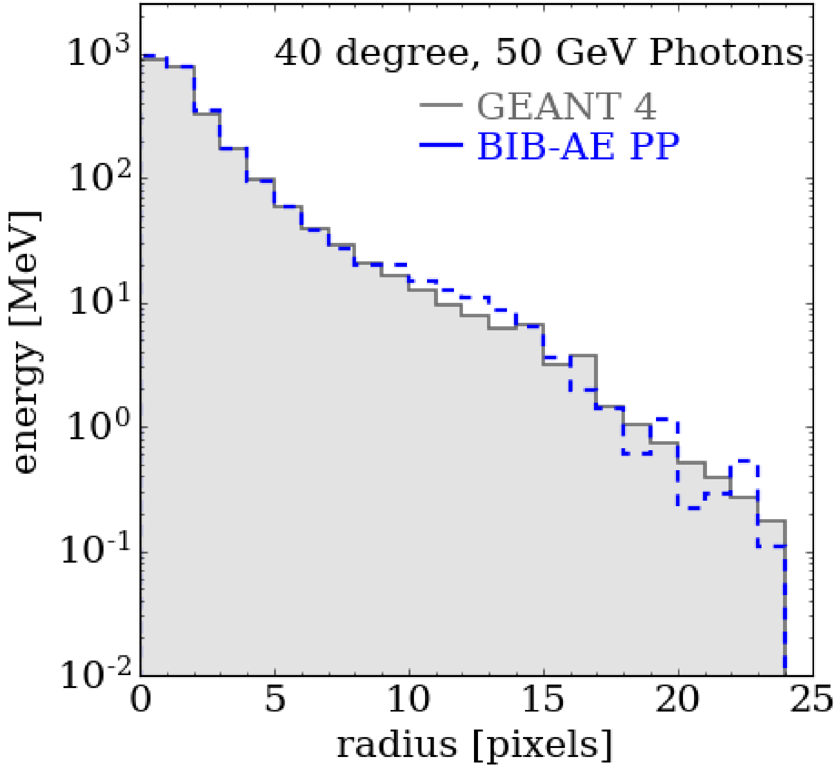
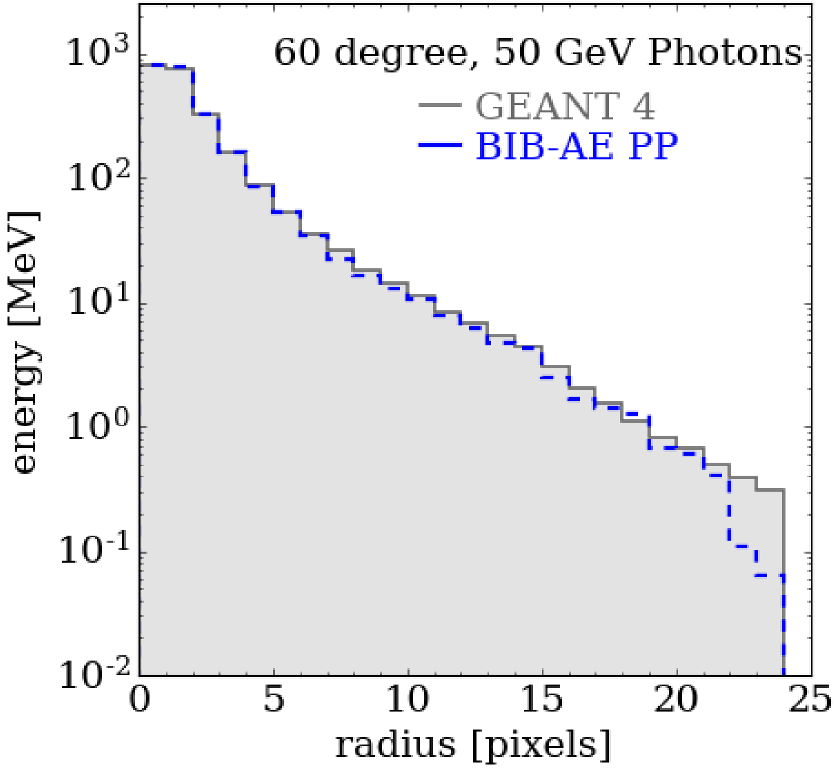


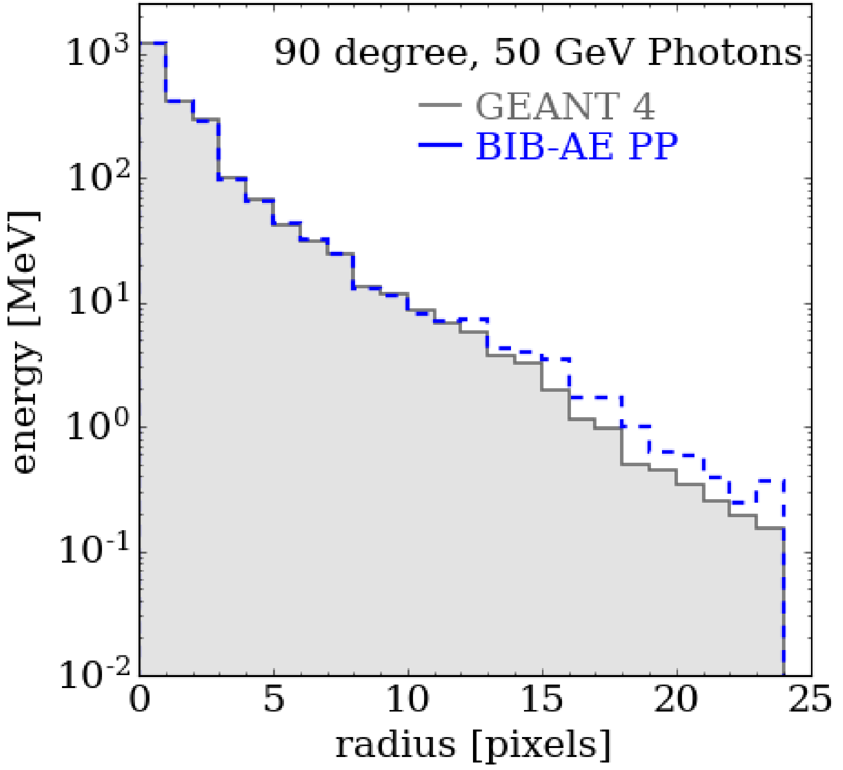
Results: Radial Profile



Results: Radial Profile







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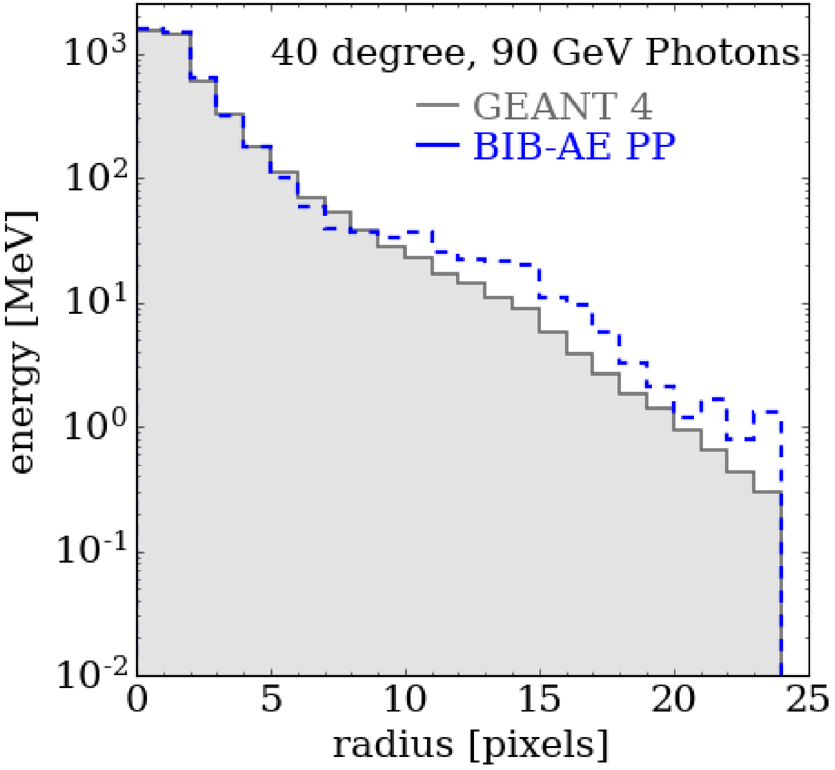
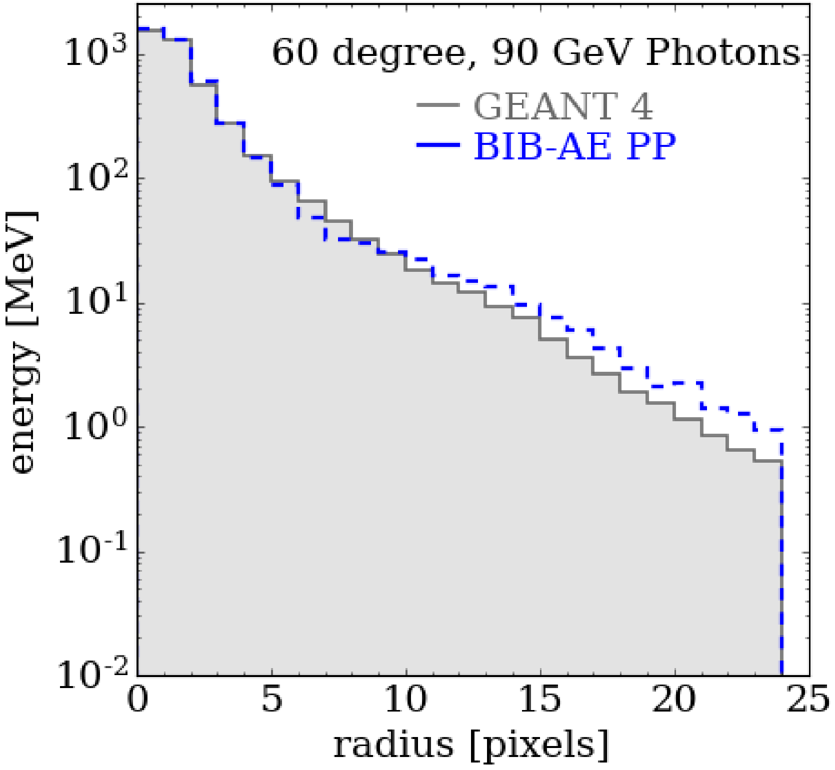
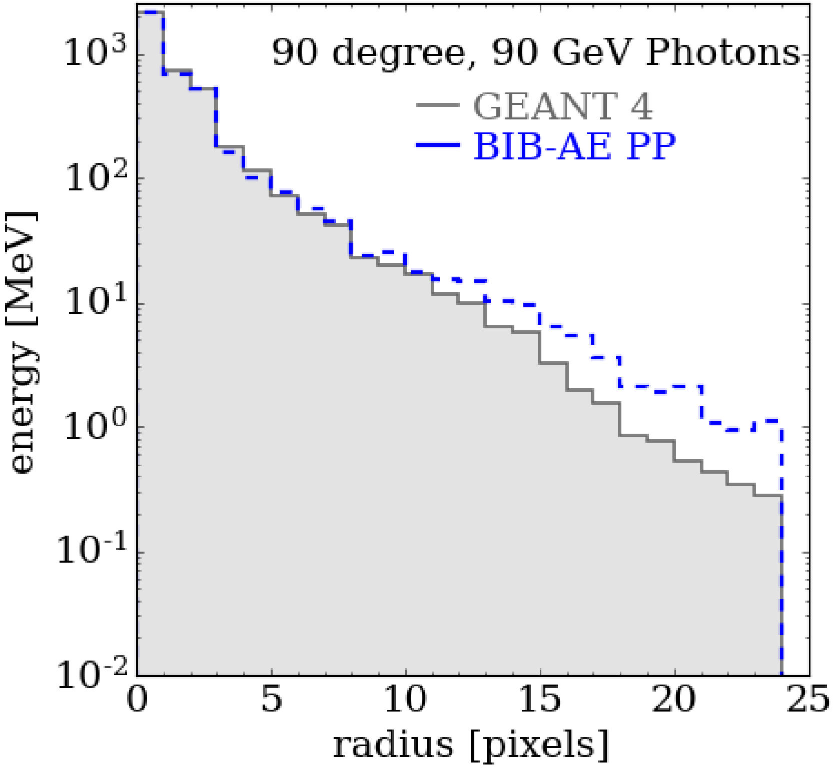
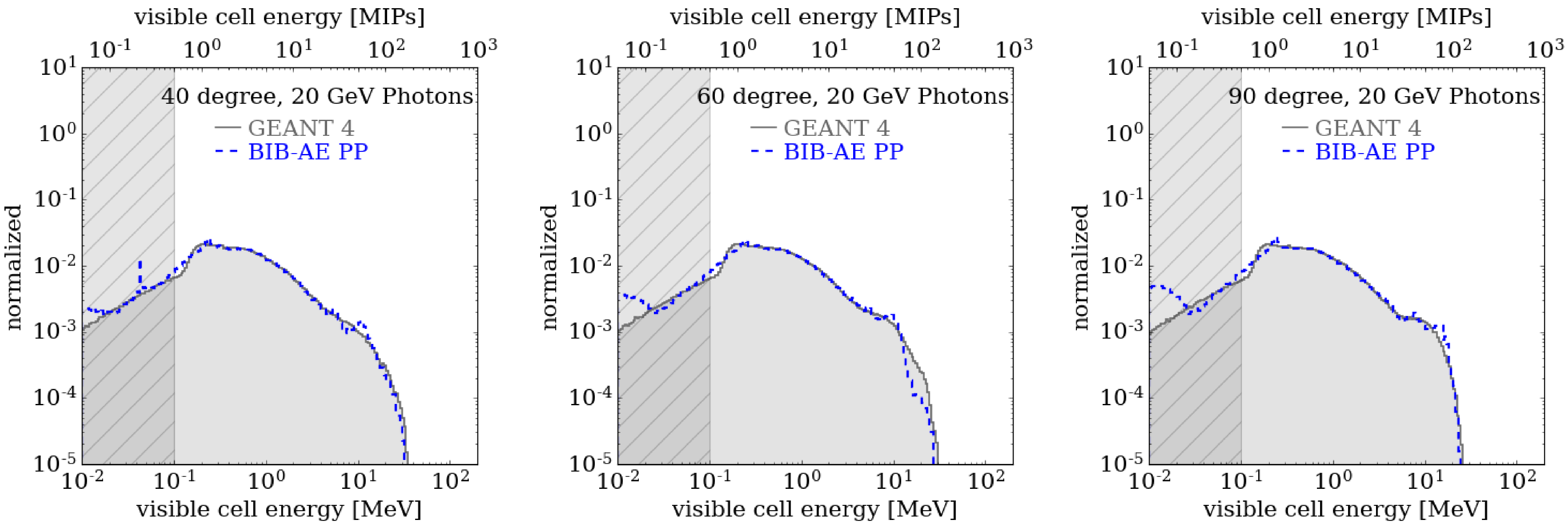






Results: Cell Energy Spectrum



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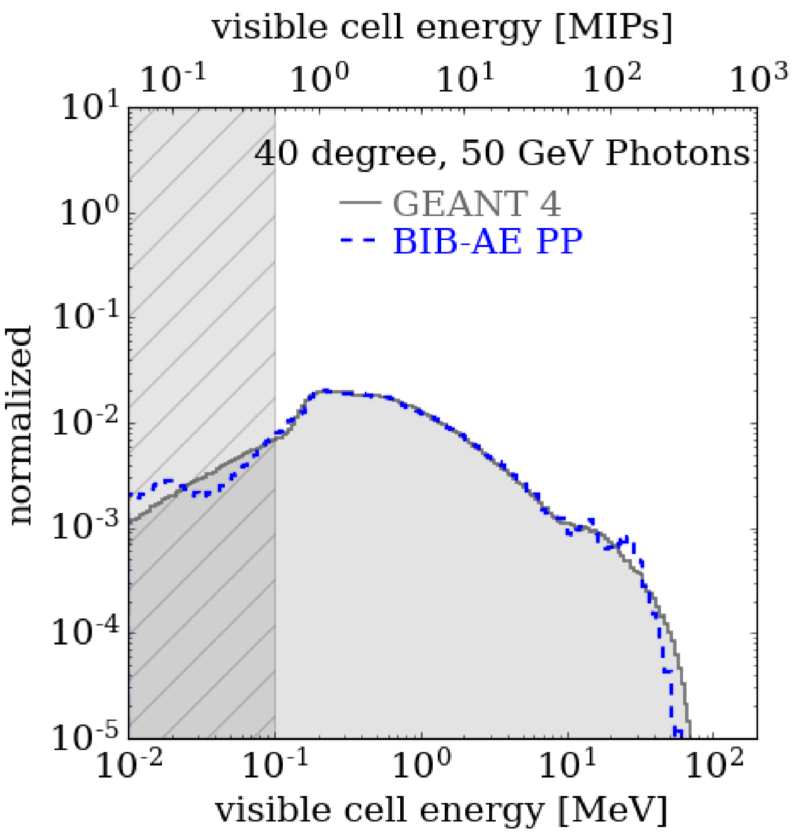

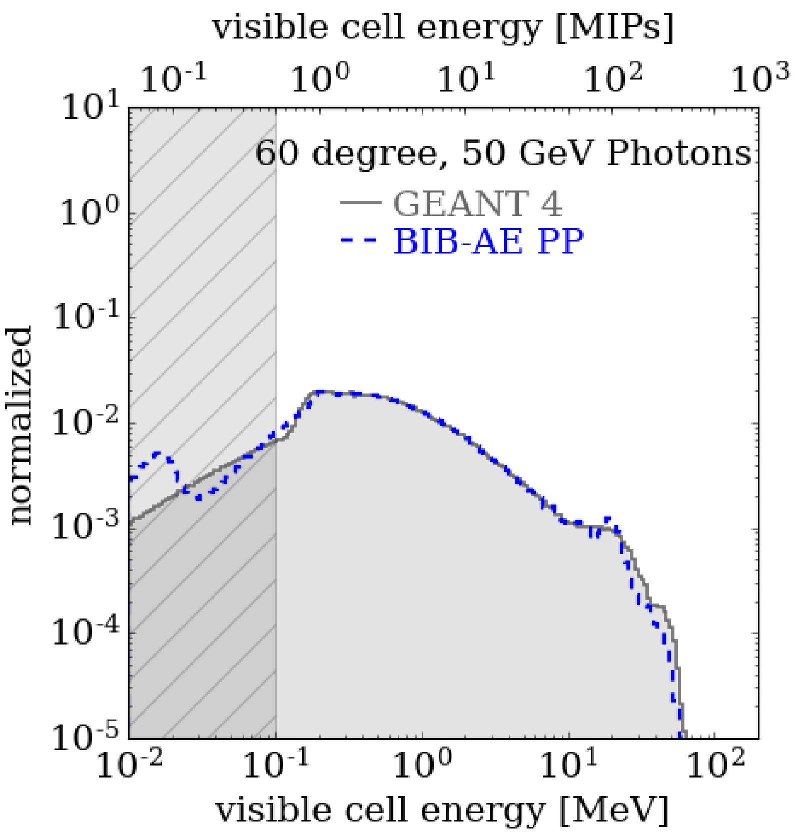

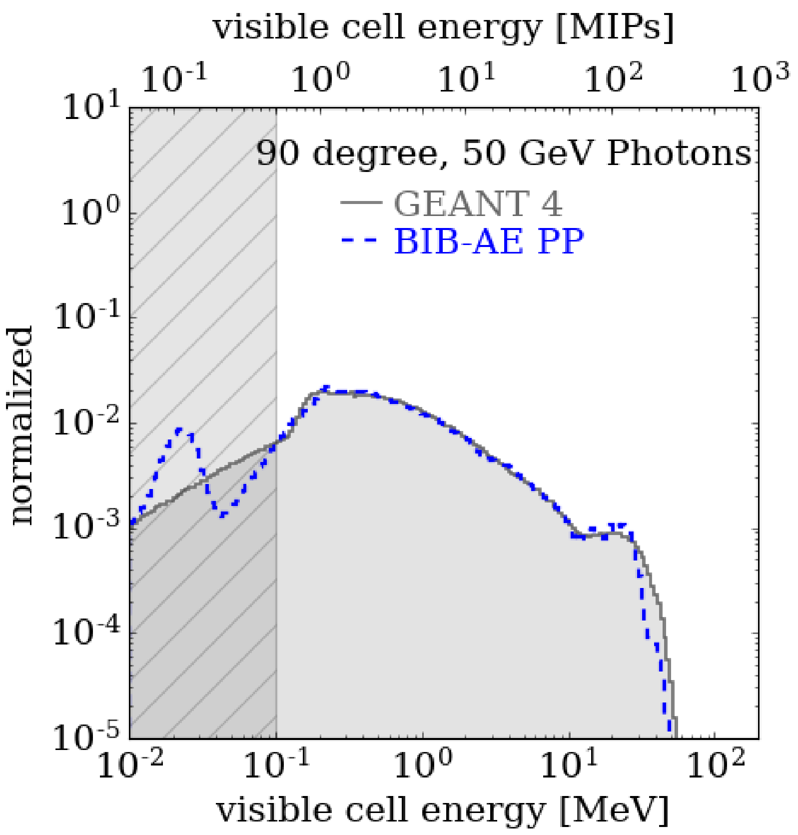

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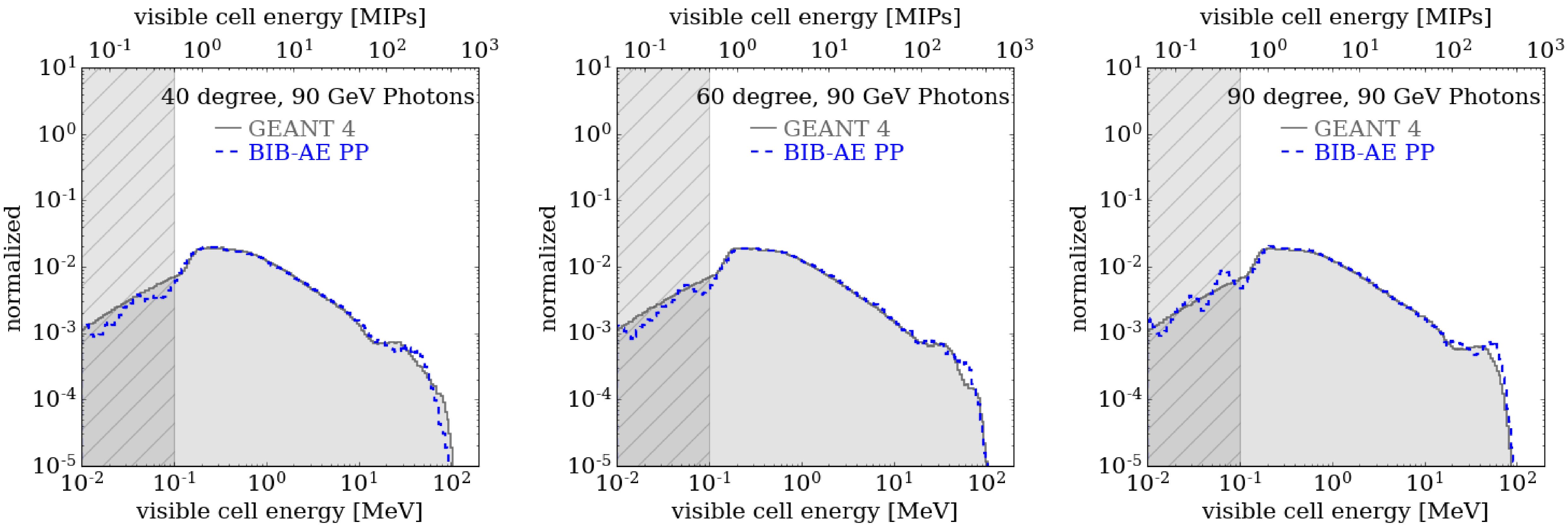
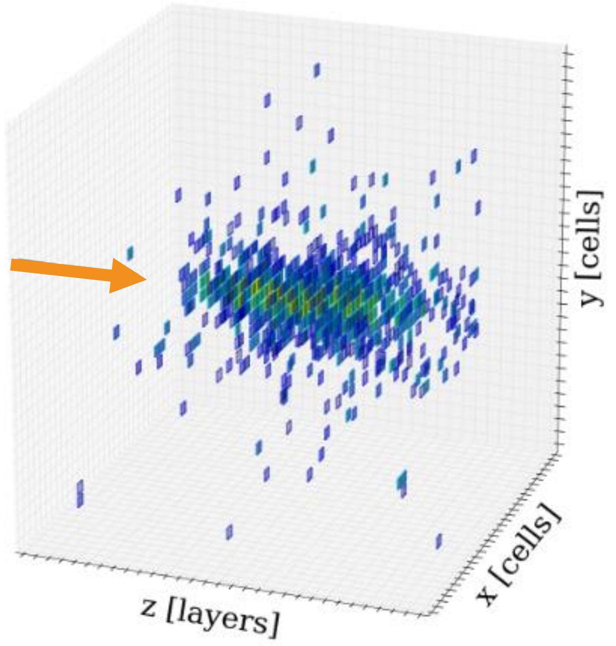


Getting High: Simulating the ILD ECAL with Deep Learning

- Previous work in our group: ILD ECAL simulation with 3 generative models
  - 30x30x30 regular grid of calorimeter cells
    - Projection from irregular geometry
  - 950k photon showers
  - Continuous and uniform range of energies: 10-100 GeV
  - Fixed incident point
  - **Perpendicular to the calorimeter face**



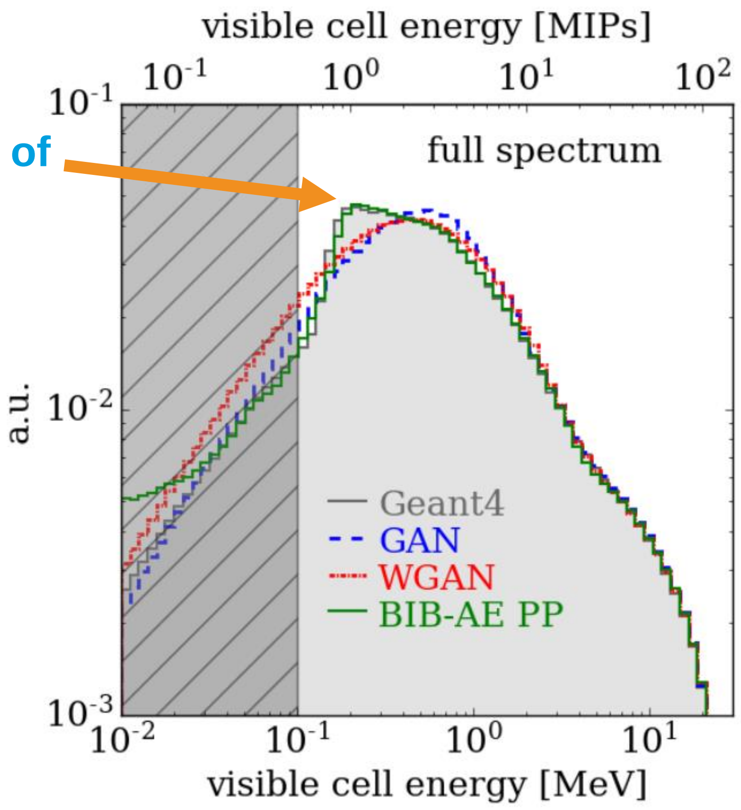
Getting High: High Fidelity Simulation of High Granularity Calorimeters with High Speed

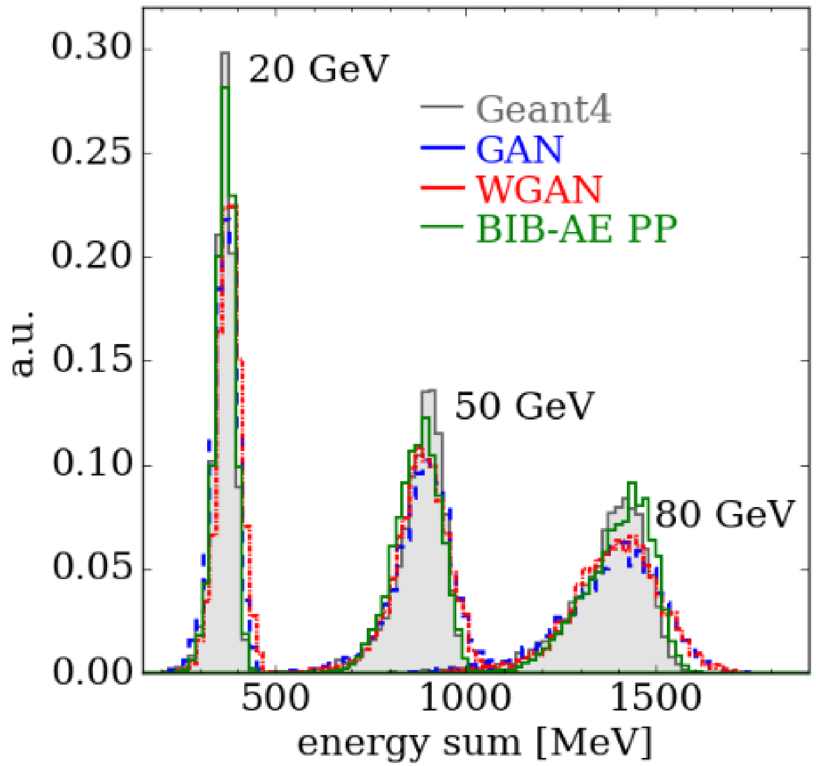
Erik Buhmann · Sascha Diefenbacher · Engin Eren · Frank Gaede · Gregor Kasieczka · Anatolii Korol · Katja Krüger

CSBS 5, 13 (2021)
https://doi.org/10.1007/s41781-021-00056-0

Getting High: High Fidelity Simulation

Energy of a MIP





- All models reproduce shape well
  - More sophisticated BIB-AE* successfully reproduces MIP peak

- Mean and width well reproduced

BIB-AE architecture described in subsequent talk by Engin
(more details: EPJ Web Conf., 251 (2021) 03003
DOI: https://doi.org/10.1051/epjconf/202125103003)

Computational performance from Getting High

Simulator	Hardware	Batch Size	15 GeV	Speed-up	10-100 GeV Flat	Speed-up
Geant4	CPU	N/A	1445.05 ± 19.34 ms	-	4081.53 ± 169.92 ms	-
WGAN	CPU	1	64.34 ± 0.58 ms	**x23**	63.14 ± 0.34 ms	**x65**
		10	59.53 ± 0.45 ms	**x24**	56.65 ± 0.33 ms	**x72**
		100	58.31 ± 0.93 ms	**x25**	58.11 ± 0.13 ms	**x70**
		1000	57.99 ± 0.97 ms	**x25**	57.99 ± 0.18 ms	**x70**
BIB-AE	CPU	1	426.60 ± 3.27 ms	**x3**	426.32 ± 3.62 ms	**x10**
		10	422.60 ± 0.26 ms	**x3**	424.71 ± 3.53 ms	**x10**
		100	419.64 ± 0.07 ms	**x3**	418.04 ± 0.20 ms	**x10**
WGAN	GPU	1	3.24 ± 0.01 ms	**x446**	3.25 ± 0.01 ms	**x1256**
		10	6.13 ± 0.02 ms	**x236**	6.13 ± 0.02 ms	**x666**
		100	5.43 ± 0.01 ms	**x266**	5.43 ± 0.01 ms	**x752**
		1000	5.43 ± 0.01 ms	**x266**	5.43 ± 0.01 ms	**x752**
BIB-AE	GPU	1	3.14 ± 0.01 ms	**x460**	3.19 ± 0.01 ms	**x1279**
		10	1.56 ± 0.01 ms	**x926**	1.57 ± 0.01 ms	**x2600**
		100	1.42 ± 0.01 ms	**x1017**	1.42 ± 0.01 ms	**x2874**