ePIC Barrel HCAL energy calibration using Machine Learning

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Data Set and Selections

- Neutral Current DIS, 26.05.0[q$^2[10 - 100]$ GeV^2] (No rad) [26.06.0 also available]
- Truth neutron selection |pdgPar-2112|<0.5
- Truth neutron energy range [1,11] GeV
- Neutron pseudorapidity (η) range [0,1.5]
- Required visible BHCal response : $E_{BHCal}^{Cluster}$>0
- Neural net-work output, E_{NN} (or E_{Pred})

Training Loss and Calorimeter Response Closure

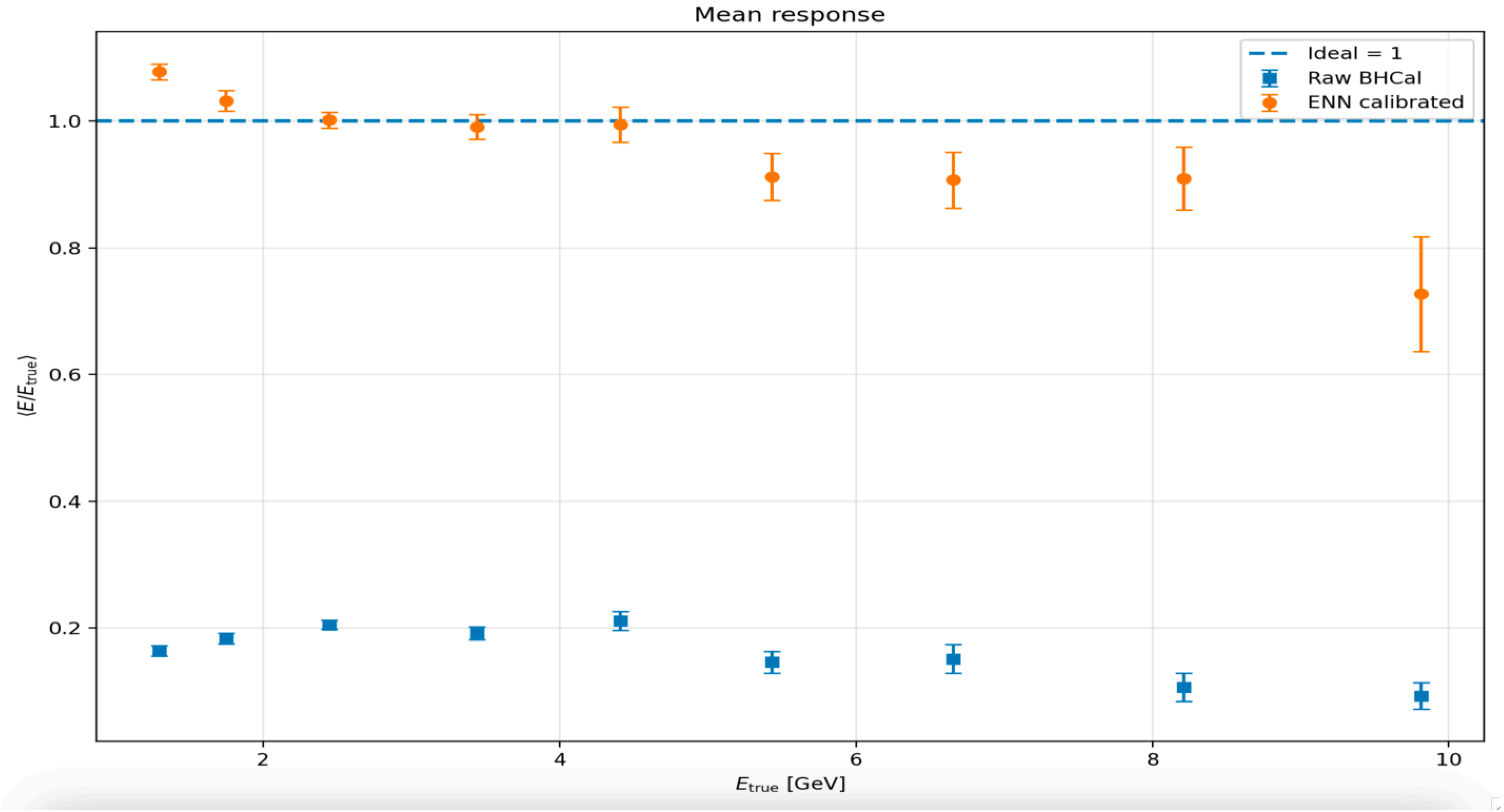
$$L_{\text{total}} = \frac{\sum_i w_i \,\text{Huber}\left(y^{\text{scaled}}_{\text{pred},i}, y^{\text{scaled}}_{\text{true},i}\right)}{\sum_i w_i} + 50\left[\frac{1}{N_{\text{bins}}}\sum_{\text{bins}}\left(\left\langle \frac{E_{\text{NN}}}{E_{\text{true}}} \right\rangle_{\text{bin}} - 1\right)^2 + 0.25\frac{\sum_i w_i \left(\frac{E_{\text{NN},i}}{E_{\text{true},i}} - 1\right)^2}{\sum_i w_i}\right]$$

The base Huber loss trains event-by-event log-energy prediction, while the added response-closure term penalizes deviations of the mean calibrated response from unity in true-energy bins.

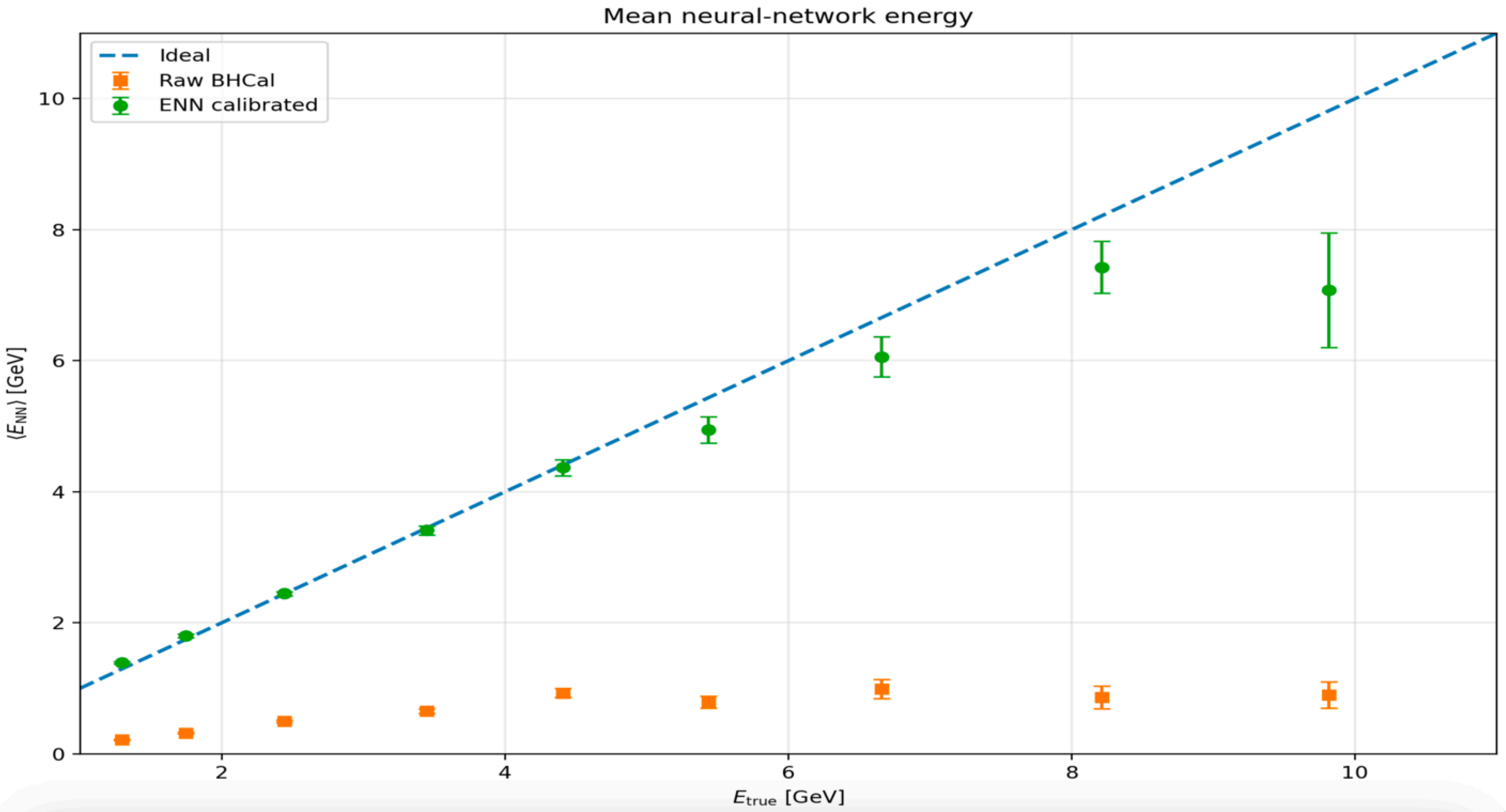
$$\text{Mean response} = \left\langle \frac{E_{\text{NN}}}{E_{\text{true}}} \right\rangle \qquad \text{Fractional residual} = \frac{E_{\text{NN}} - E_{\text{true}}}{E_{\text{true}}}$$

$$\text{Bias} = \left\langle \frac{E_{\text{NN}} - E_{\text{true}}}{E_{\text{true}}} \right\rangle \qquad \frac{\sigma_E}{E} = \text{std}\left[\frac{E_{\text{NN}} - E_{\text{true}}}{E_{\text{true}}}\right]$$

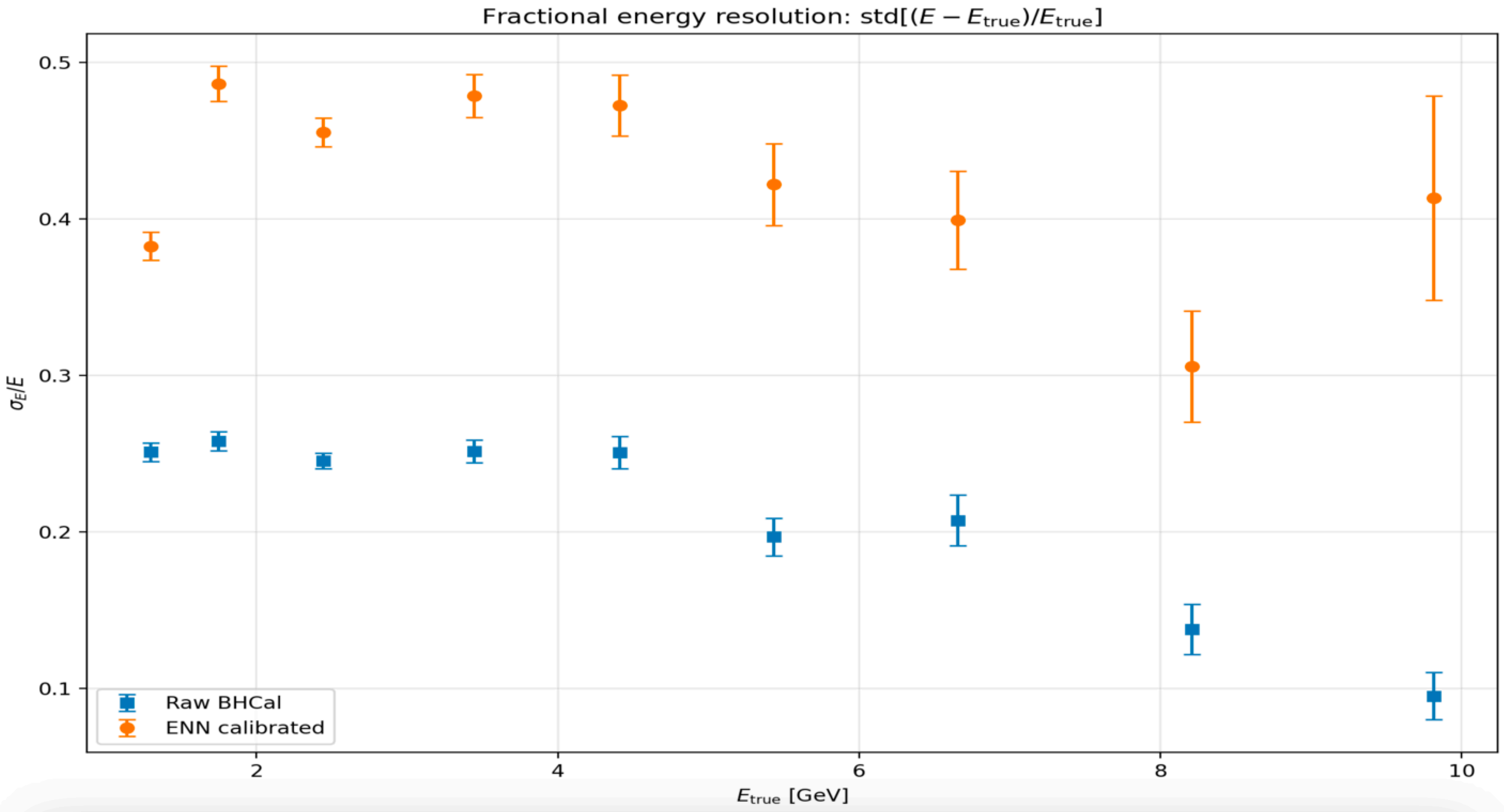
Mean Response vs True energy



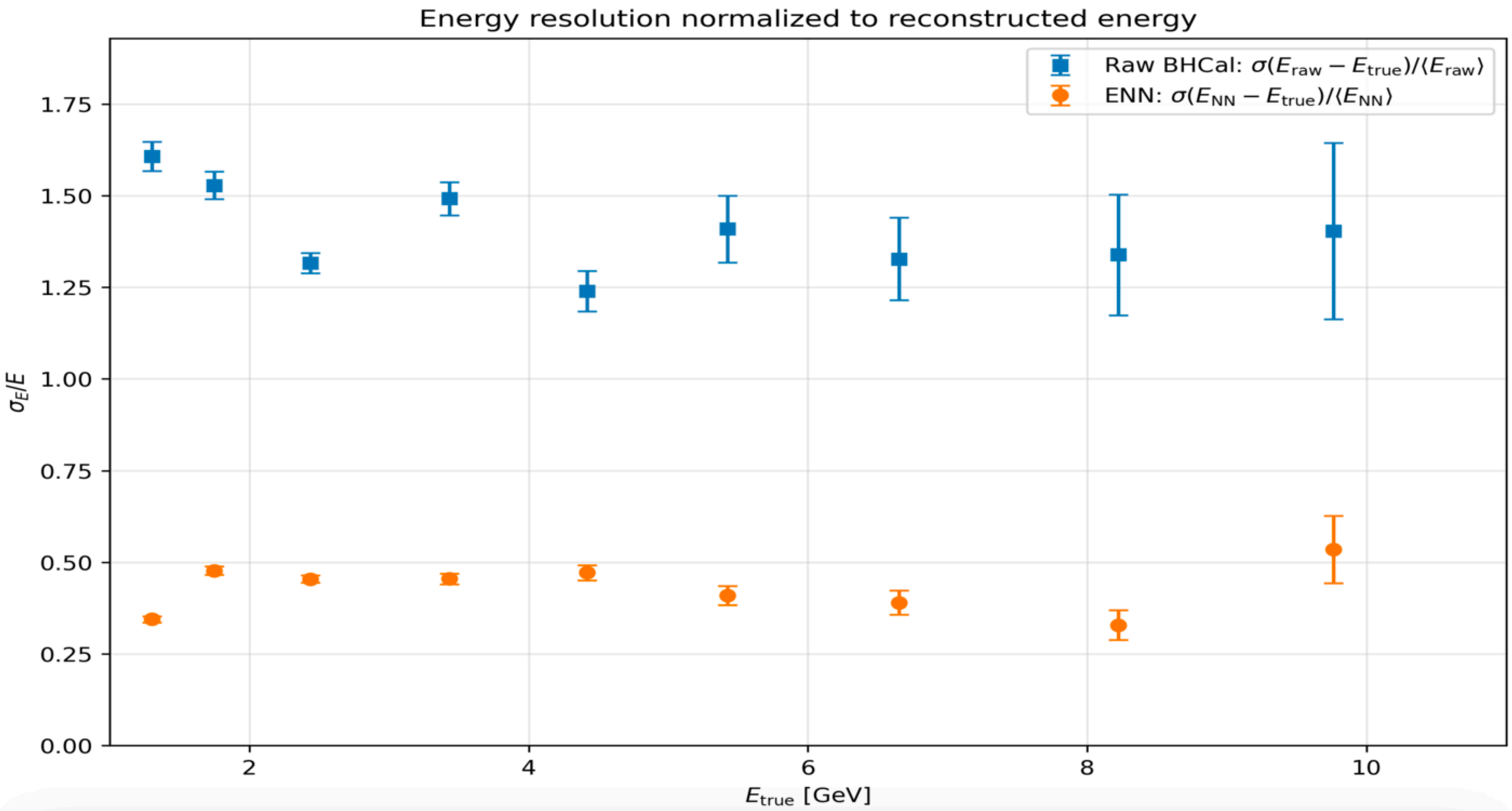
Mean Neural-Network Energy (ML Predicted)



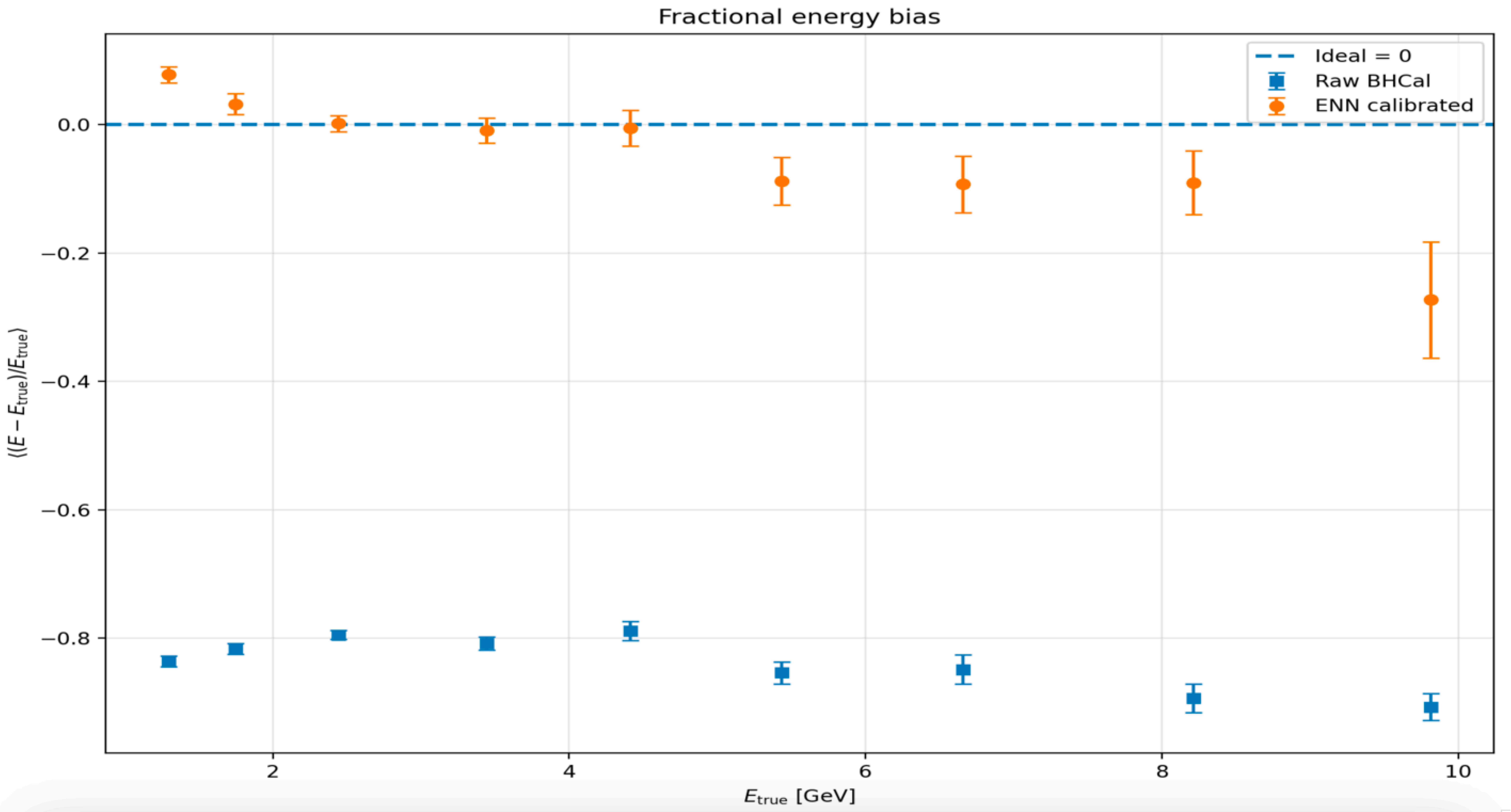
Energy-resolution vs True energy



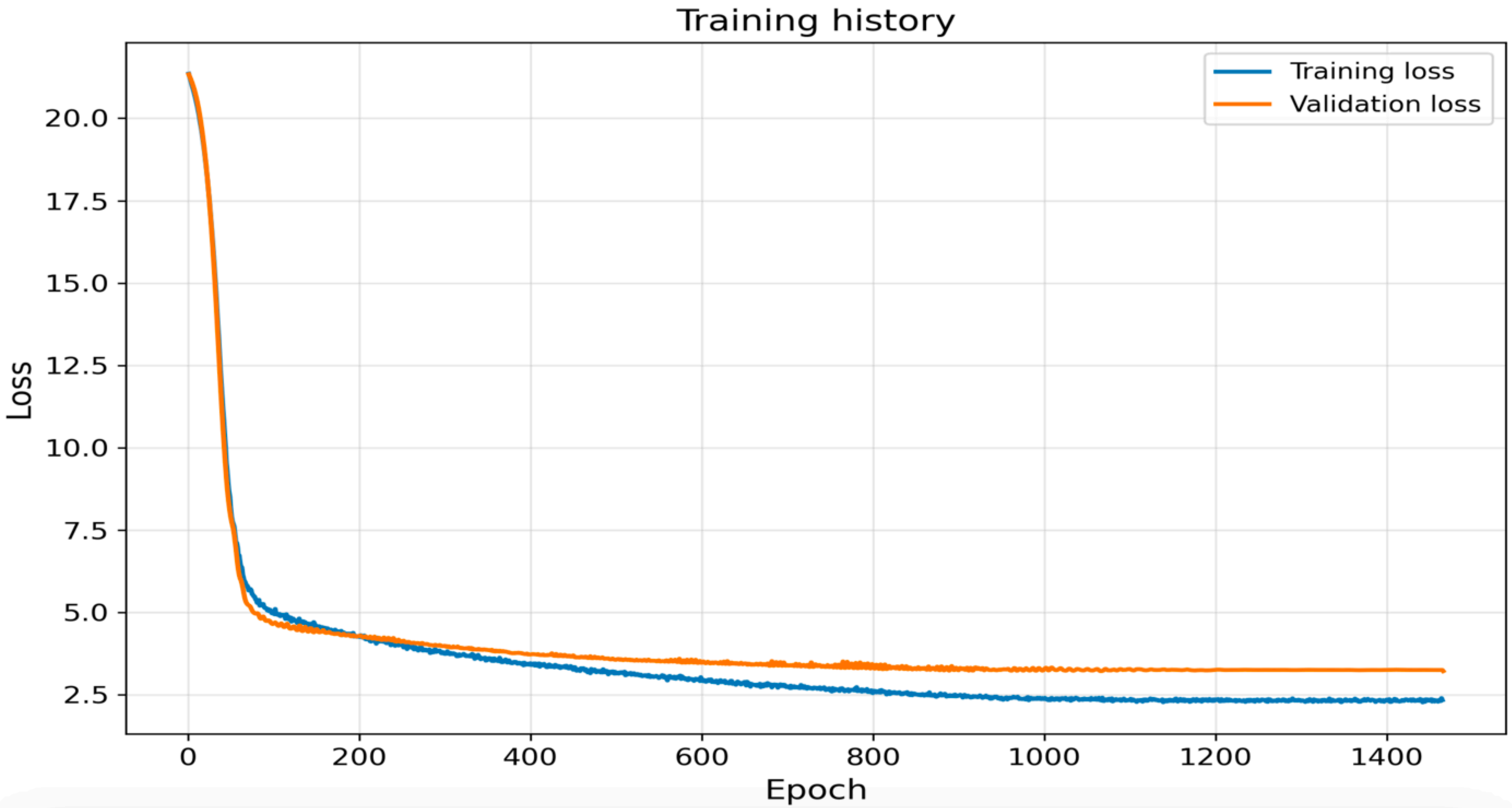
Energy Resolution normalized to E_{NN}



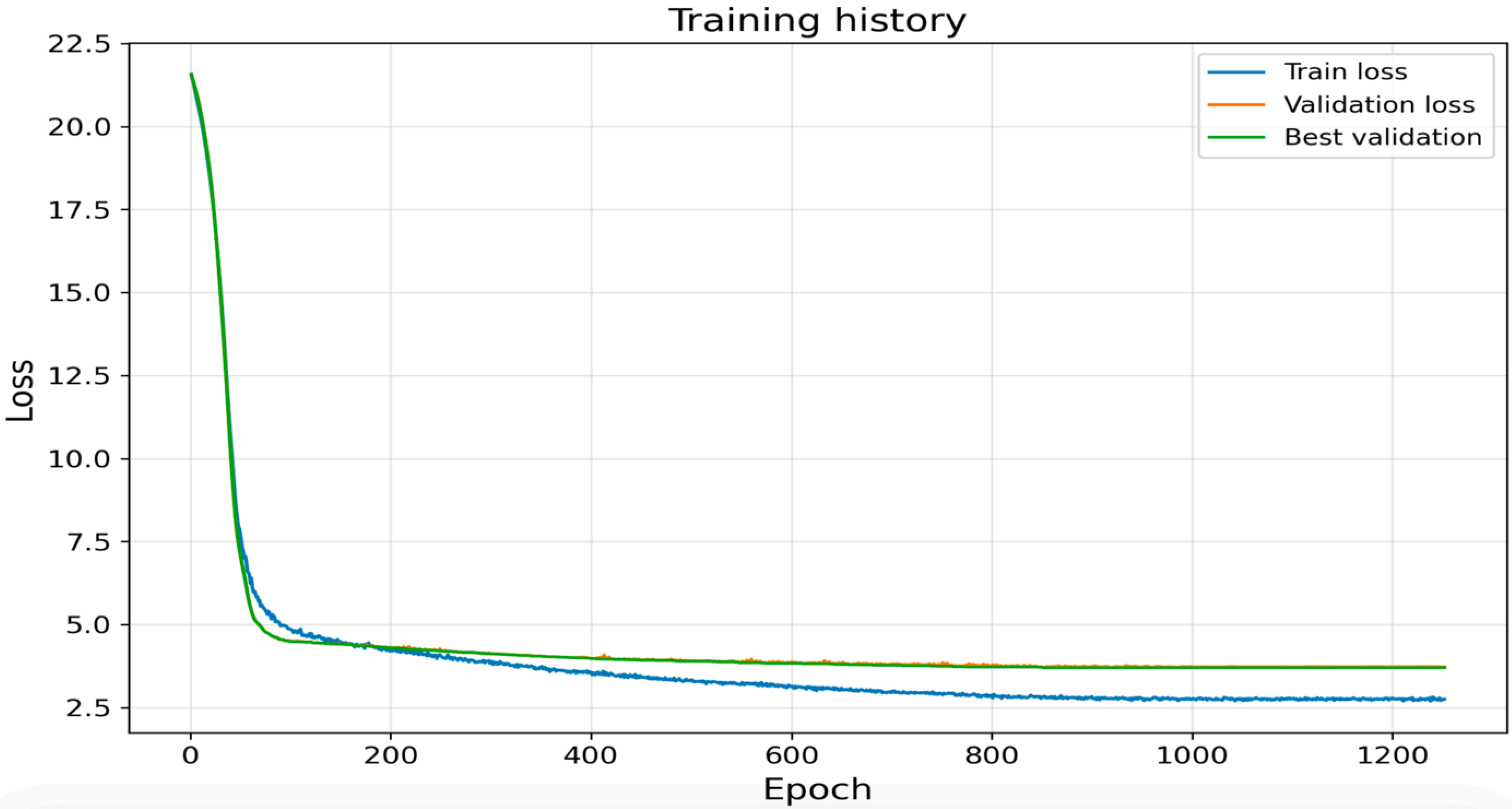
Fractional energy bias



Loss vs epochs



Loss vs epochs

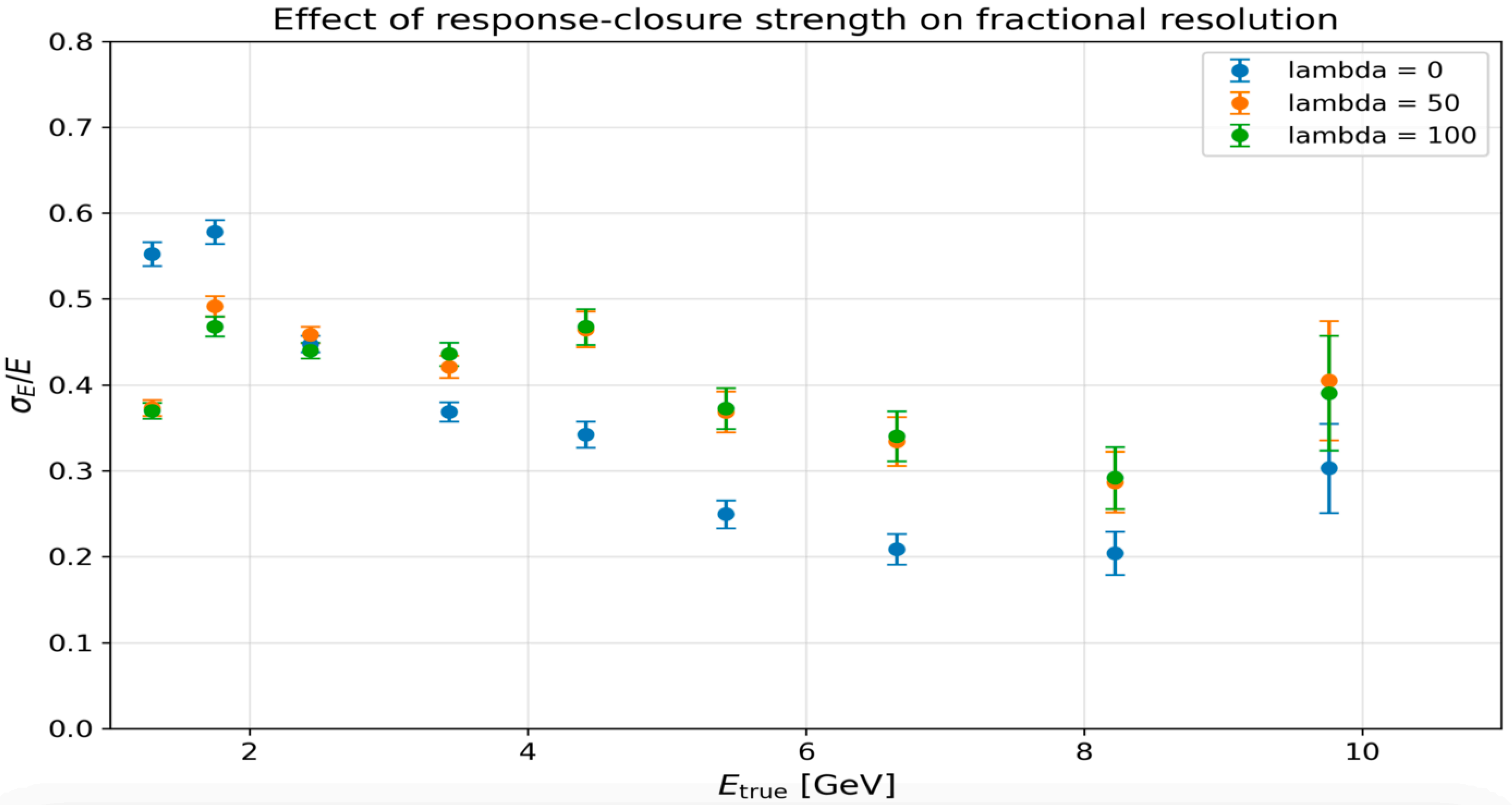


Summary

- Response-closure helps low/middle energy calibration but not high energy and at this q^2, training suffers from low statatistics for high energy neutrons
- Train q^2(100-1000) sample as a next step

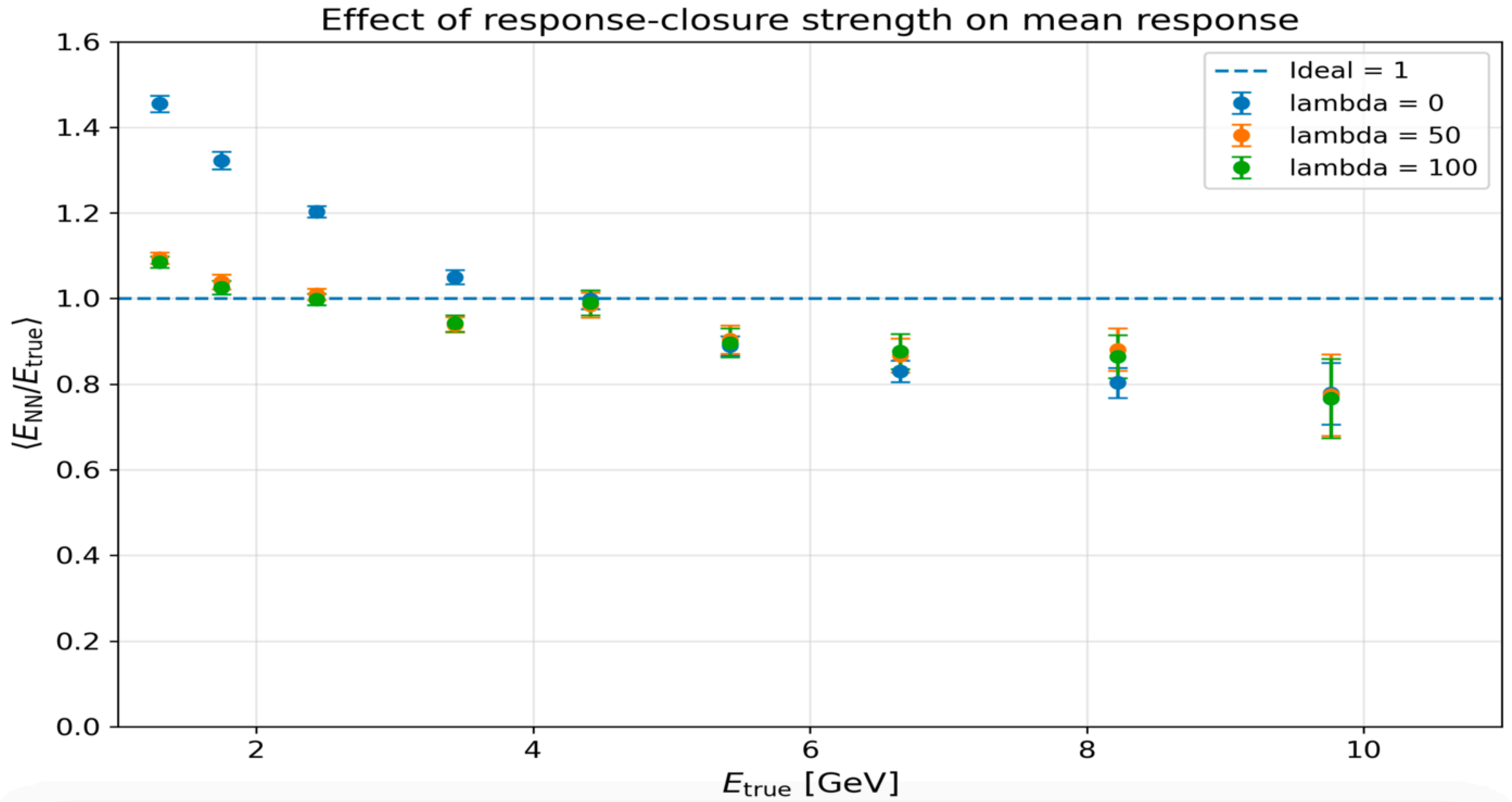
Backup

Effect of response-closure on fractional resolution



Effect of response-closure strength on mean response

- To check whether the response-closure penalty is over-constraining the model, I trained otherwise identical models with different lambda_response values. Lambda = 0 is the baseline without closure regularization, lambda = 50 is the current working model, and lambda = 100 tests a stronger closure penalty. I compare mean response, bias, and fractional resolution on the validation sample.



Effect of response-closure strength on bias