Atmospheric Background Reduction using CNNs in DSNB Searches at SuperK-Gd

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on behalf of the Super Kamiokande Collaboration

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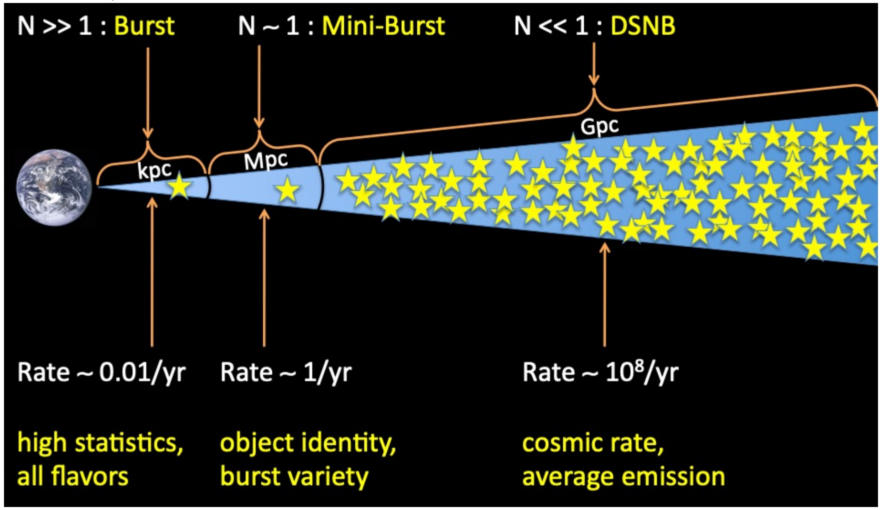
UNIVERSITY OF OXFORD

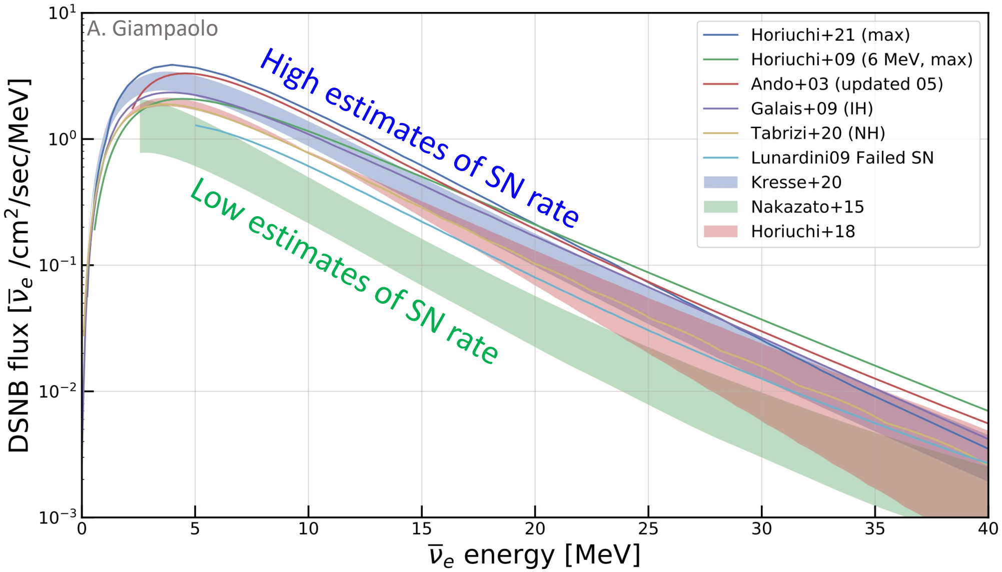
TAUP VIENNA 2023

SUPER K

The Diffuse Supernova Neutrino Background

J.Beacom, TAUP 2011





- Integrated neutrino flux from past core-collapse supernovae
- Detectable range within redshift $z \approx 1 - 2$
- Supernova physics, star formation and neutrino properties

$$\Phi_{DSNB}(E,z) = \frac{c}{H_0}\int_0^{z_{max}} R_{SN}(z)\, F_\nu\,[E(1+z)]\,\frac{dz}{\sqrt{\Omega_M(1+z)^3+\Omega_\Lambda}}$$

- Elusive low energy signal!

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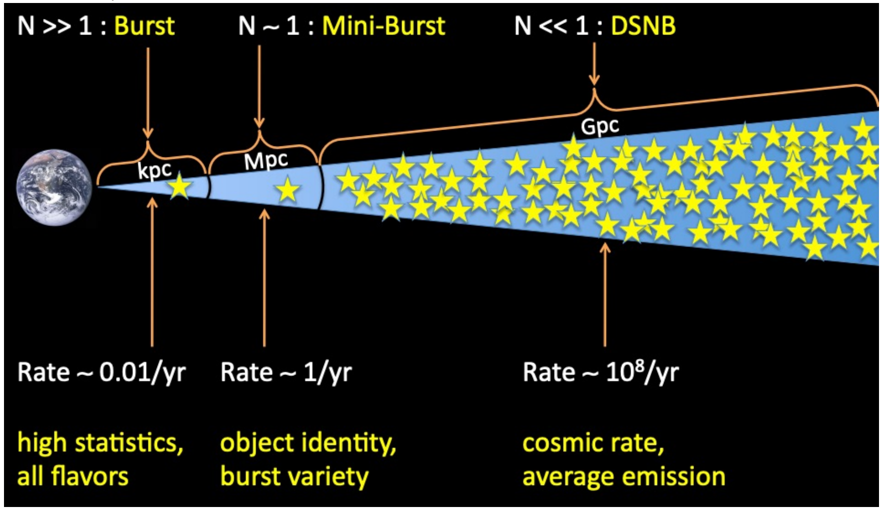

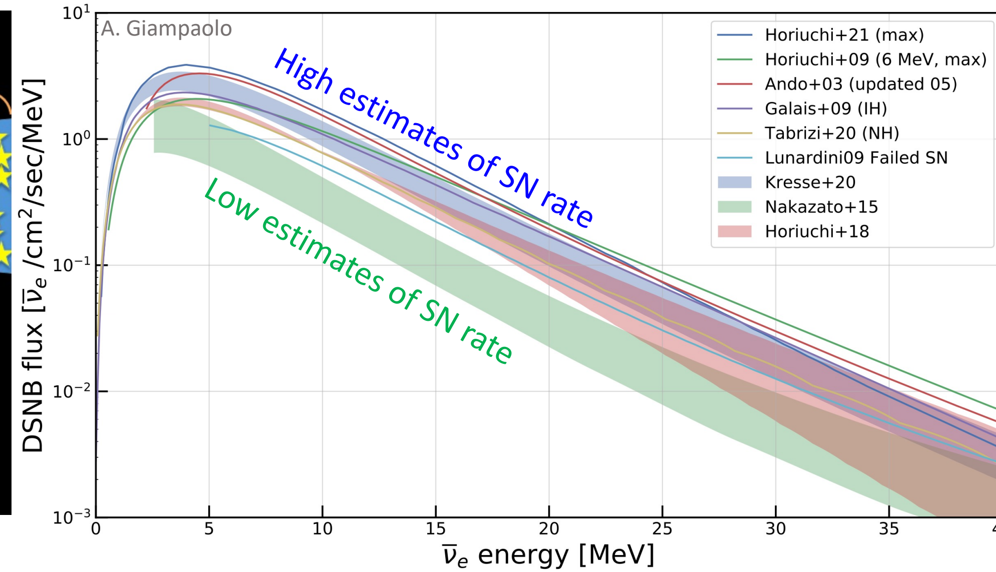

- Integrated neutrino flux from past core-collapse supernovae
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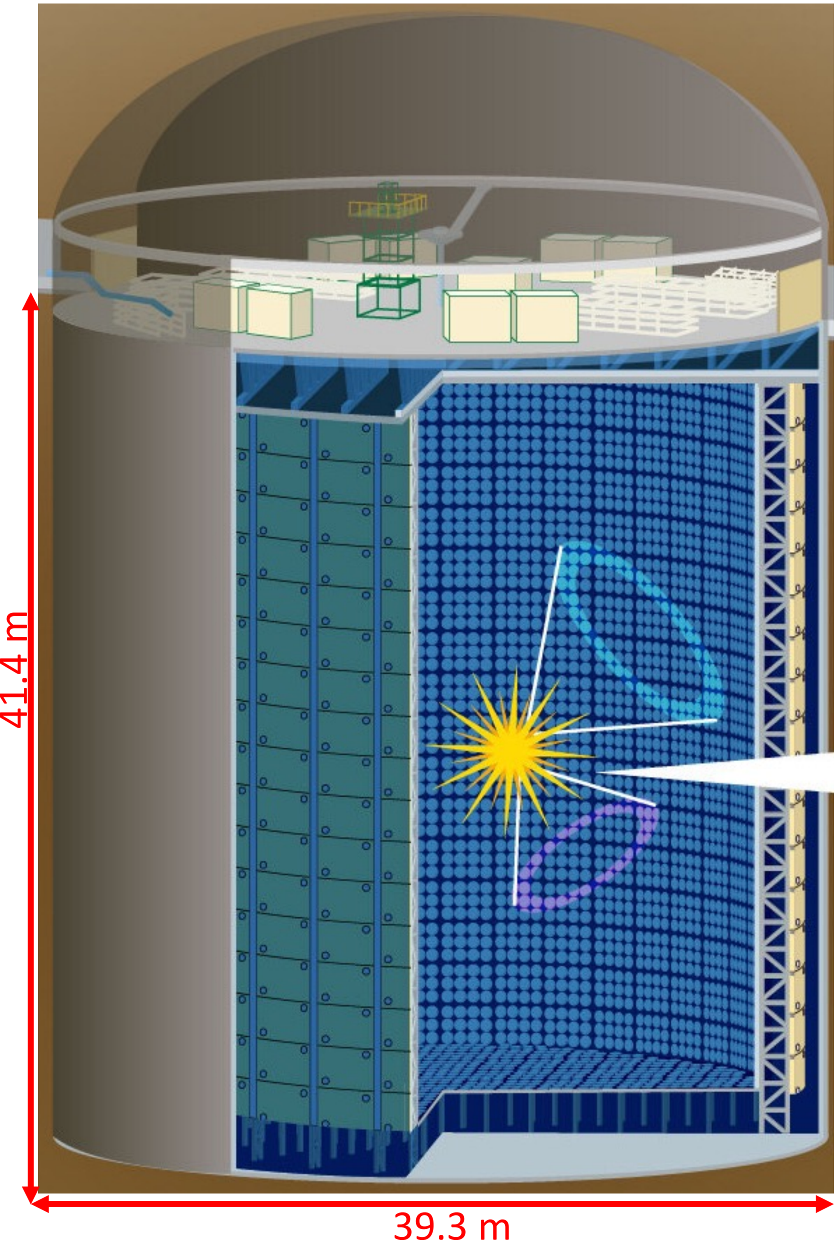
- Supernova physics, star formation and neutrino properties

$$\Phi_{DSNB} \propto \int \left[\text{SN Rate}\right] \otimes \left[\nu \text{ emission}\right] \otimes \left[\text{Cosmic Expansion}\right]$$

- Elusive low energy signal!

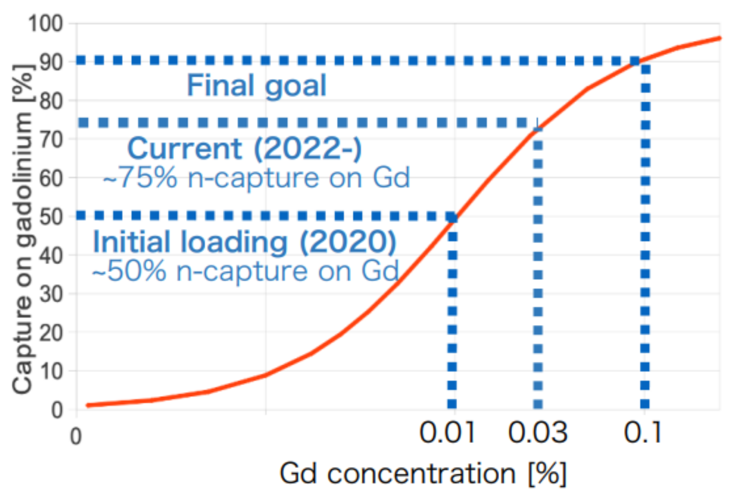
Super Kamiokande with Gd



- Located in Kamioka mine, Japan
- 50 kton water Cherenkov detector
- 22.5 kton fiducial volume
- **Inner Detector (ID)**: 11,129 50 cm PMTs
- **Outer Detector (OD)**: 1,885 20 cm PMTs + Wavelength Shifting Plates
- Low energy threshold ~ 4 MeV
- Neutron tagging via Gd loading

Enhanced capability of DSNB detection!

Neutron capture efficiency on Gd

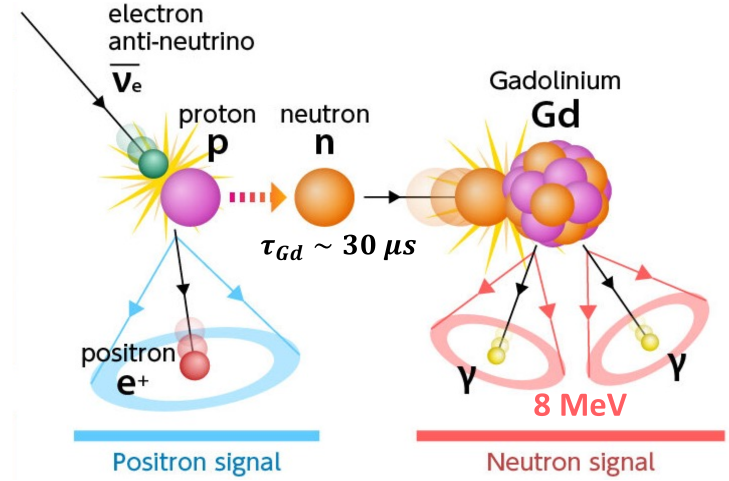


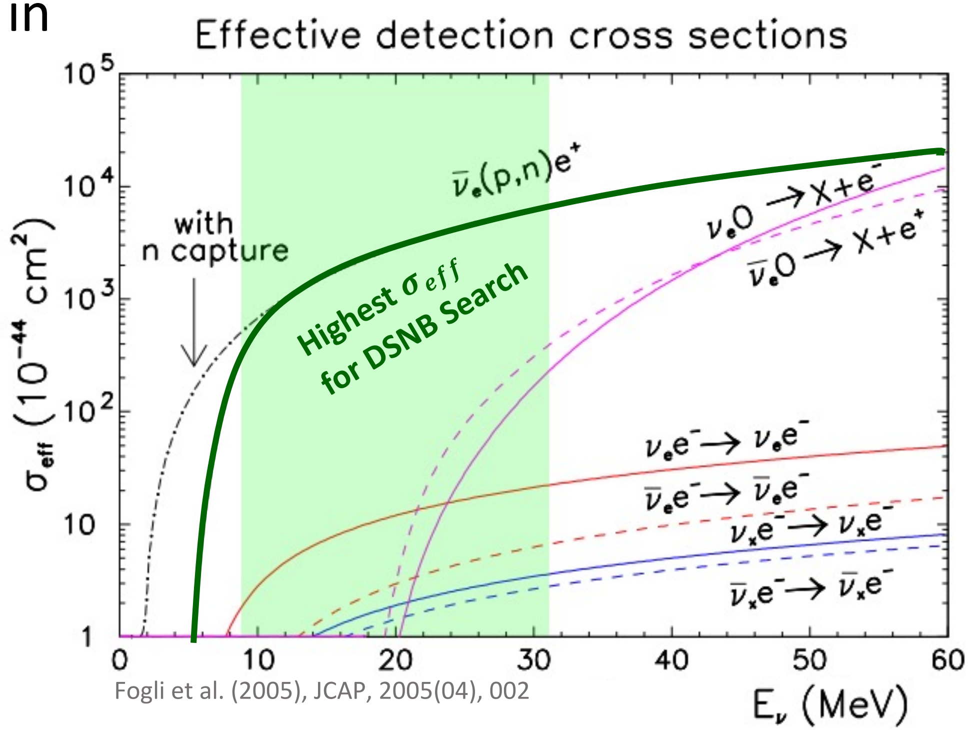
DSNB Detection in Super-Kamiokande

- **Inverse Beta Decay ($\beta + n$):**

$$\bar{\nu}_e + p \rightarrow e^+ + n$$

- **Largest interaction cross-section** for all other detection modes (2x)
- **8 – 30 MeV** DSNB Search Window in reconstructed visible energy





Fogli et al. (2005), JCAP, 2005(04), 002

DSNB Detection in Super-Kamiokande

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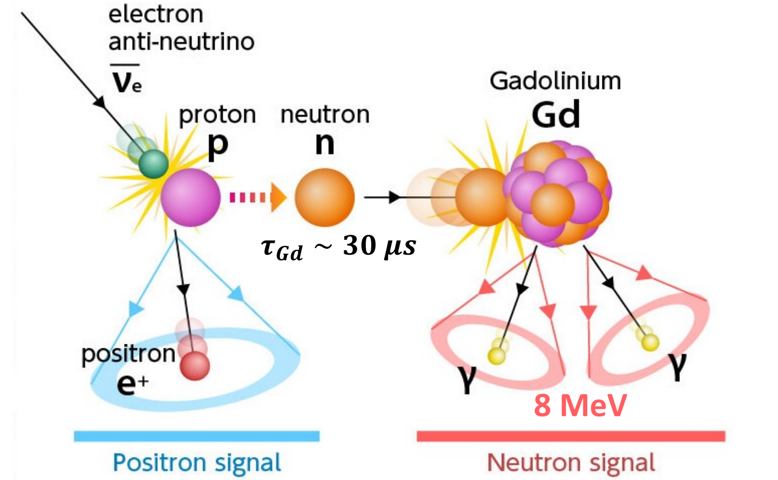
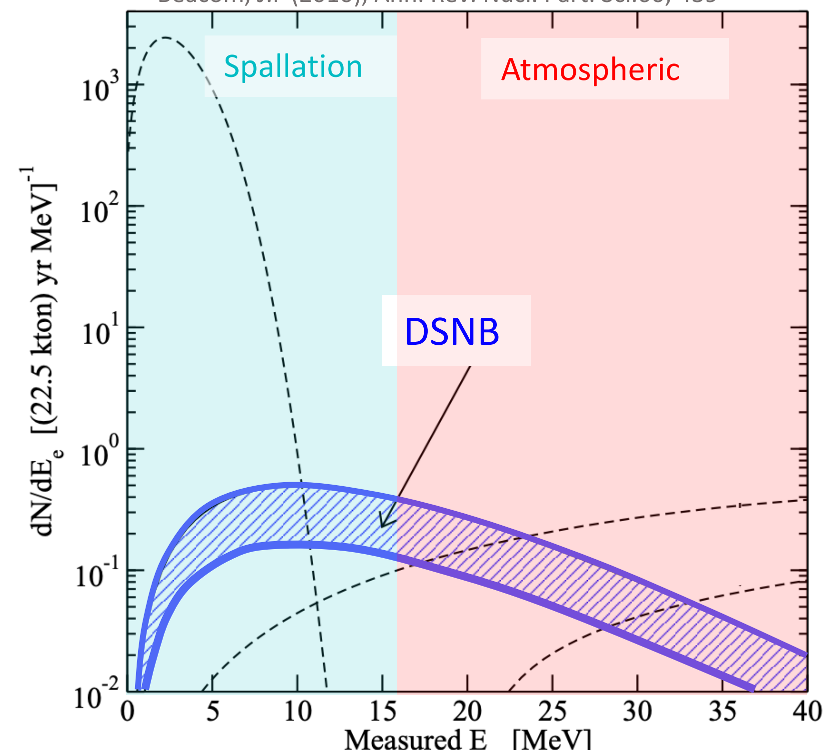
- **Largest interaction cross-section** for all other detection modes (2x)
- **8 – 30 MeV** DSNB Search Window in reconstructed visible energy
- **Few events** per year expected in the search window
- Dominated by backgrounds:
  - **Muon Spallation**
  - **Atmospheric Neutrinos**
- Require thorough background characterisation

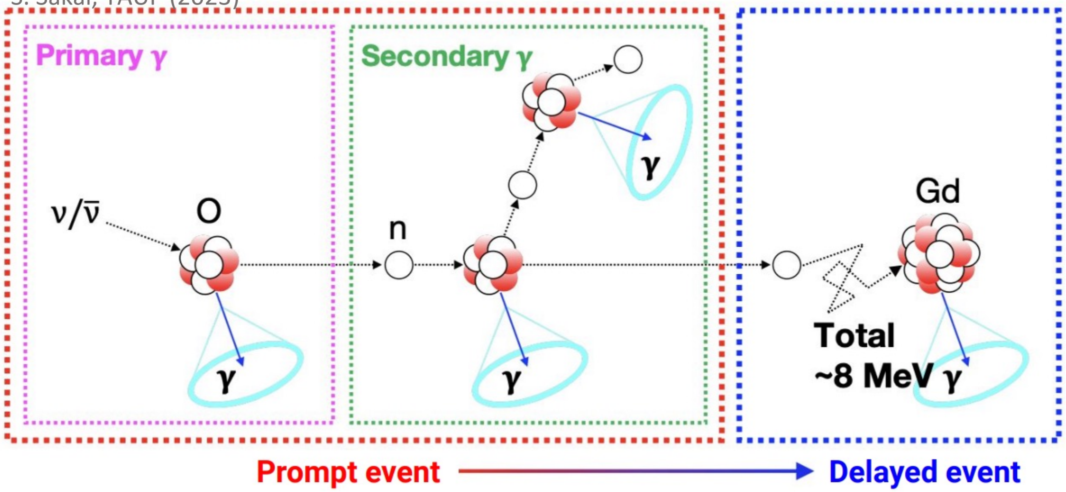


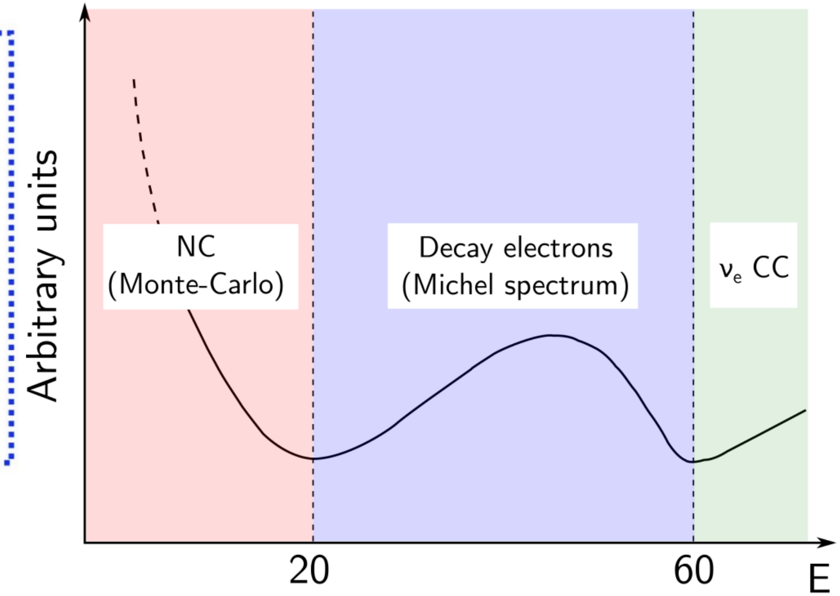
Beacom, J.F (2010), Ann. Rev. Nucl. Part. Sci.60, 439



NCQE Atmospheric Neutrino Interactions

S. Sakai, TAUP (2023)





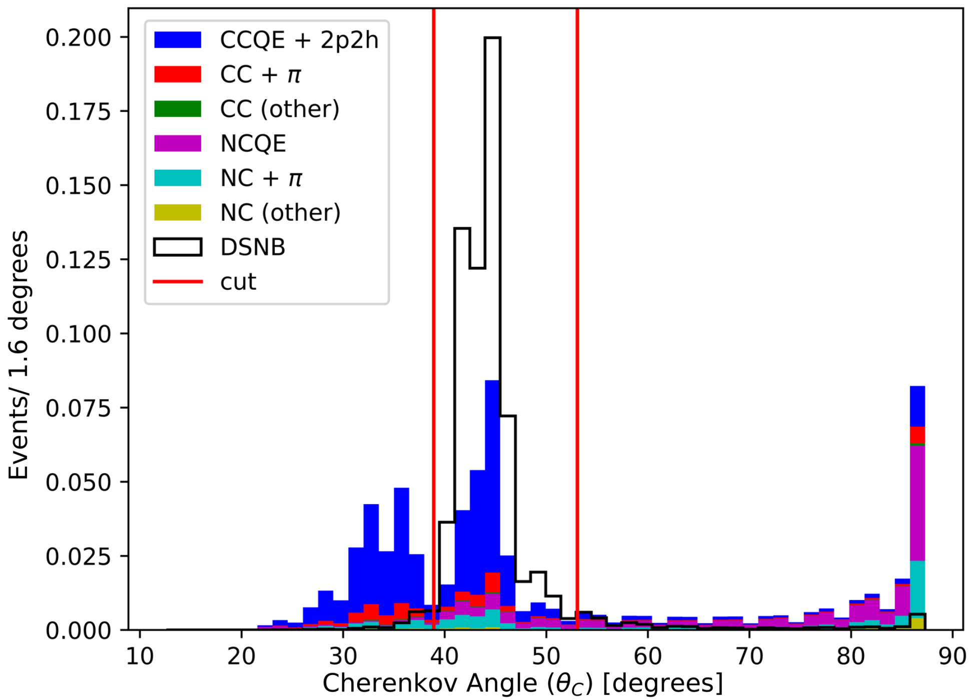
- Neutral Current Quasi-Elastic (**NCQE**) interactions:

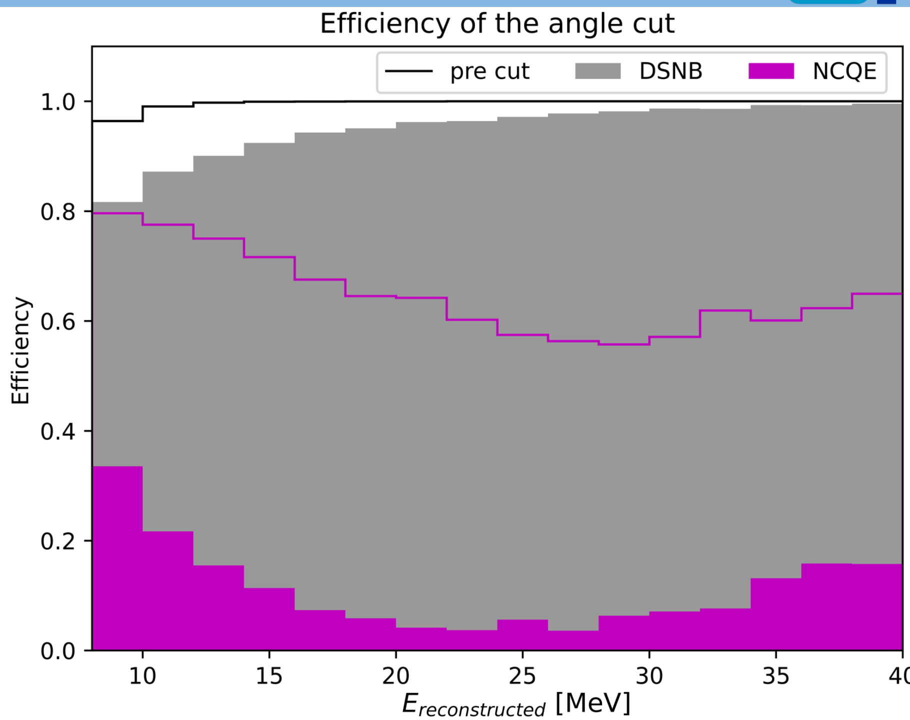
$$\nu(\bar{\nu}) + O^{16} \rightarrow \nu(\bar{\nu}) + \mathrm{n} + O^{15*}$$

$$\nu(\bar{\nu}) + O^{16} \rightarrow \nu(\bar{\nu}) + \mathrm{p} + N^{15*}$$

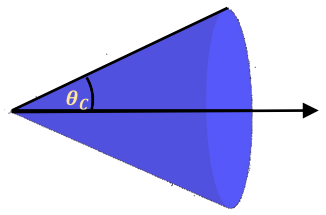
- De-excitation **primary γ-ray + neutron** (mimics IBD signal)
- Multiple **secondary γ-rays** from nucleon interactions in prompt window
- Dominant **below 20 MeV**
- Currently a **residual background** in the DSNB search

Reducing the NCQE Background



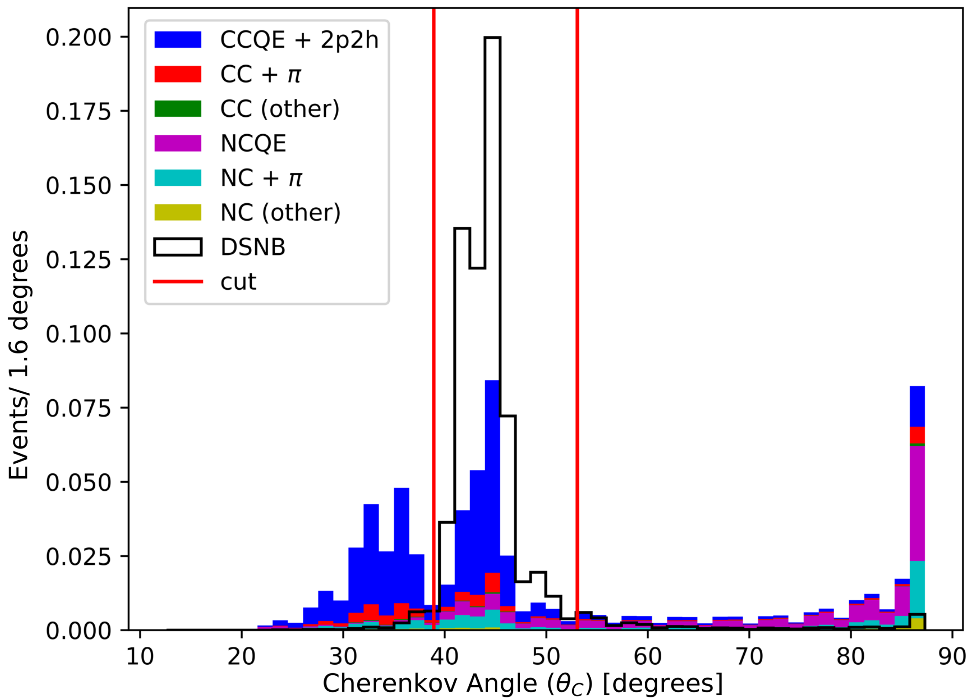


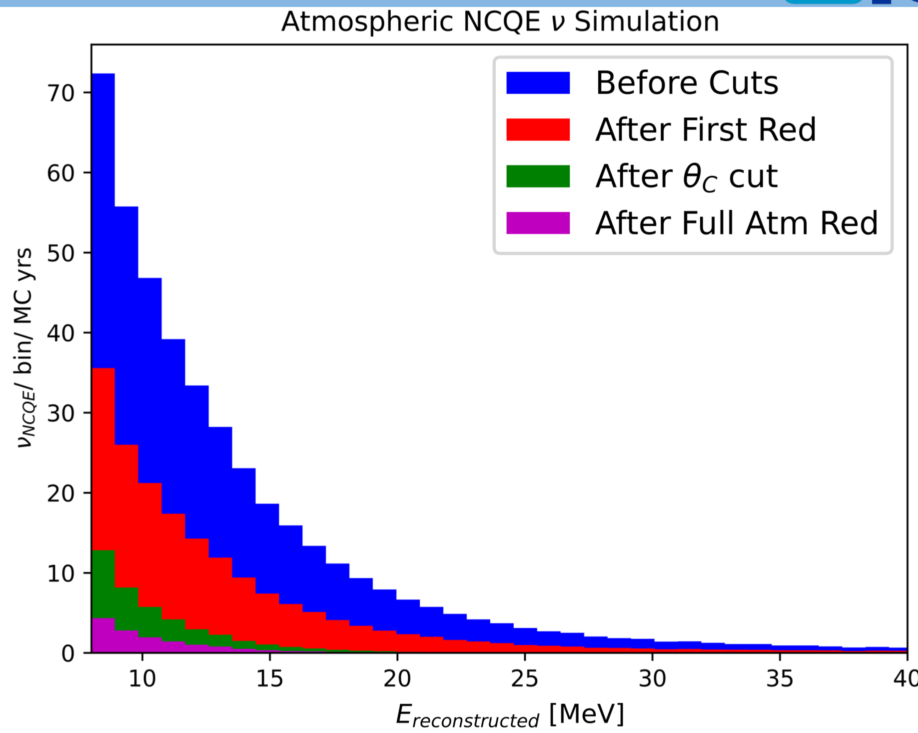
- Powerful discriminator based on the **Cherenkov opening angle** $(\boldsymbol{\theta_C})$
  - $\boldsymbol{\theta_C \sim 42^\circ}$ for IBD interactions (**DSNB**)
  - $\boldsymbol{\theta_C}$ **is large** for **NCQE** events due to multiple secondary γ-rays



- DSNB search window (current analysis cut) $\boldsymbol{\theta_C}$: $[38^\circ, 53^\circ]$
- Large residual NCQE contribution after angle cut applied – challenging background requires new reduction techniques

Reducing the NCQE Background





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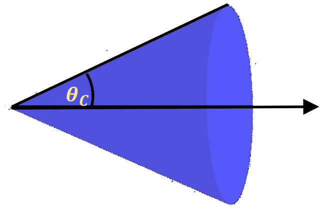


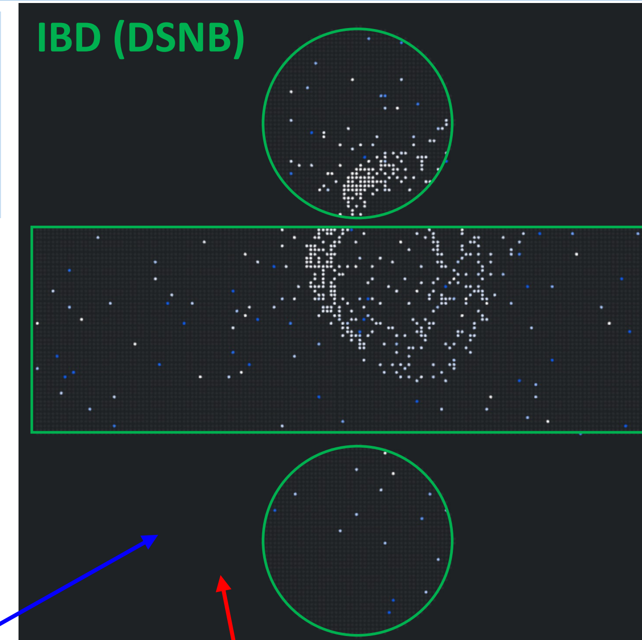
- DSNB search window (current analysis cut) $\boldsymbol{\theta_C}$: $[38^{\circ}, 53^{\circ}]$
- Large residual NCQE contribution after angle cut applied – challenging background requires new reduction techniques, **such as Convolutional Neural Networks!**

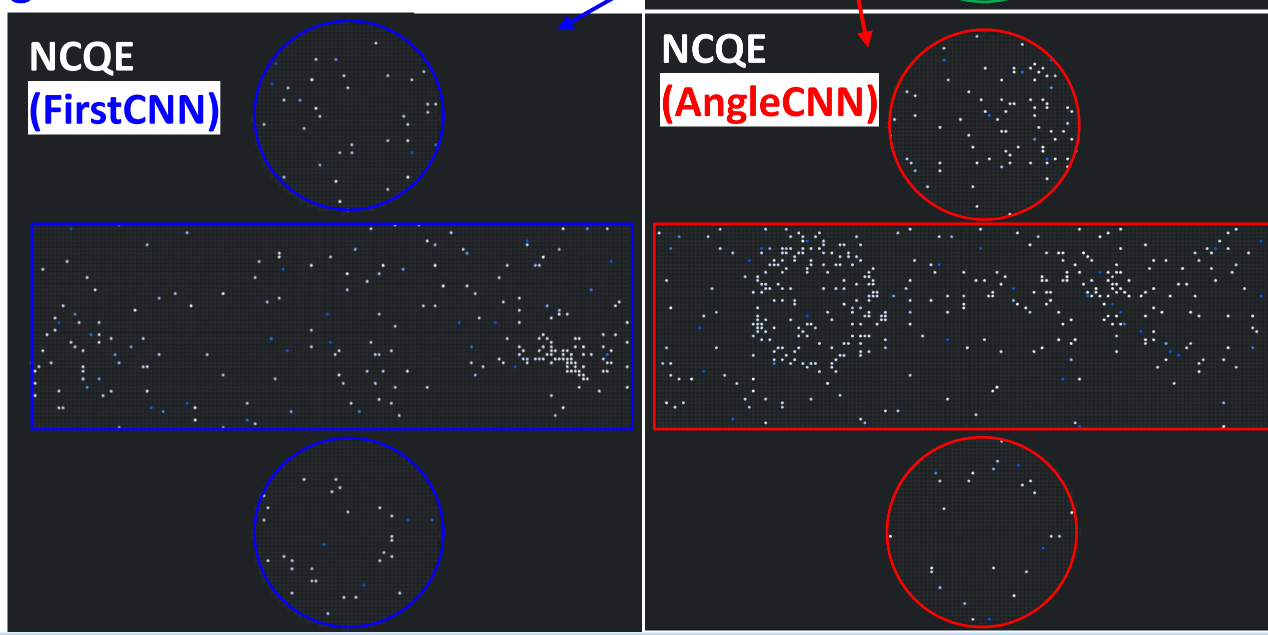
CNN Models: Event Selection for Training

Convolutional Neural Networks (CNNs) trained **with**/**without** **the θ_C cut** to investigate a new method for targeted NCQE reduction.

FirstCNN Model:

- First reduction of the DSNB analysis applied to IBD and NCQE Super-K (Gd) simulation
- This includes **only energy window, fiducial volume and noise cuts** to remove obvious and mis-reconstructed backgrounds
- Select events with **one tagged neutron**

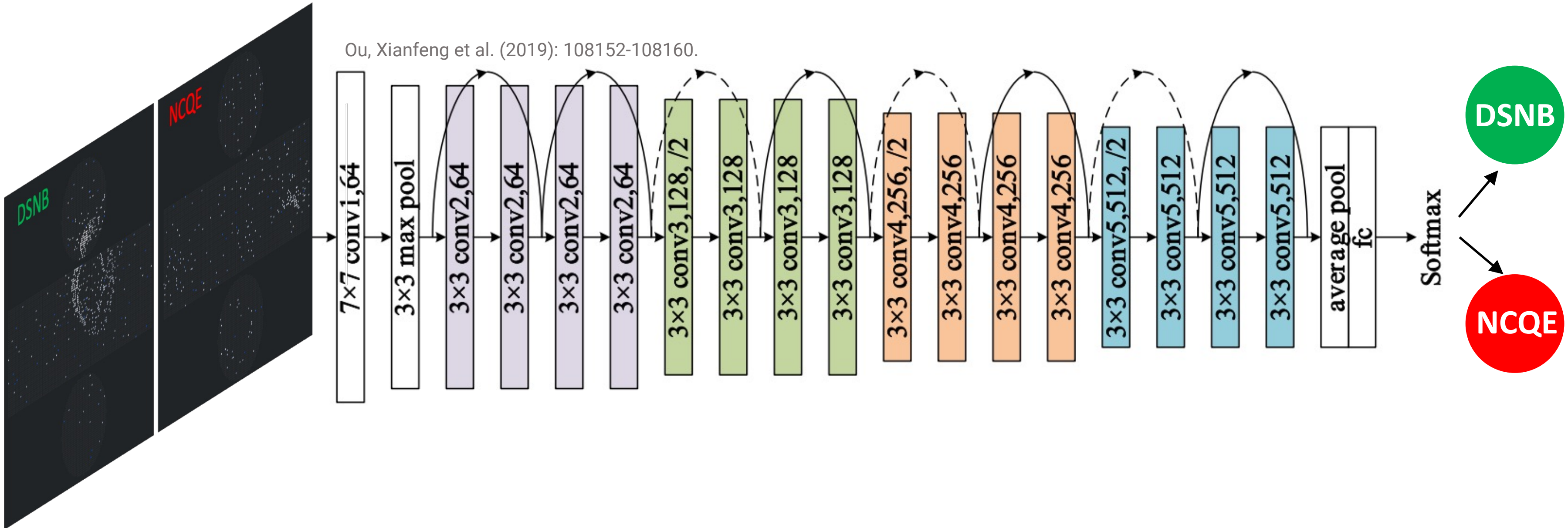




AngleCNN Model:

- Used FirstCNN event selection, then applied **the Cherenkov angle cut**

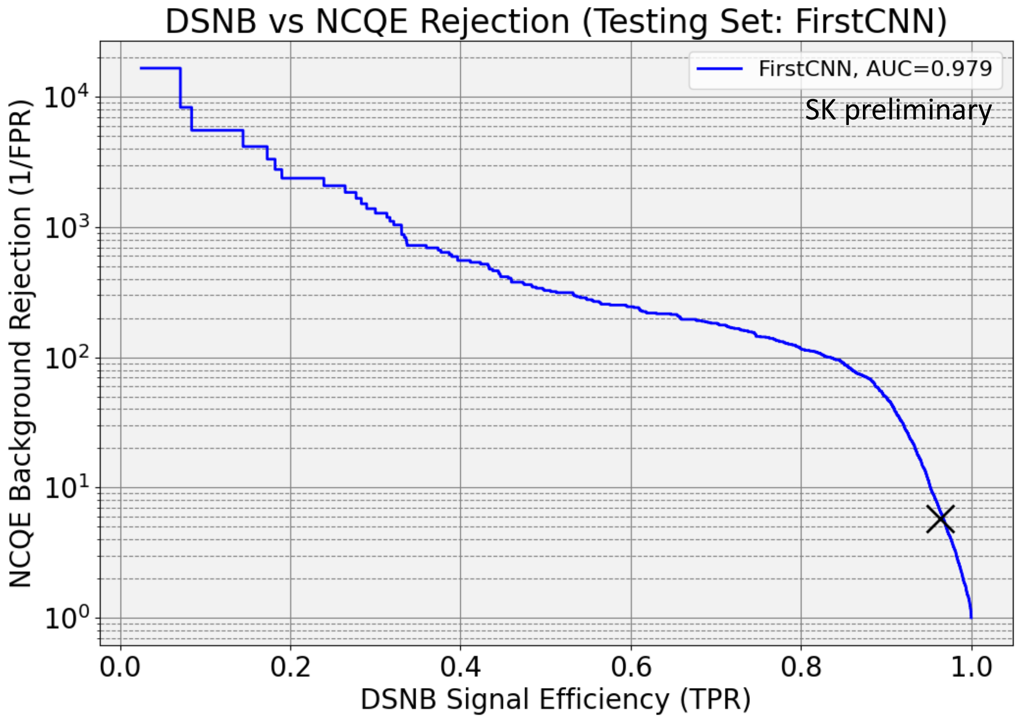
Convolutional Neural Networks

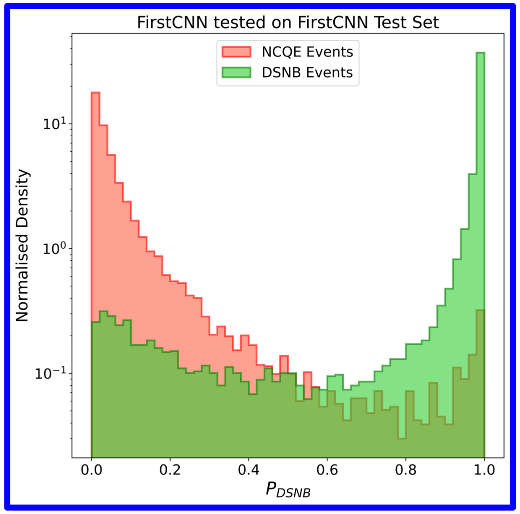


- **ResNet-18 Convolutional Neural Network (CNN):** 18 layers with residual connections to enable faster training for deeper networks.
- Using the Water Cherenkov Machine Learning (**WatChMaL**) framework 
- **Input:**
  - Standard SuperK event display (timing and charge) to 2D image mapping
  - Prompt event only for e/ γ classification
- **Training:**
  - Optimised hyper-parameters for training (see backup)

Model Performance on FirstCNN Test Set

- **FirstCNN – Clear Backgrounds:**
  - Test set includes many NCQE events with ambiguous Cherenkov rings
  - Classifies apparent NCQE events that lack distinctive Cherenkov ring to enhance signal purity





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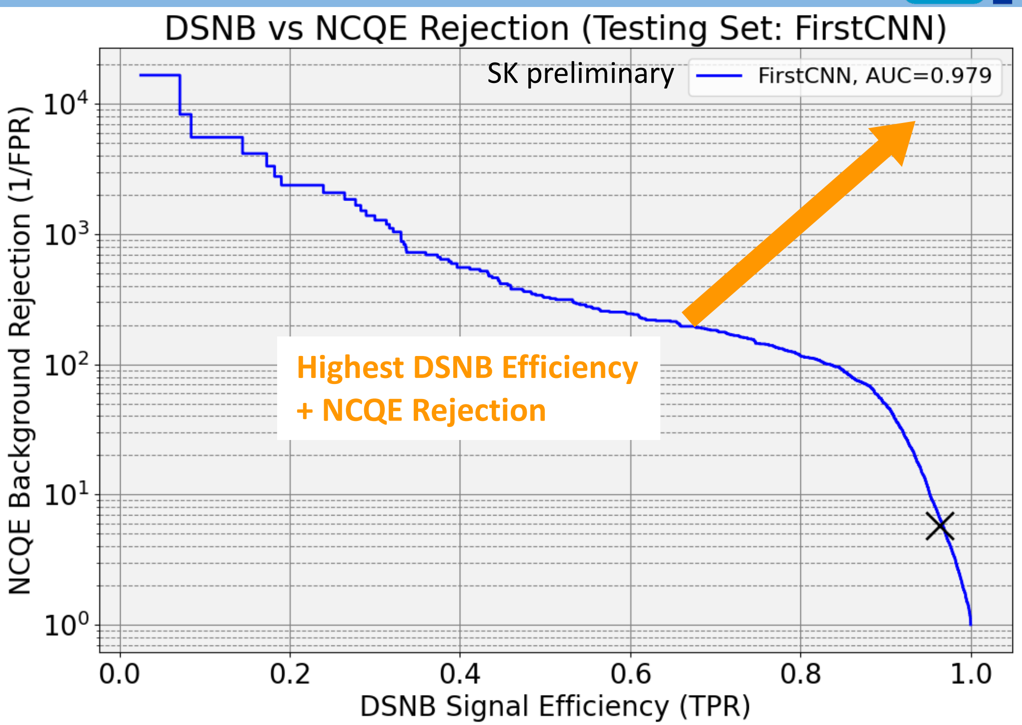

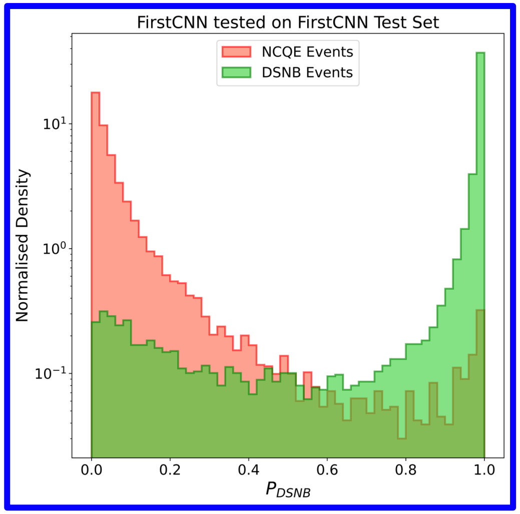

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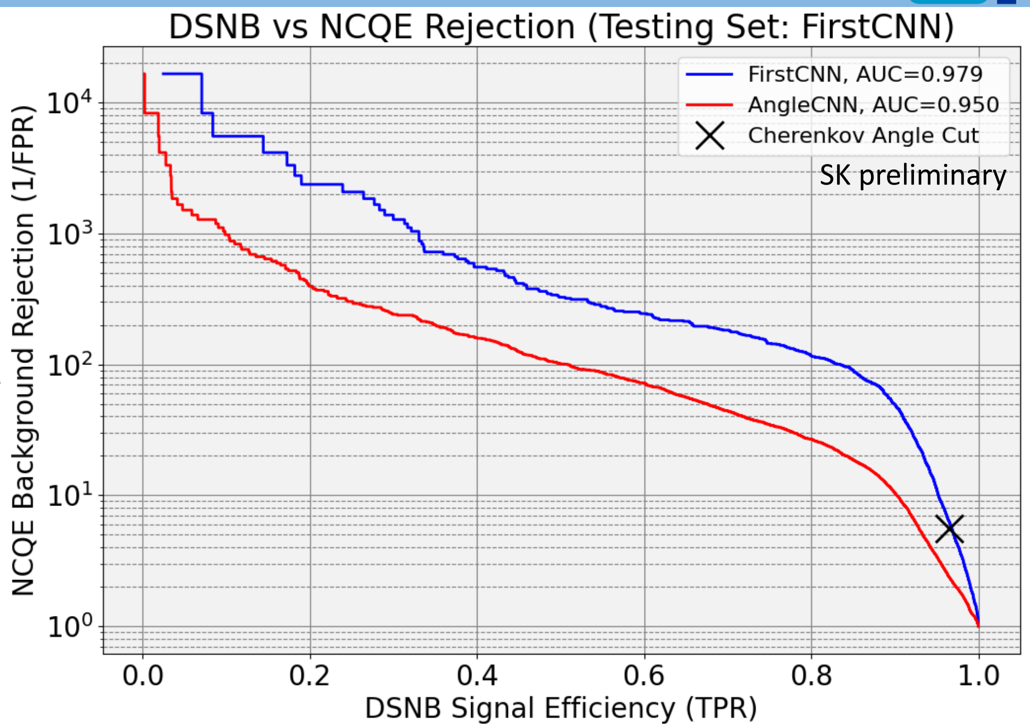
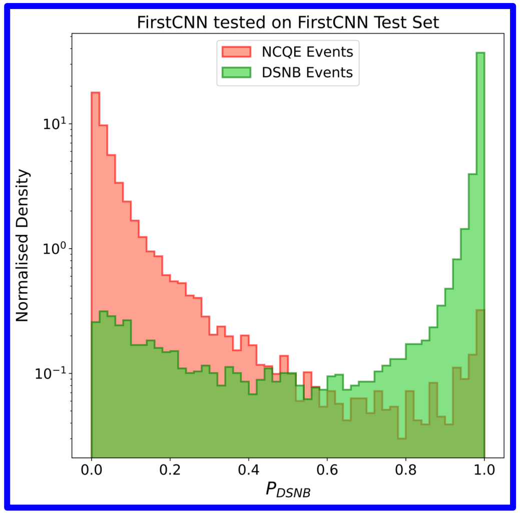
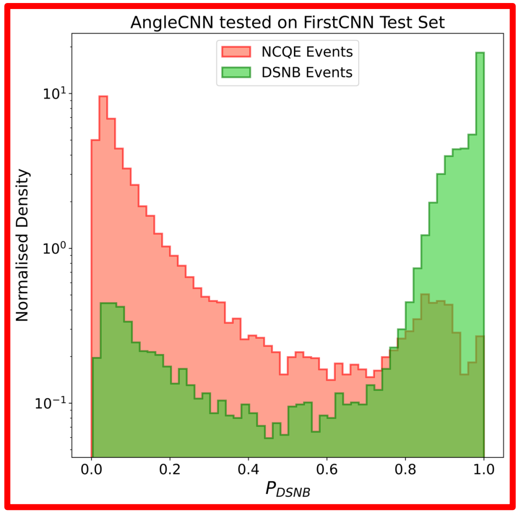
- **AngleCNN – Enhanced Reduction:**
  - Focused learning on subtle topological features of e and γ – induced Cherenkov ring
  - Distinguishes events with similar hit distributions, with Cherenkov ring characteristics







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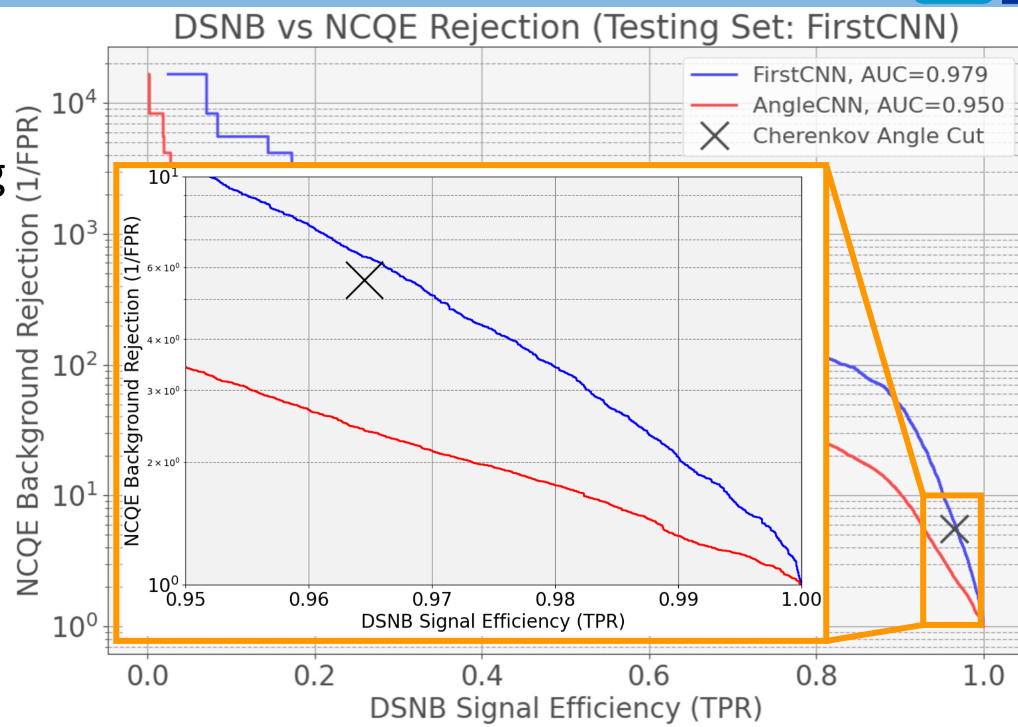
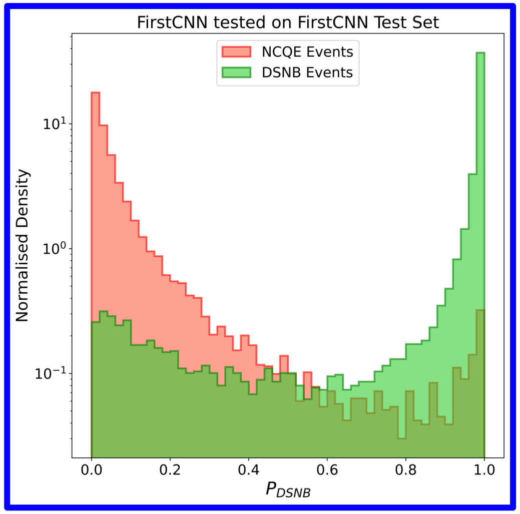
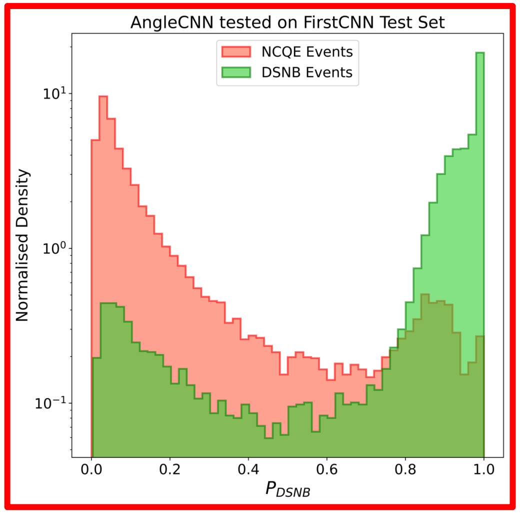
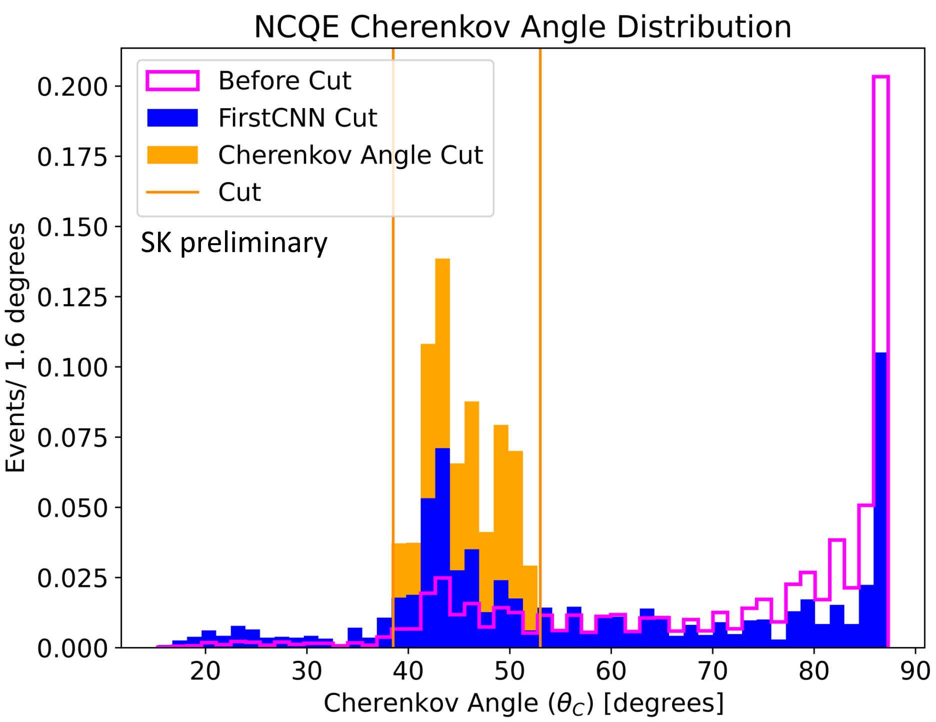
- **FirstCNN > Angle Cut**
  - Marginal improvement at signal efficiency of Cherenkov angle cut

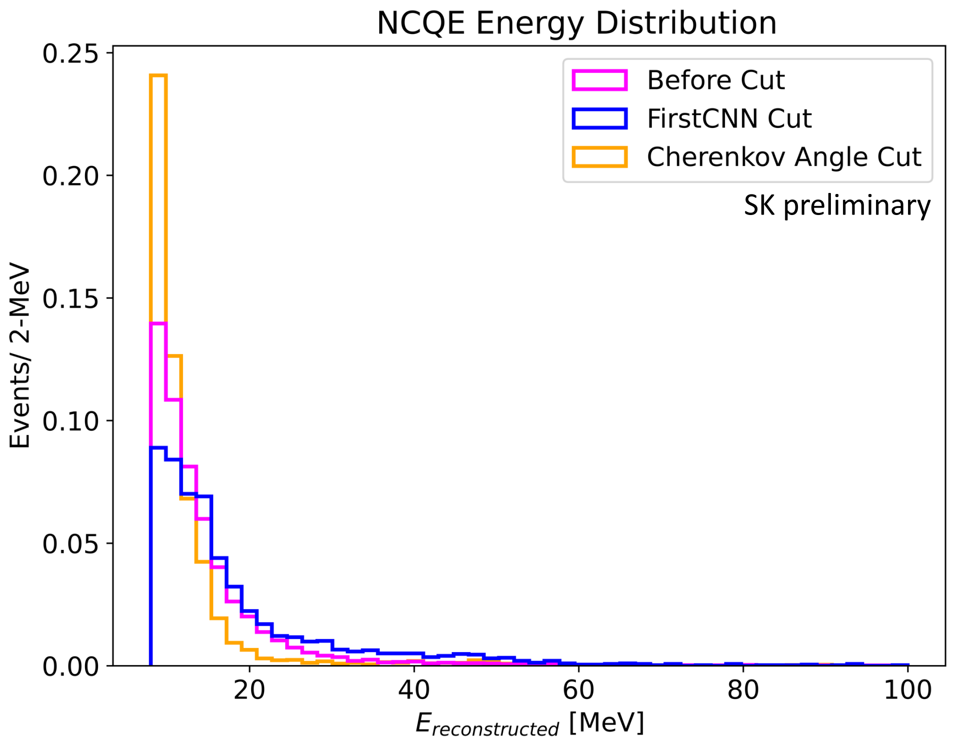






Understanding CNN Performance





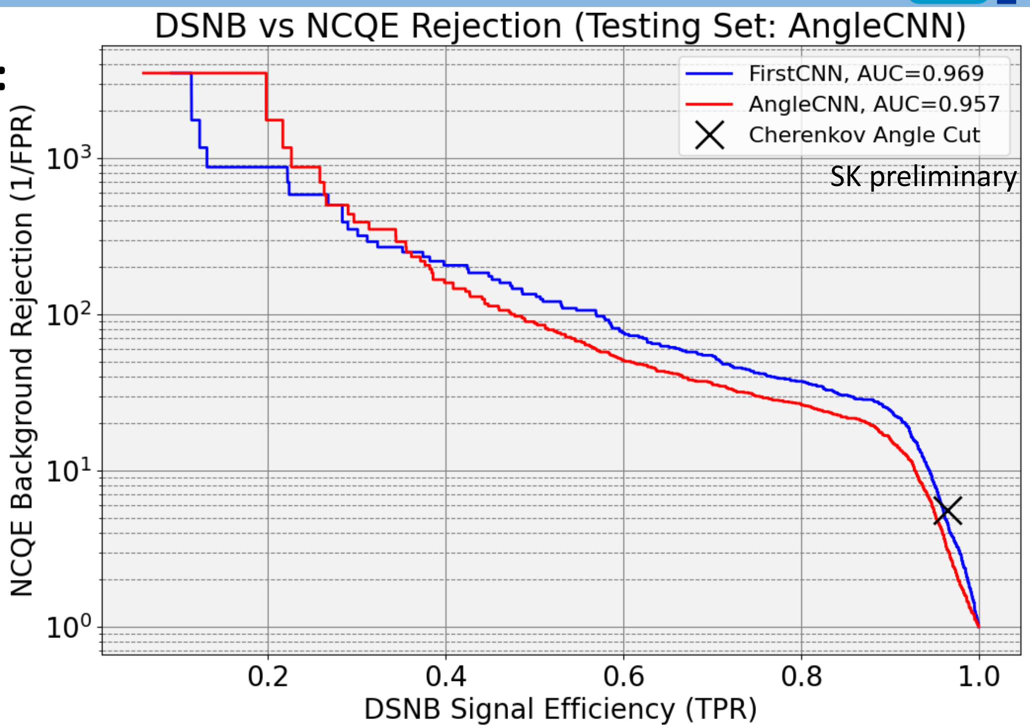
- **NCQE Angle and Energy distributions – Before any cuts**
- **Cherenkov Angle Cut:**
  - DSNB search window (current analysis cut) $\boldsymbol{\theta_C : [38^{\circ}, 53^{\circ}]}$
  - **Residual background at low energy**

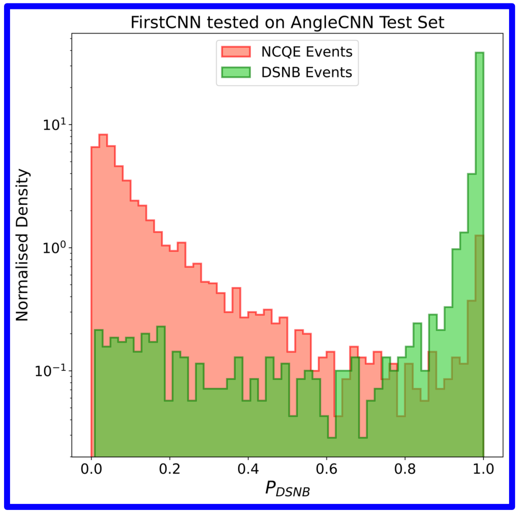
Evaluate at the Cherenkov Angle Signal Efficiency ($\sim$96%)

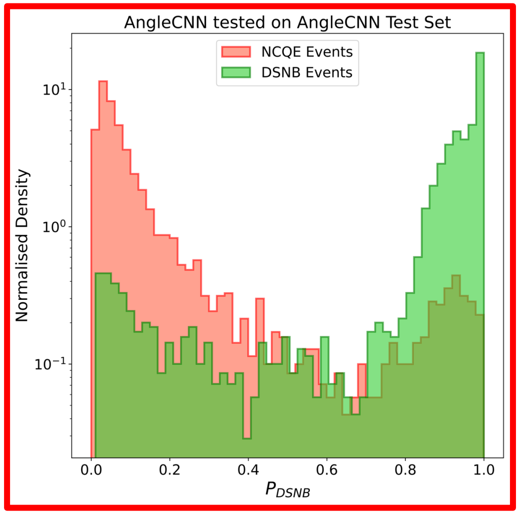
- **FirstCNN Cut:**
  - Applies an energy dependent cut – inferred from PMT hit distribution
  - **Combination of CNN and optimised Cherenkov Angle cut - effective reduction**

Model Performance on AngleCNN Test Set

- **FirstCNN outperforms AngleCNN:**
  - **Effective features**: Captures crucial event features of Cherenkov ring
  - **Generalisation**: Avoids overfitting to generalise well to unseen data
  - **Training Data**: Benefits from training data that includes both ambiguous and clear Cherenkov rings for NCQE events
  - Performance declines at high NCQE rejection
  - AngleCNN effective at discriminating challenging NCQE events at low signal efficiency





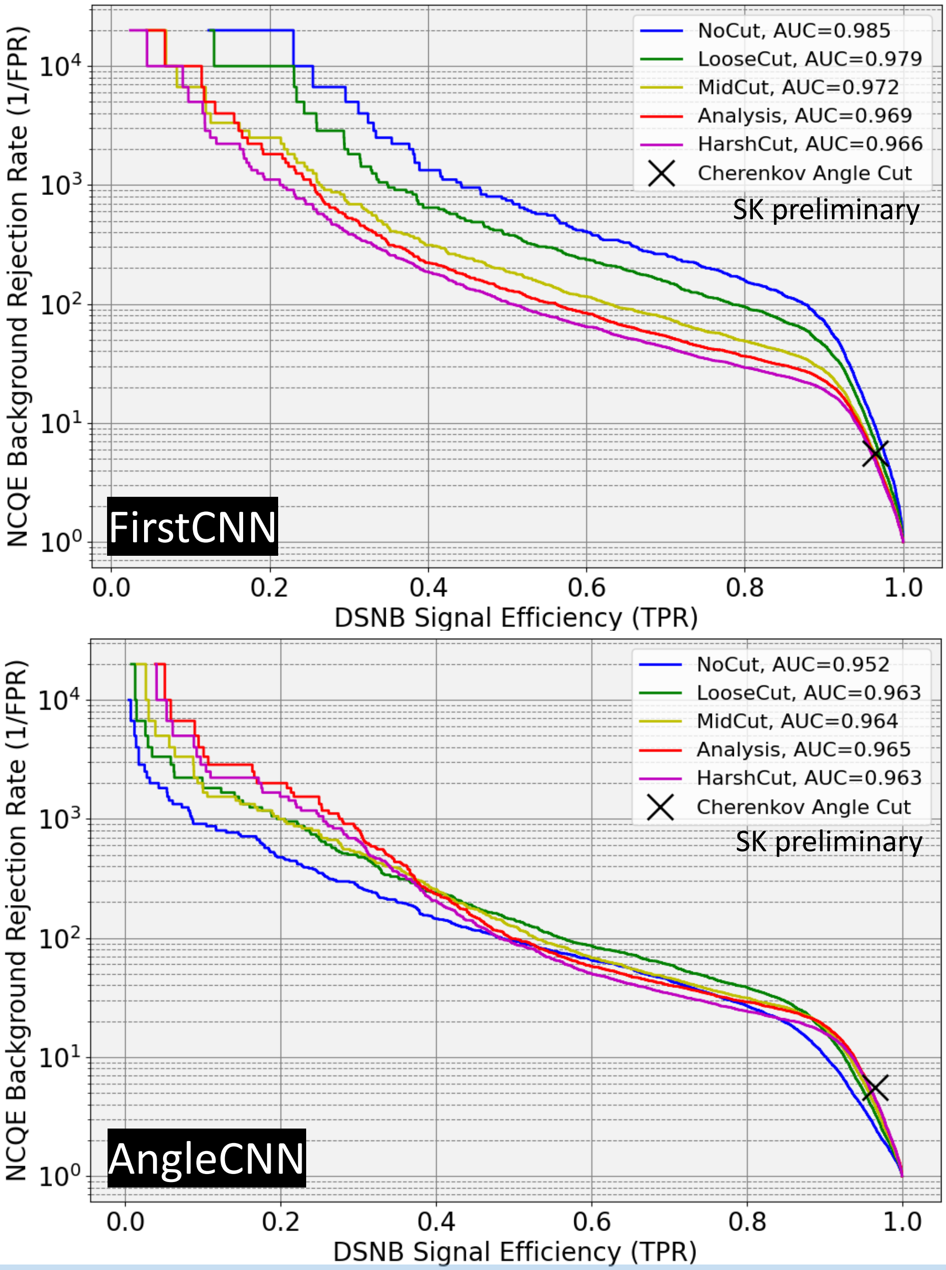


Robustness Analysis

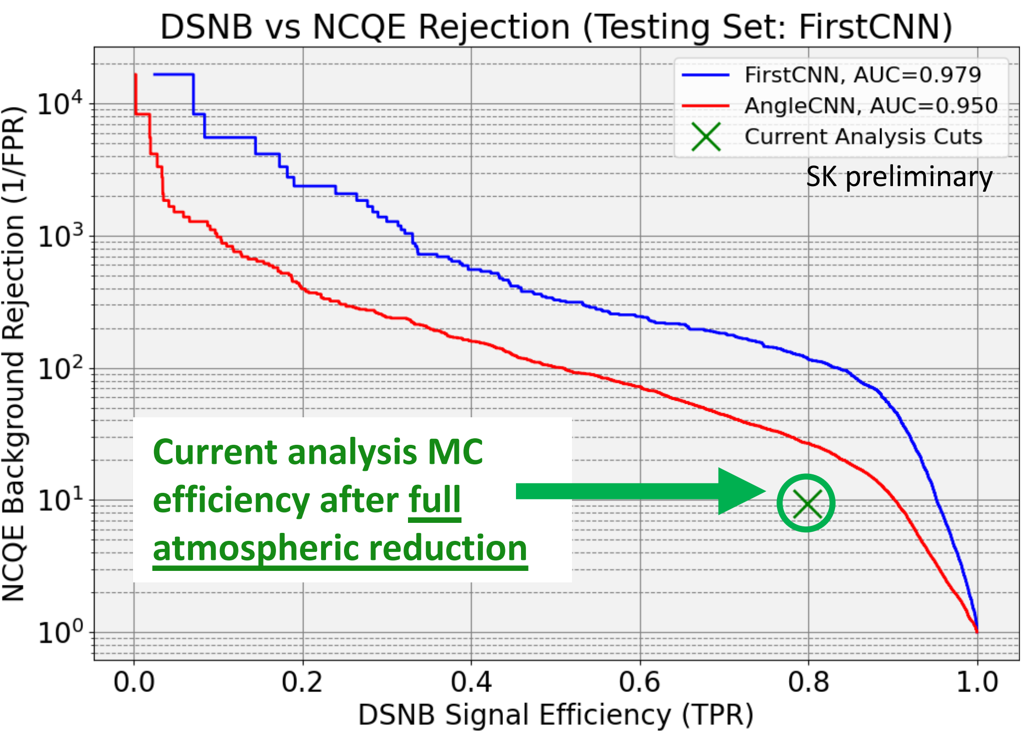
- **Testing on different angle cuts (θ_C)**
  - **NoCut⇔FirstCNN** test set $[0^\circ, 90^\circ]$
  - **LooseCut**: $[30^\circ, 80^\circ]$
  - **MidCut**: $[35^\circ, 60^\circ]$
  - **Analysis⇔AngleCNN** test set $[38^\circ, 53^\circ]$
  - **HarshCut**: $[40^\circ, 50^\circ]$

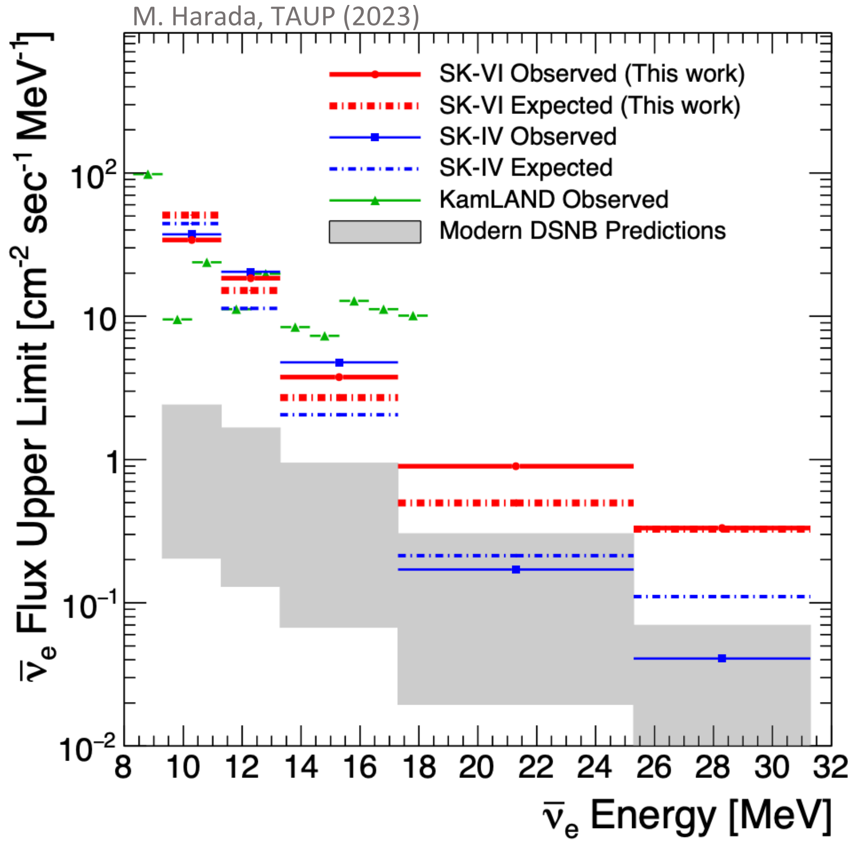
- **FirstCNN's Performance Decline:** Performance drops with more stringent cuts. Still outperforms AngleCNN at DSNB traditional analysis efficiency

- **AngleCNN's Robust Adaptability:** Maintains performance with stricter angle cut due to specialised training



DSNB Current Upper Limits





- Develop an effective reduction method to **enhance signal and background efficiencies beyond current level**
- Current **best upper limits achieved in SK-VI** (see talk by M.Harada, Thursday August 31st)

Summary

- **Dominant contribution of NCQE Background** in DSNB Search Window
- Current best handle is cut on **reconstructed Cherenkov angle**
- **Residual background at low energy** – in region of the highest flux prediction of DSNB models
- Investigated **new reduction techniques using CNNs** – ResNet-18 models trained on samples with/without Cherenkov cut applied
- **FirstCNN moderately improves reduction** at Cherenkov angle cut efficiency
- Combination of **CNN cut + optimised angle cut** will likely be an effective reduction method

Next Steps

- Explore deeper ML methods – **Graphical Neural Networks**
- **Integrate novel reduction approach into full energy bin-by-bin analysis**
- Aim to **improve DSNB upper limit constraints**

Thank You!

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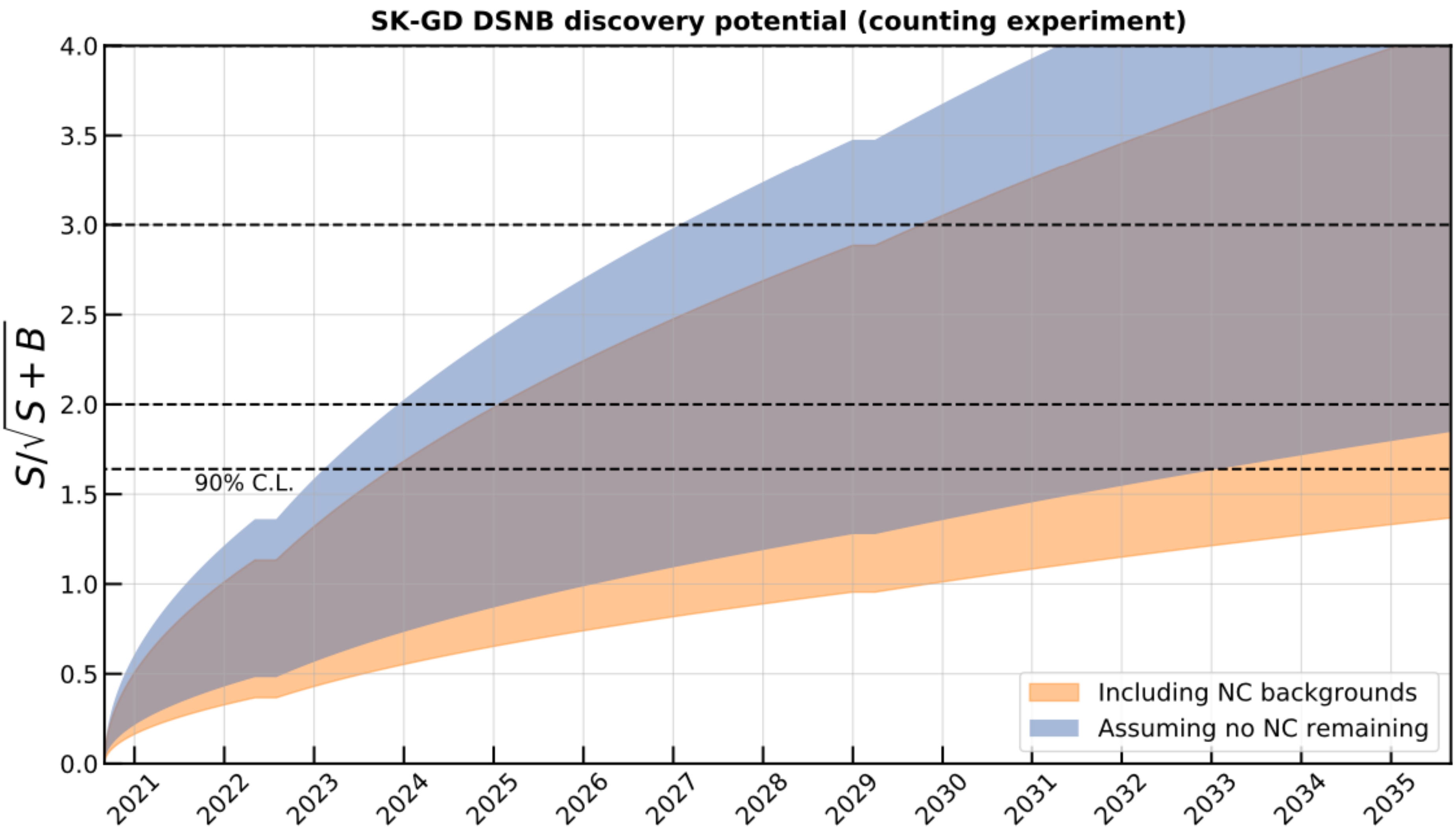
BACKUP – DISCOVERY POTENTIAL

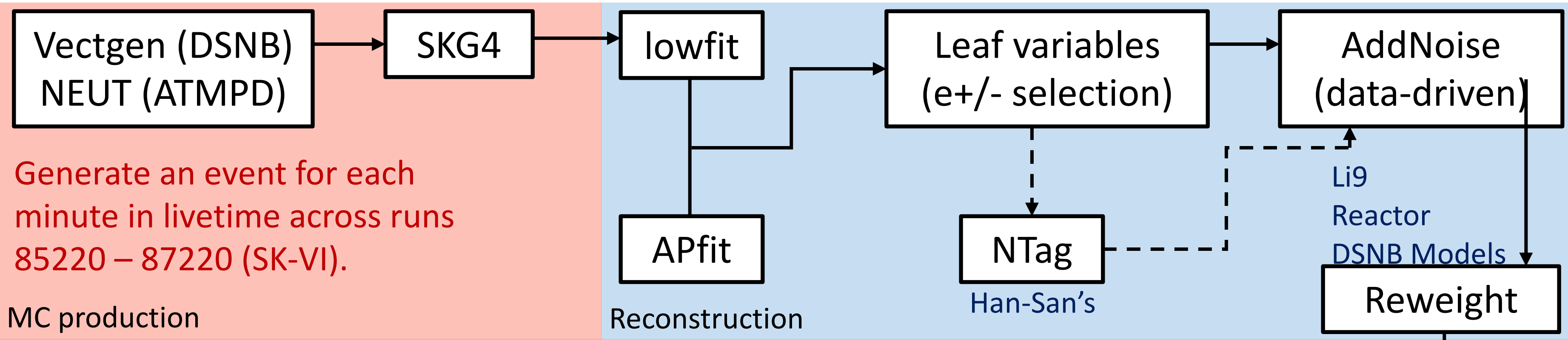
DSNB Discovery Potential



Study done by A. Giampaolo

BACKUP – TRADITIONAL ANALYSIS

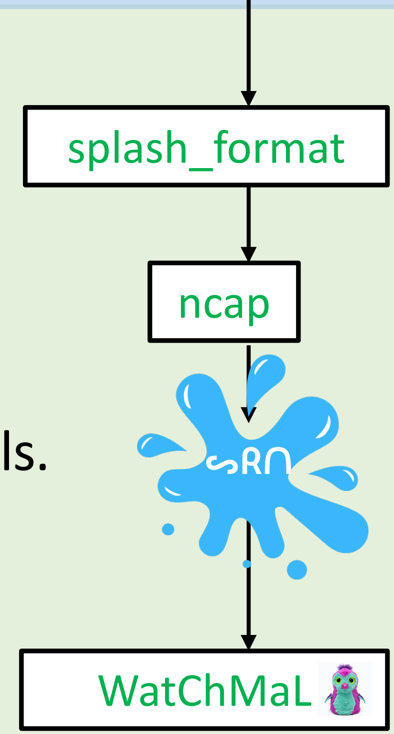
IBD and Atmospheric MC Generation



Analysis:

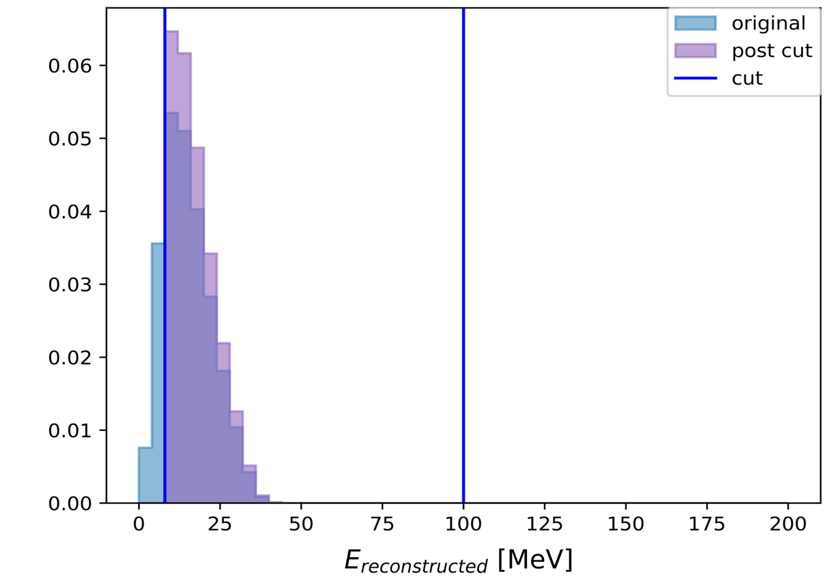
- DSNB MC: 522 livetime days of full SK-VI duration
- ATM MC: 500 years of atmospheric neutrino events, with an additional 5000 years equivalent NCQE MC.

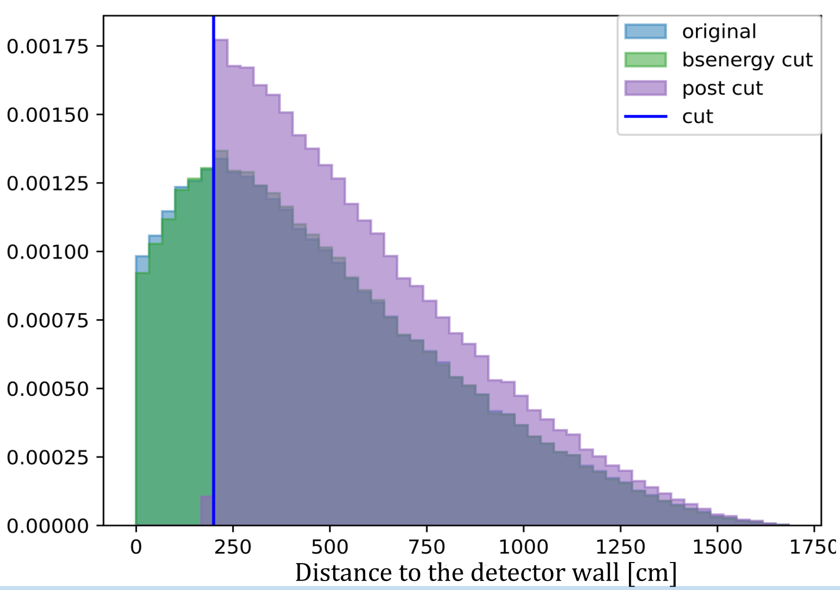
1. Atmospheric modelled with HKKM-2011 flux with NEUT.
2. Kresse spectrum for IBD MC – reweighting to DSNB models.
3. Low energy reconstruction
4. Inject data-driven noise
5. Apply neutron tagging
6. Event selection – efficiency calculations
7. Format for CNN input



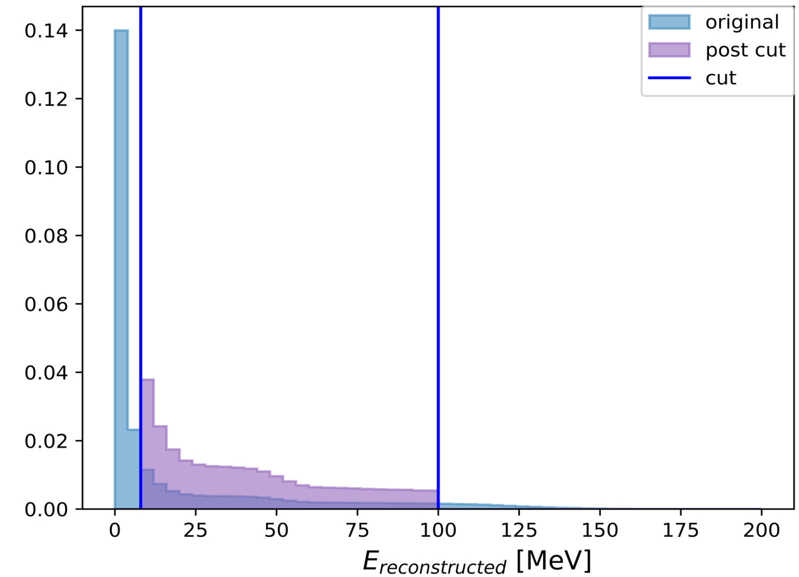
Event Selection – First Reduction

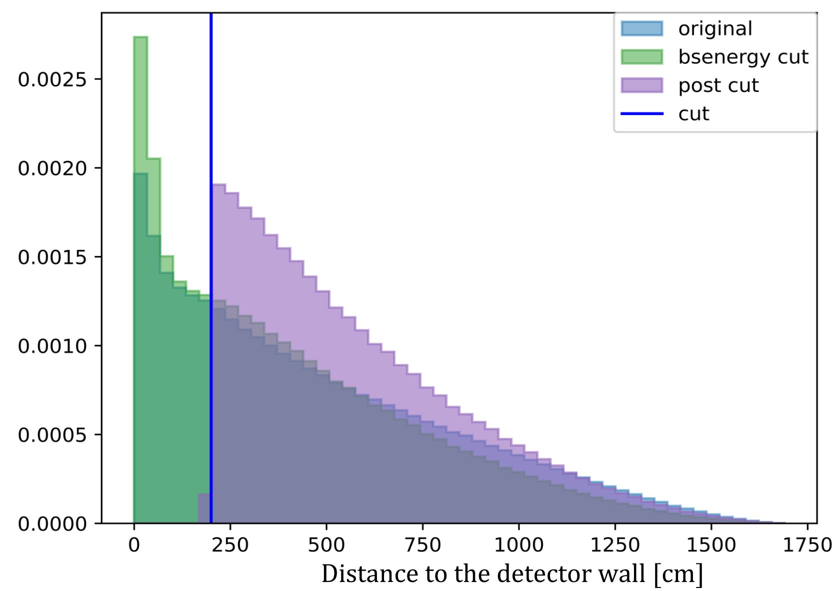
DSNB (Horiuchi)





Atmospheric Background





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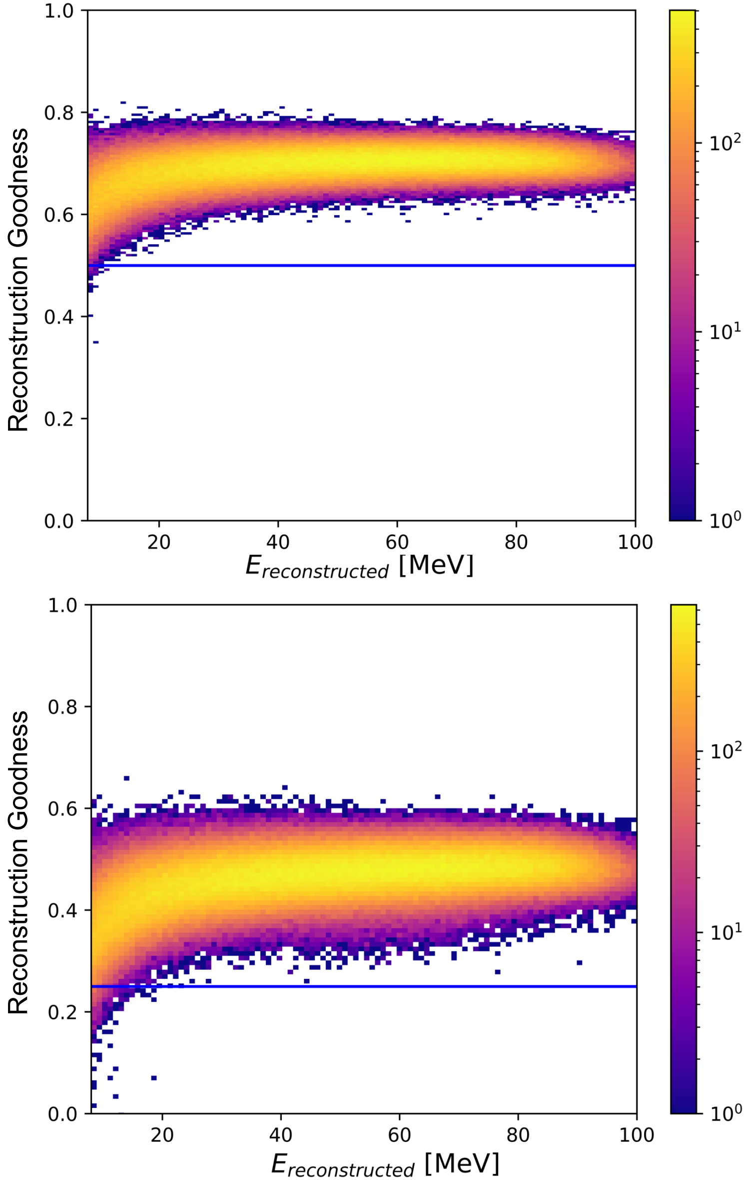

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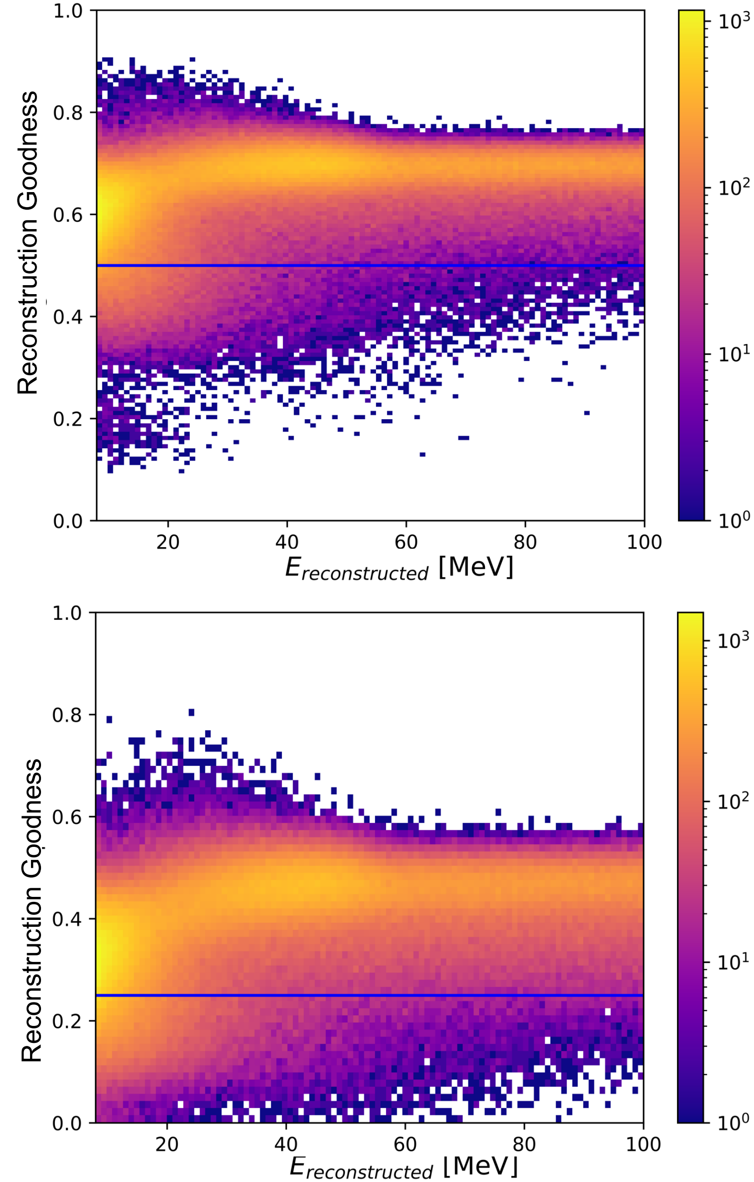
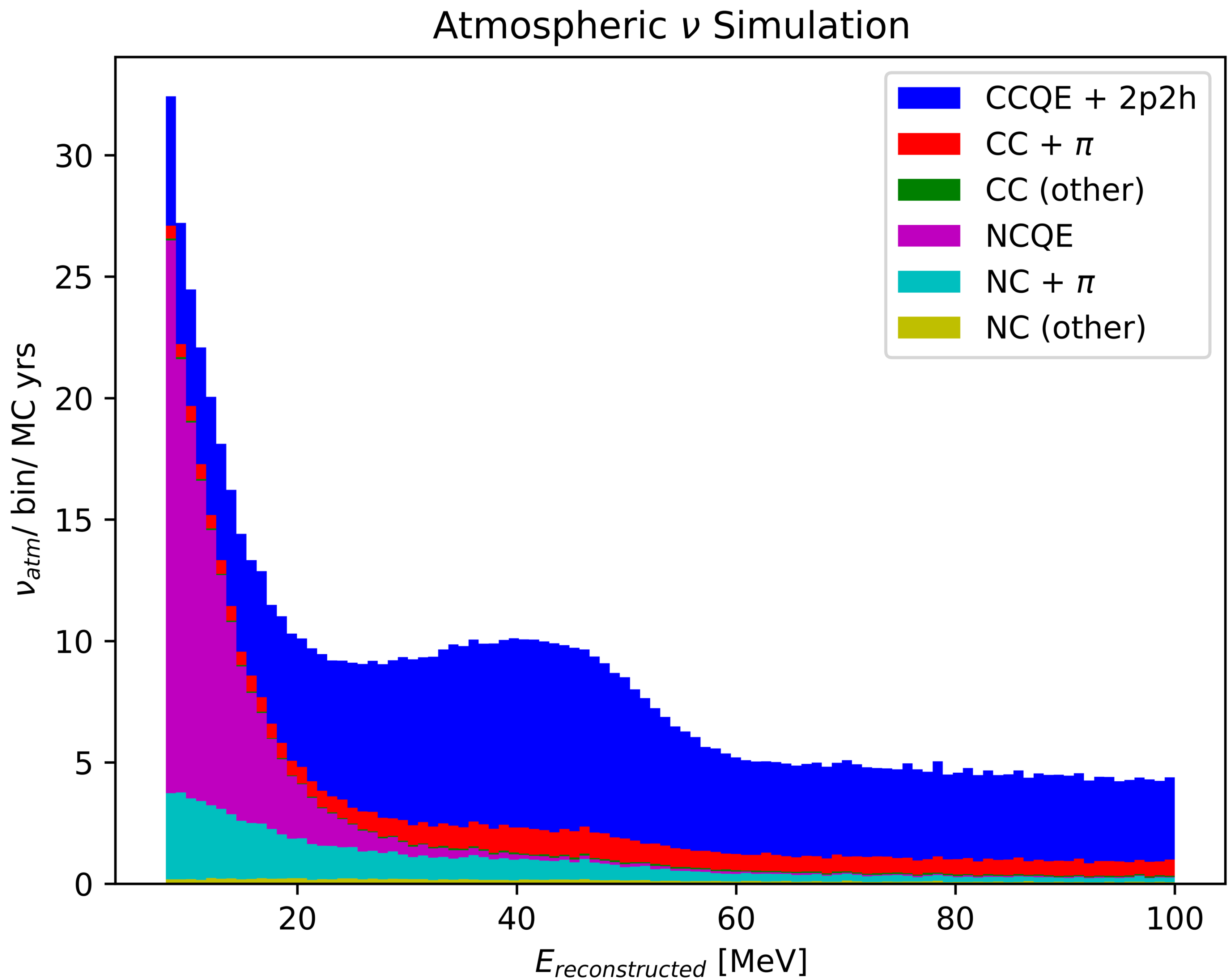
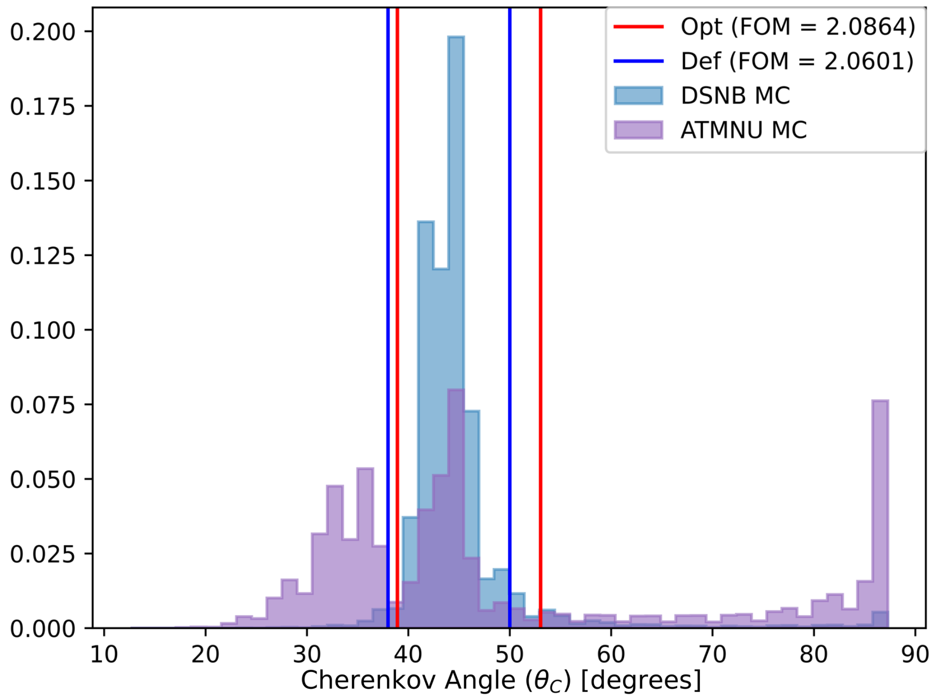
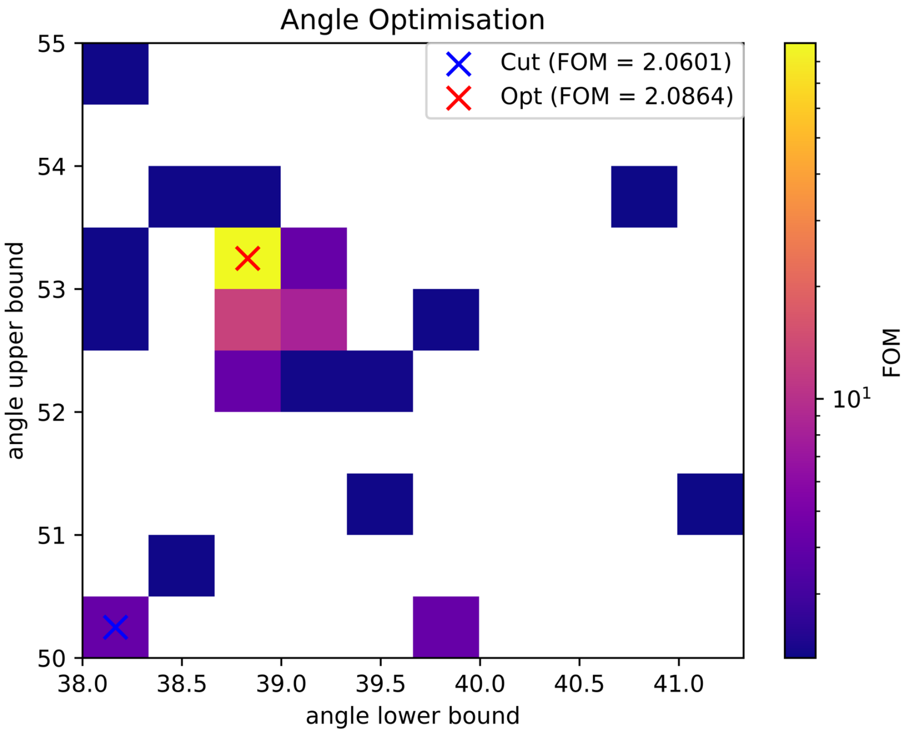


Efficiency after First Reduction



Cherenkov Angle (θ_C)

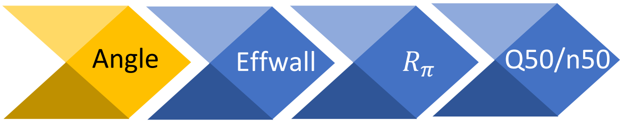




- Powerful discriminator based on the opening angle θ_C of the Cherenkov cone.
  - IBD $\theta_C \sim 42^\circ$
  - Heavier particles (μ/π) at low θ_C.
  - NC events mostly at higher θ_C due to multiple gamma emission.

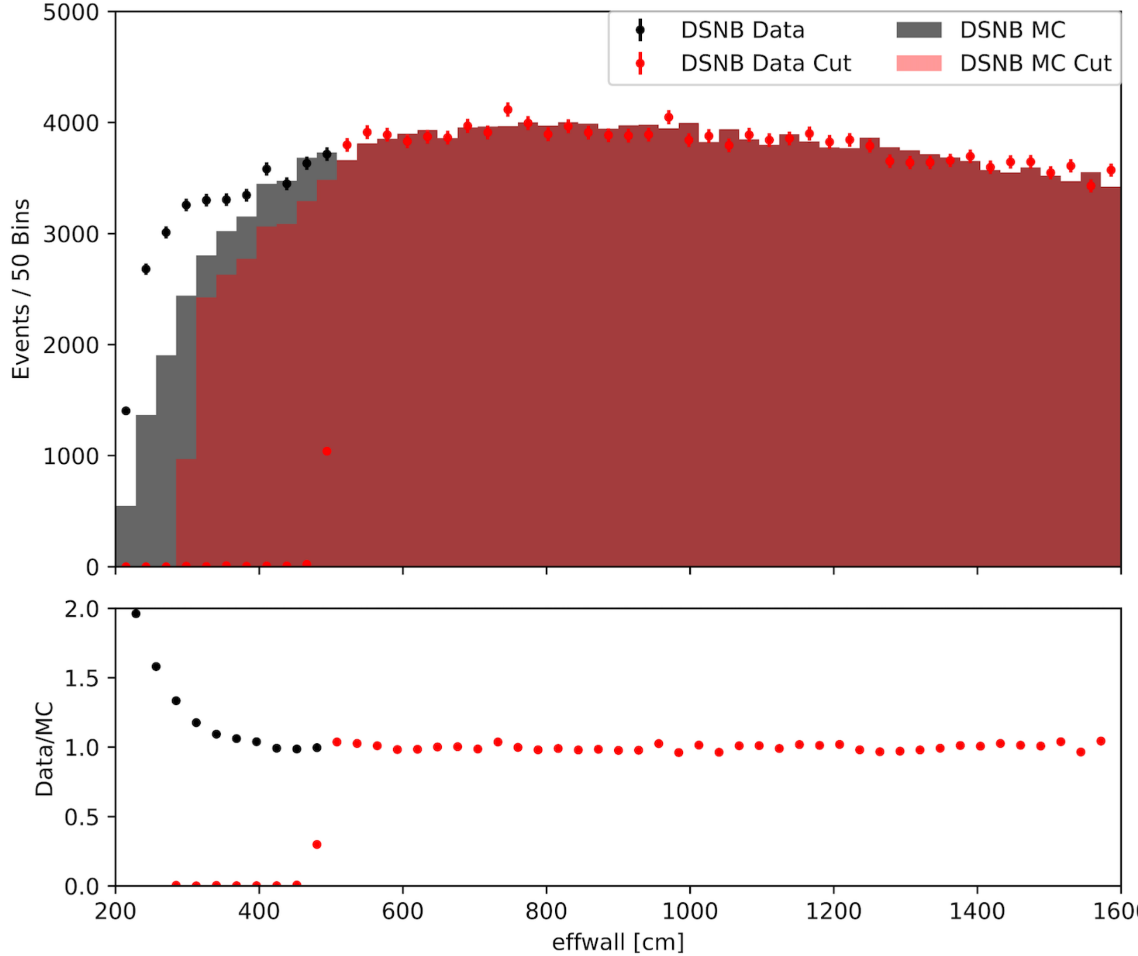
Default (SK-IV)	Optimised (SK-VI)
$38.0^\circ < \theta_C < 50.0^\circ$	$38.92^\circ < \theta_C < 53.05^\circ$

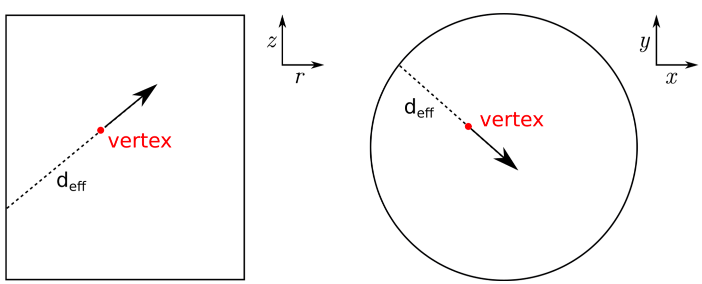
$$\text{FOM} = \frac{S}{\sqrt{S+B}}$$



Effwall (d_{eff})

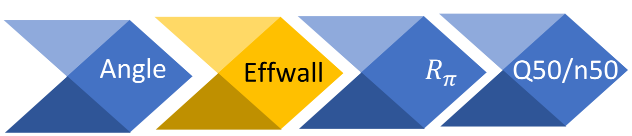
- Removes residual radioactive events from surrounding rock and detector walls.
- Since no available simulation, comparing data to IBD MC, normalised to the same area above 1000 cm, is evaluated .
- Radioactivity observed as an excess at low effwall values.
- Energy-dependent cut as background is dominant at low energy (same as SK-IV).



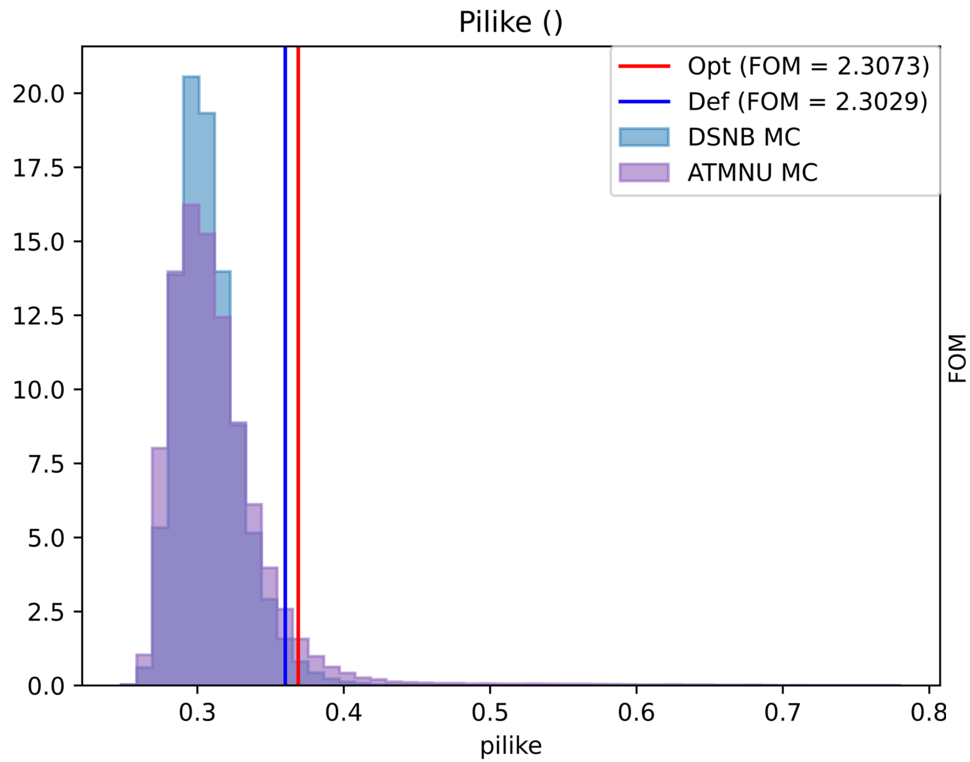


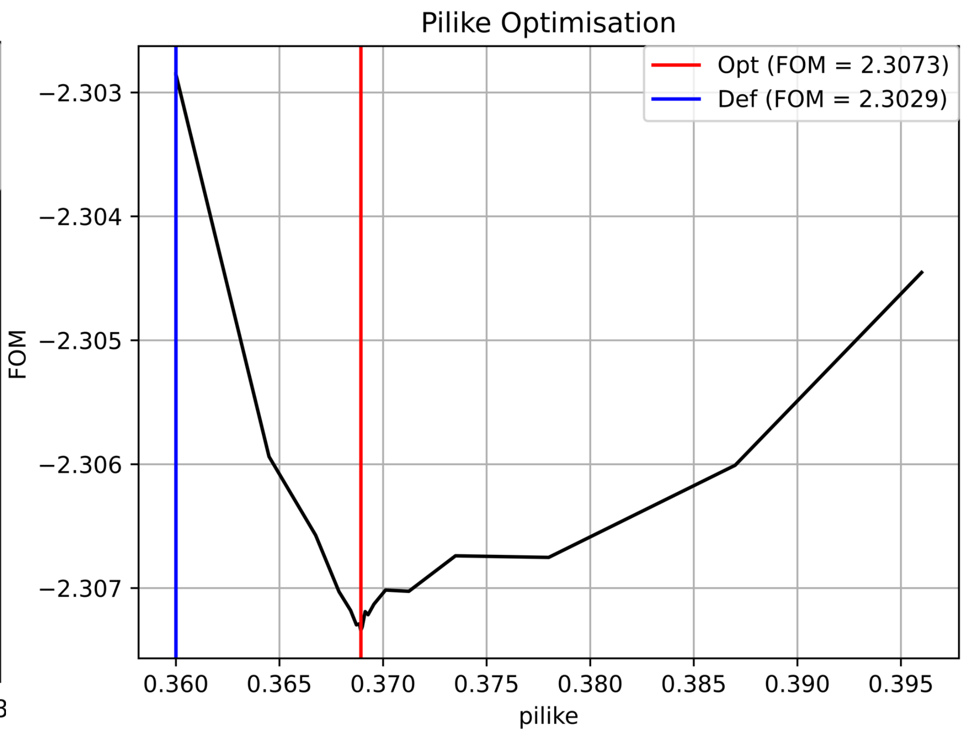
Default (SK-IV)

$$\max[300\ cm, 500\ cm\ - 50(E_{rec}\ - 16\ MeV)]$$



Ring Clearness (R_π)





- Ring clearness to remove pion-like events.

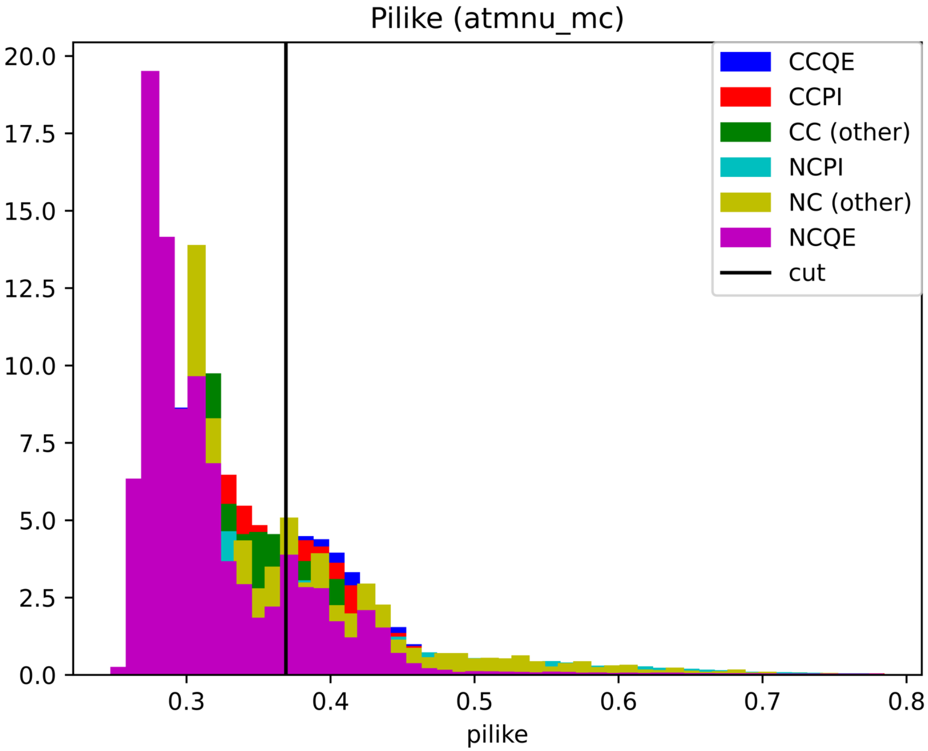
$$R_\pi = \frac{N_{triplets}(\theta_C \pm 3^\circ)}{N_{triplets}(\theta_C \pm 10^\circ)}$$

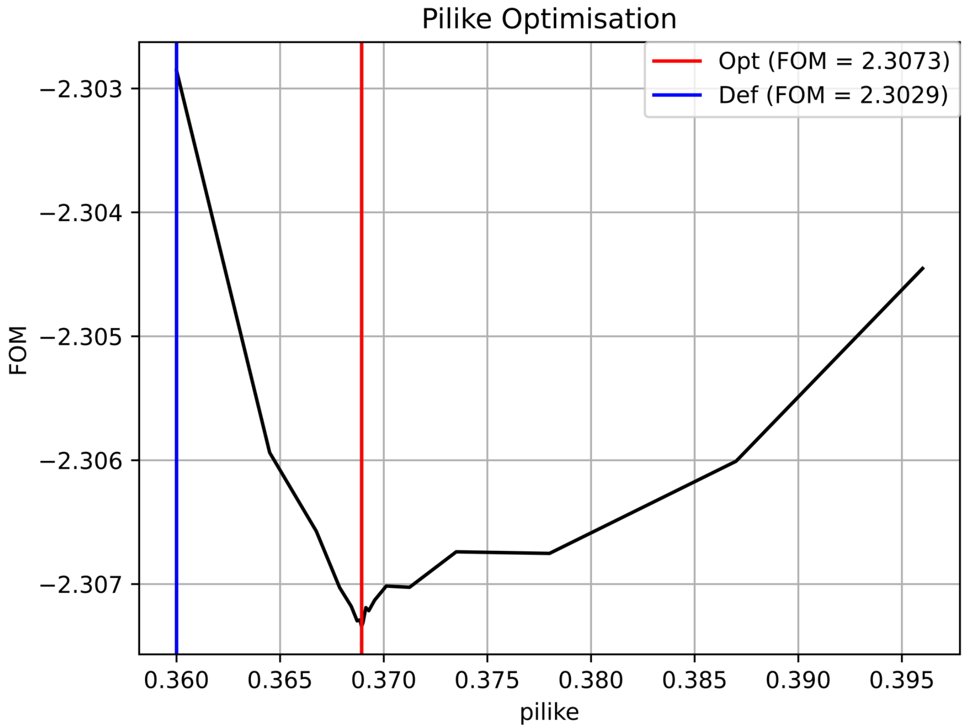
- High momentum particles tend to produce clearer Cherenkov ring.

Default (SK-IV)	Optimised (SK-VI)
< 0.36	< 0.369

$$\mathrm{FOM} = \frac{S}{\sqrt{S + B}}$$

Ring Clearness (R_π)





- Ring clearness to remove pion-like events.

$$R_\pi = \frac{N_{triplets}(\theta_C \pm 3^\circ)}{N_{triplets}(\theta_C \pm 10^\circ)}$$

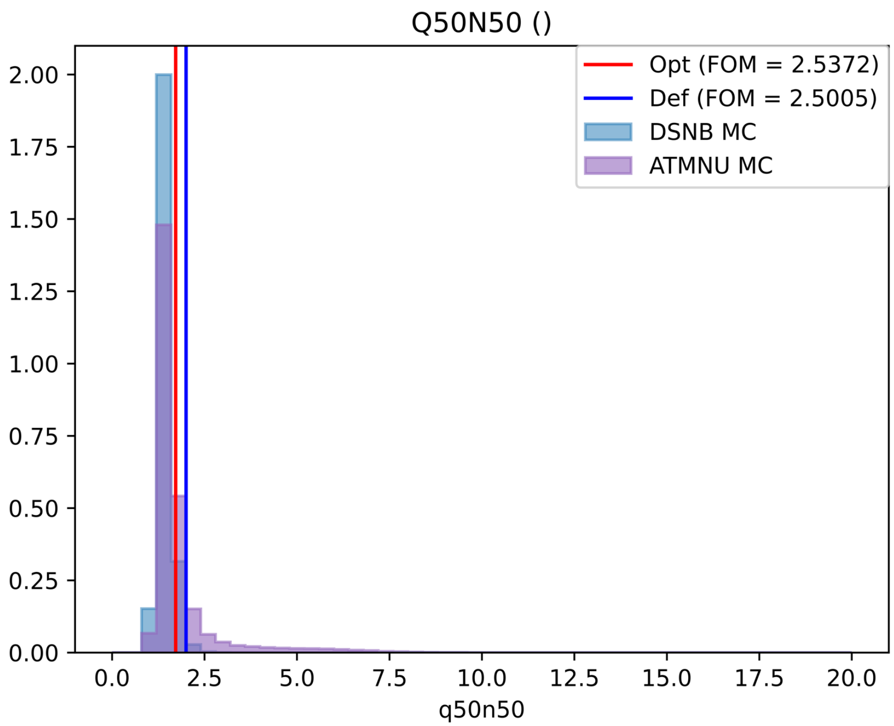
- High momentum particles tend to produce clearer Cherenkov ring.

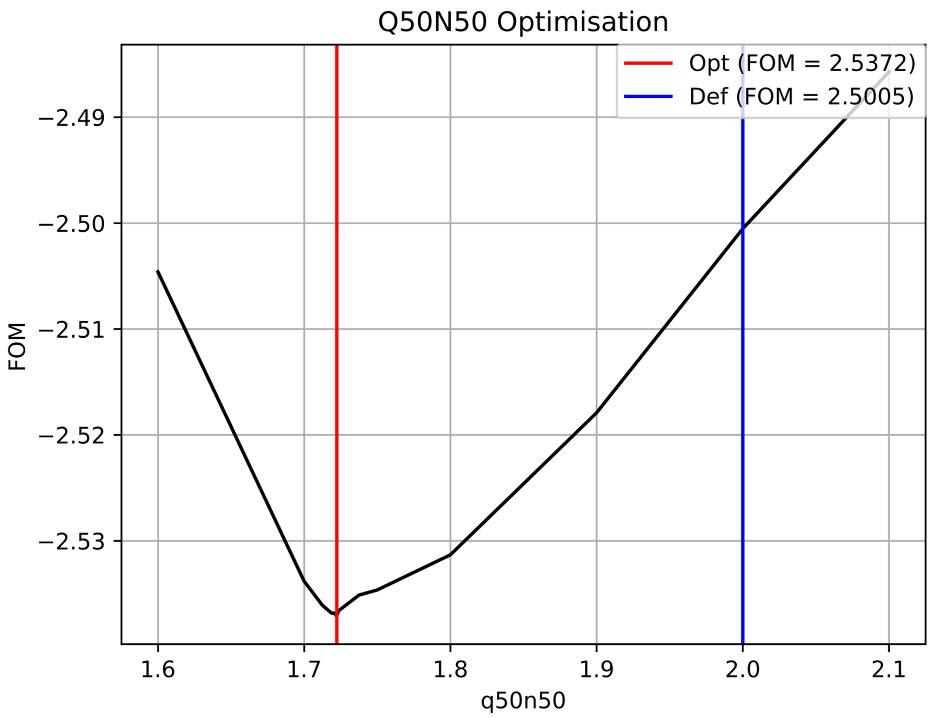
Default (SK-IV)	Optimised (SK-VI)
< 0.36	< 0.369

$$\text{FOM} = \frac{S}{\sqrt{S+B}}$$

Angle → Effwall → R_π → Q50/n50

Average Charge Deposition (q_{50}/n_{50})

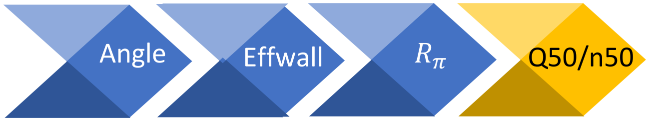




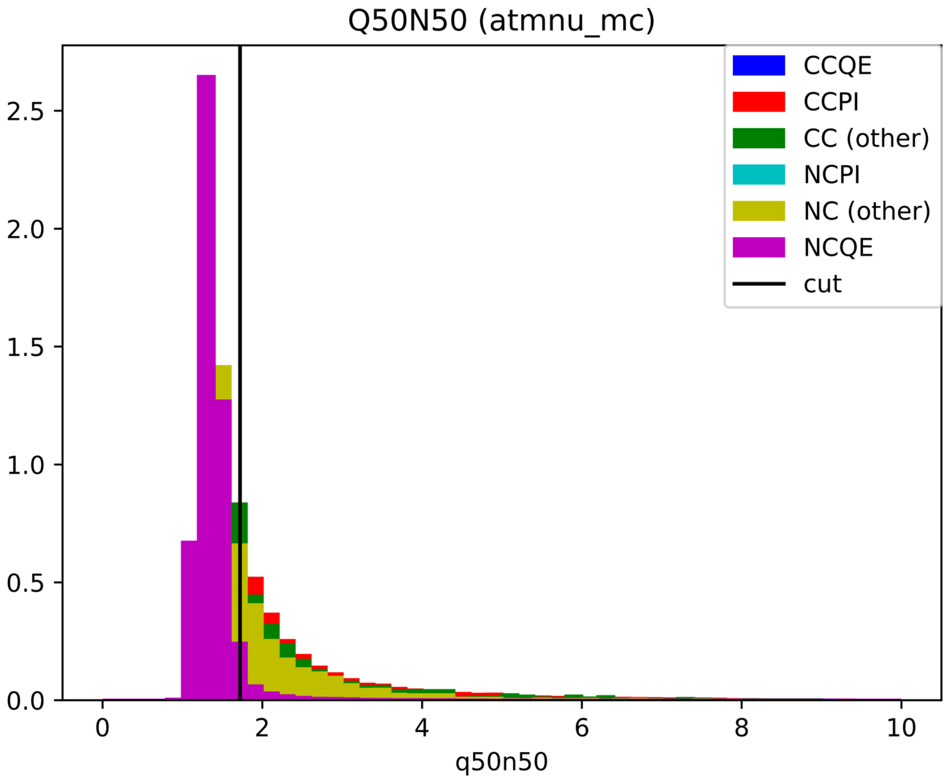
- Higher momentum particles tend to deposit more charge.
- Scan average charge deposited in 50 ns TOF window.

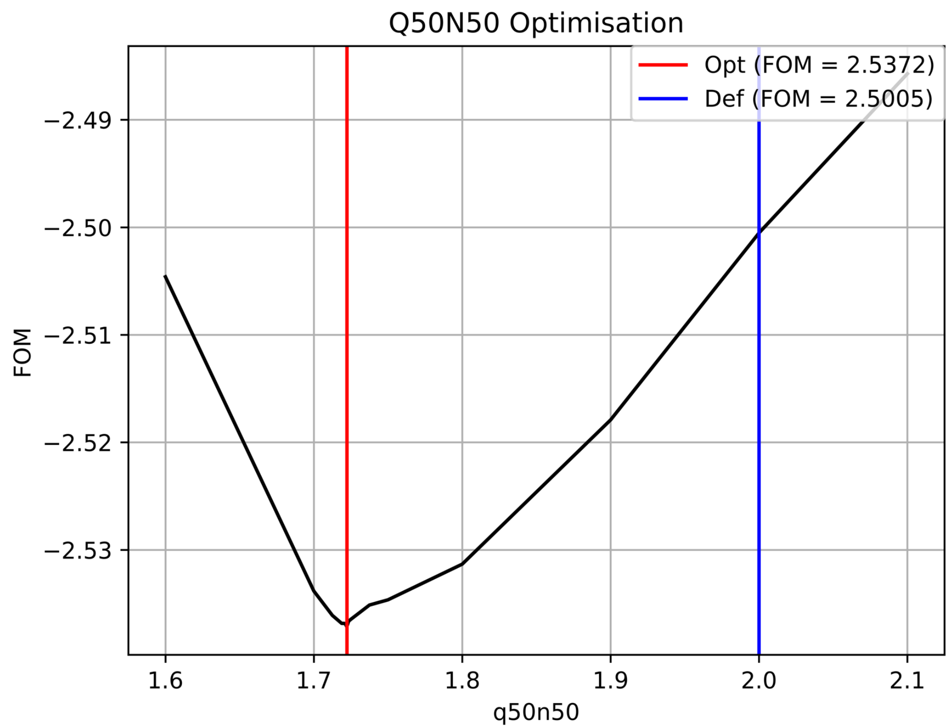
Default (SK-IV)	Optimised (SK-VI)
< 2.0	< 1.722

$$\mathrm{FOM} = \frac{\mathrm{S}}{\sqrt{\mathrm{S}+\mathrm{B}}}$$



Average Charge Deposition (q_{50}/n_{50})

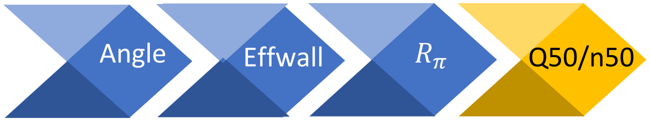




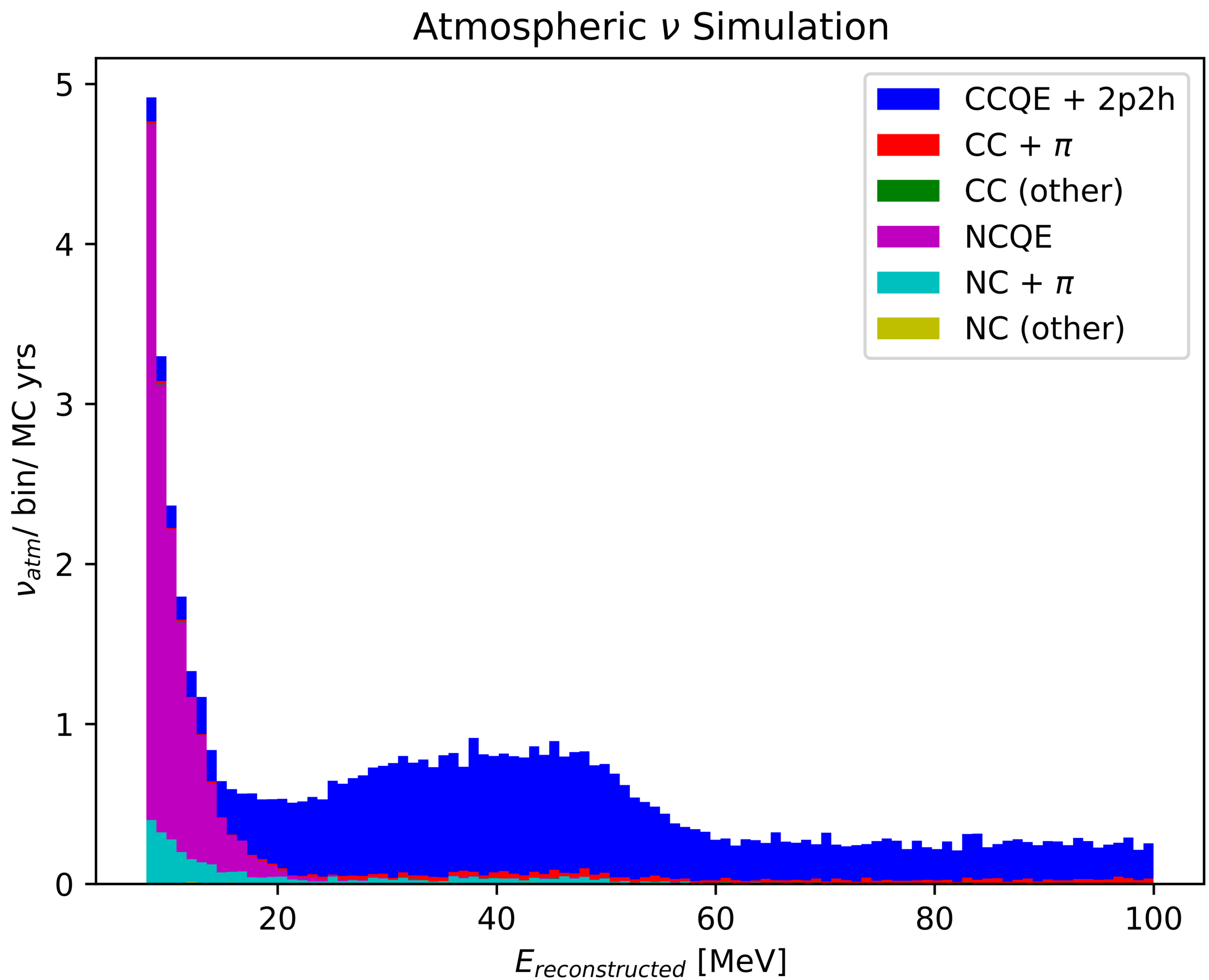
- Higher momentum particles tend to deposit more charge.
- Scan average charge deposited in 50 ns TOF window.

Default (SK-IV)	Optimised (SK-VI)
< 2.0	< 1.722

$$\mathrm{FOM} = \frac{\mathrm{S}}{\sqrt{\mathrm{S}+\mathrm{B}}}$$



Efficiency after Full Atmospheric Reduction

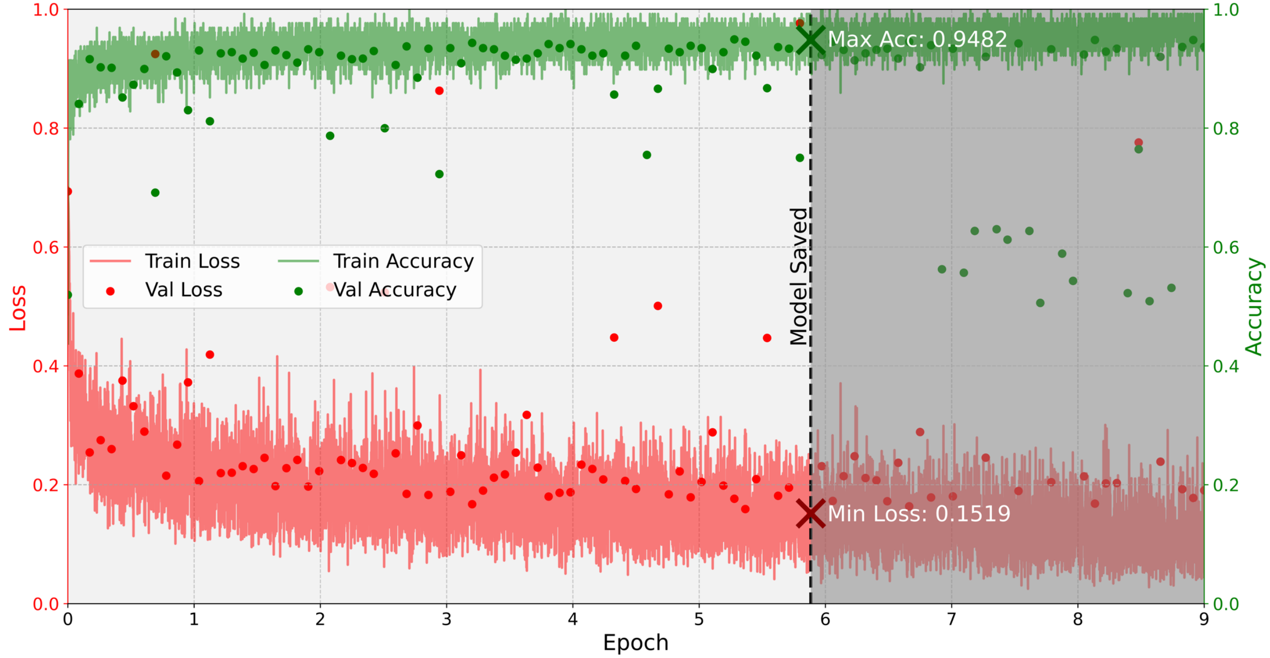


Efficiency after Atmospheric Reduction

Cut	Value	Signal Efficiency [PREV]	Signal Efficiency [TOTAL]
θ_C	$[\,38.92^{\circ}, 53.05^{\circ}]$	92.2%	92.2%
d_{eff}	Energy dependent	94.4%	86.9%
R_{π}	< 0.369	98.6%	85.6%
q_{50}/n_{50}	< 1.722	93.7%	80.2%
N_{pre}^{max}	< 12	100%	80.2%
$N_{pre}^{maxgate}$	< 5	100%	80.2%
$N_{decay-e}$	< 0	98.1%	78.6%

BACKUP – CNN ANALYSIS

FirstCNN Training

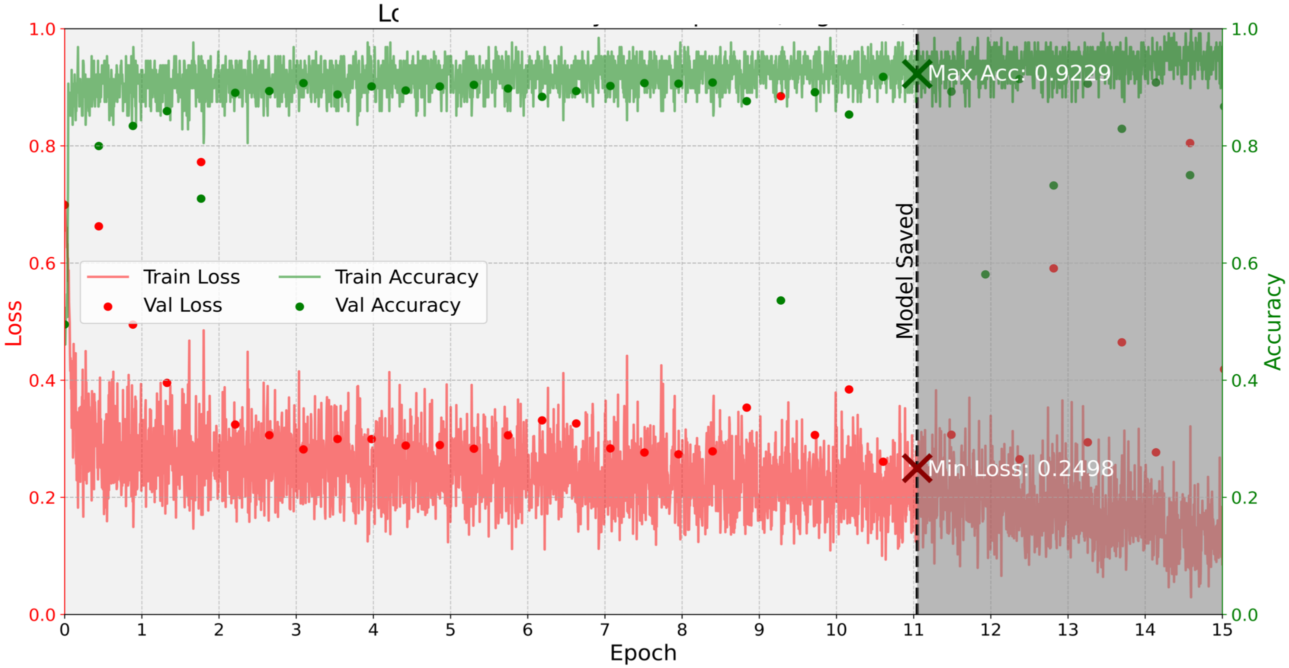


Training Parameters

Lr = 0.001
Epochs = 6
Batches= 256
Network = ResNet-18
Training Set = 400,000 events
Validation Set = 20,000 events
Testing Set = 20,000 events

- **CNN (Convolutional Neural Network):** Deep learning model designed using convolutional layers to automatically learn hierarchical patterns and features for classification of images.
- **ResNet-18:** Consists of 18 layers, utilises residual connections, enabling easier training for deeper networks.
- **SK event display** timing and charge as inputs.
- **Select 300 ns around the prompt window for e/ γ classification.**

AngleCNN Training



Training Parameters

Lr = 0.001
Epochs = 11
Batches= 256
Network = ResNet-18
Training Set = 100,000 events
Validation Set = 5,000 events
Testing Set = 5,000 events

- **CNN (Convolutional Neural Network):** Deep learning model designed using convolutional layers to automatically learn hierarchical patterns and features for classification of images.
- **ResNet-18:** Consists of 18 layers, utilises residual connections, enabling easier training for deeper networks.
- **SK event display** timing and charge as inputs.
- **Select 300 ns around the prompt window for e/ γ classification.**

CNN Model Performance Scaling

- **FirstCNN:**
  - Tested on FirstCNN test set
- **AngleCNN – Enhanced Reduction:**
  - Tested on AngleCNN test set
  - Scaled according to the signal and background efficiency of the Cherenkov angle cut
  - $\varepsilon_{sig} = 0.96$
  - $\varepsilon_{bkg} = 0.28$
- **AngleCNN > FirstCNN**
  - Marginal improvement for most of the ROC curve.
  - AngleCNN performance declines at the signal efficiency of Cherenkov angle cut