

# Modeling charged-particle spectra in pp collisions with deep neural networks

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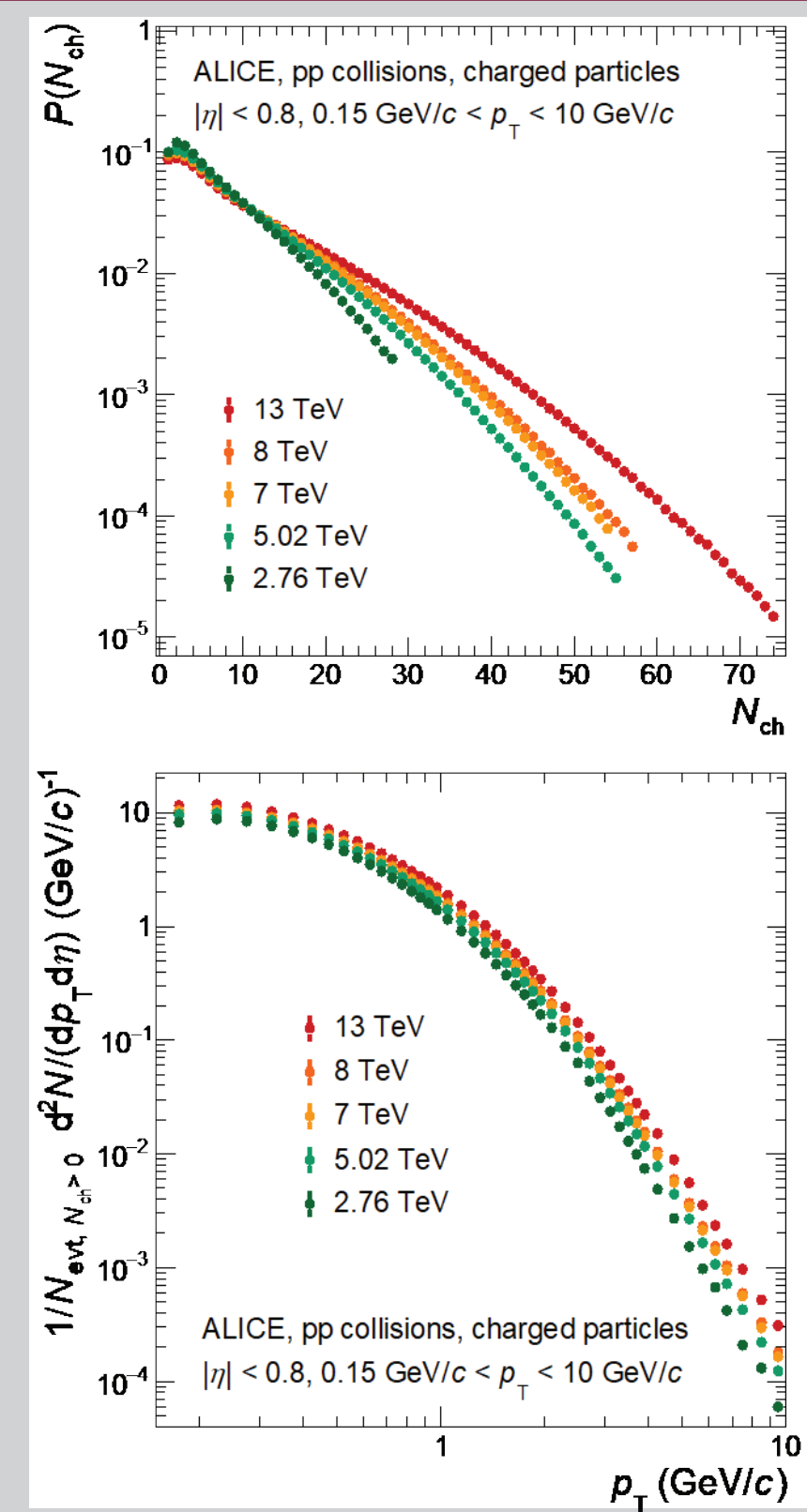
## Motivation

Fundamental observables, like the inclusive charged-particle multiplicity ( $N_{ch}$ ) distributions and transverse momentum ( $p_T$ ) spectra, precisely characterize the final state of pp collisions

ALICE published a comprehensive dataset of  $N_{ch}$  distributions and  $p_T$  spectra within  $0.15 \text{ GeV}/c < p_T < 10 \text{ GeV}/c$  and  $|\eta| < 0.8$  for pp collisions ranging from  $\sqrt{s} = 2.76\text{-}13 \text{ TeV}$  [1]

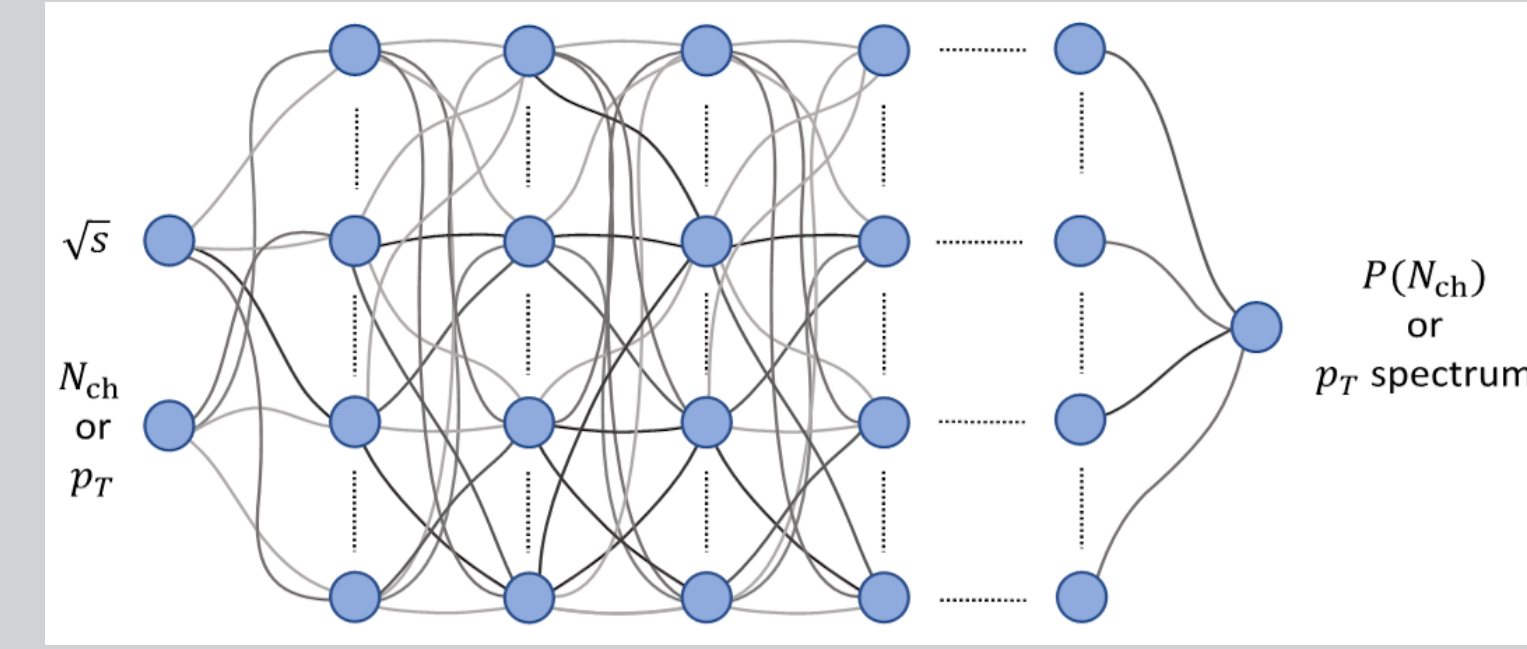
Those results demonstrate that predicting the collision-energy dependence of these observables remains a challenging task for PYTHIA simulations using the Monash13 tune [2]

Deep neural networks (DNNs) provide a purely data-driven alternative to predict these observables at unmeasured energies → Proof of principle with provided by MC-based study in [3]



## Approach

### Model sketch:



- Fully connected DNN implemented with Tensorflow & Keras
- Two separate models for the prediction of  $N_{ch}$  and  $p_T$  yields
- Two inputs each  $N_{ch}$  |  $p_T$  and  $\sqrt{s}$
- Fixed number of nodes per layer
- Model configuration determined in hyperparameter scan

### Data preparation:

- Logarithmic scaling of  $p_T$ ,  $N_{ch}$  and  $\sqrt{s}$  → More linear tail for better extrapolation capabilities
- Data shuffling and splitting into training and validation sets (80% / 20%)
- Data augmentation by redefining each initial data point N times within its range of uncertainties → Better training performance and stability

## Model Tuning & Uncertainties

### Hyperparameter scan:

Bayesian-optimization [4] search for best model architecture

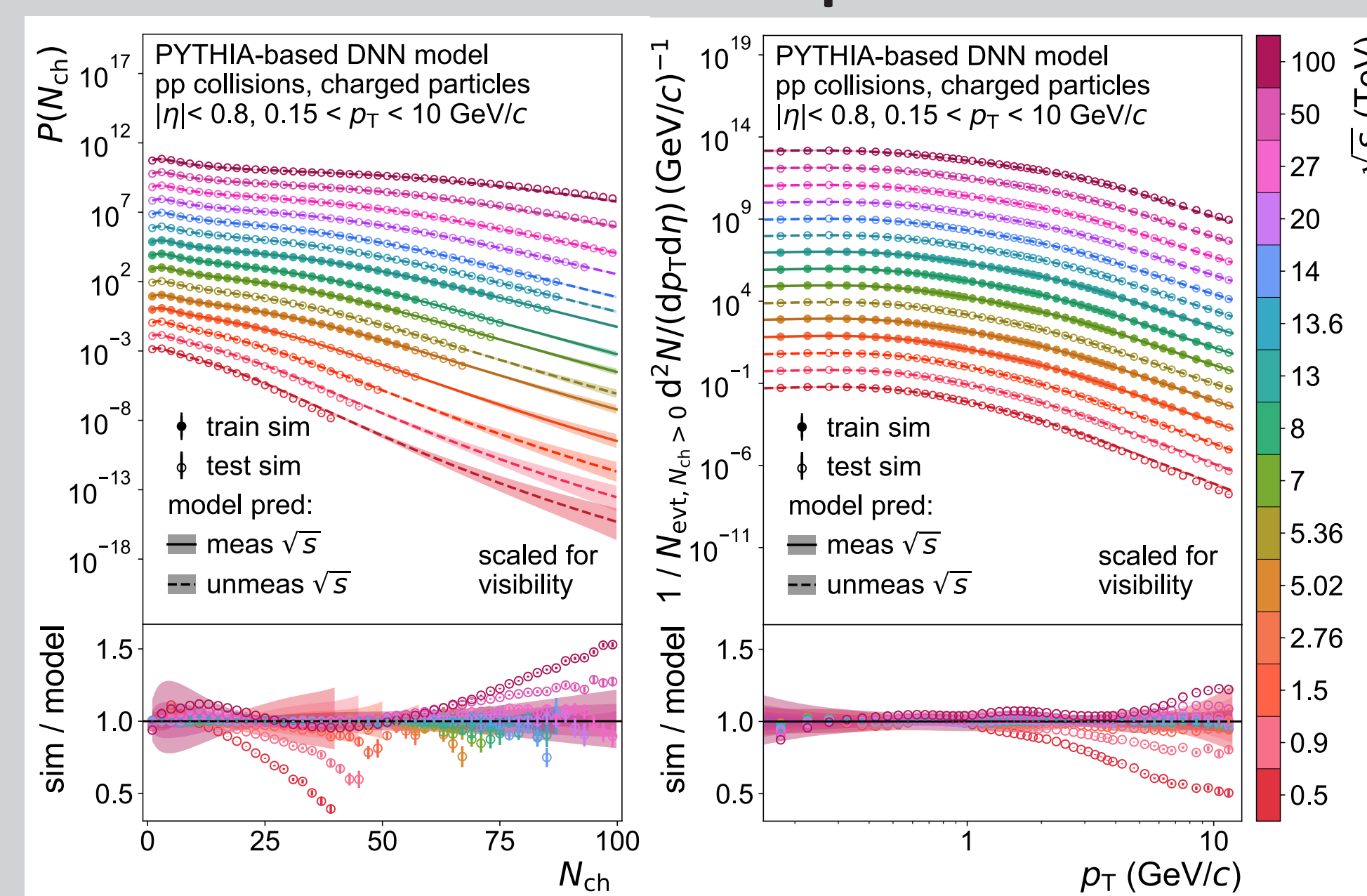
sampling: discrete values			
layers	neurons per layer	activation function	initializer
2	32	TanH (TH)	RandomUniform (RU)
3	64	ReLU (RE)	RandomNormal (RN)
4	128	SeLU (SE)	TruncatedNormal (TN)
5	256	Swish (SW)	GlorotUniform (GN)
	512	Mish (MI)	GlorotNormal (GU)
		Softplus (SP)	
sampling: intervals (logarithmic)			
	$\lambda_1$	$\lambda_2$	learning rate (lr)
min	$5 \cdot 10^{-8}$	$5 \cdot 10^{-8}$	$1 \cdot 10^{-5}$
max	$5 \cdot 10^{-1}$	$5 \cdot 10^{-1}$	$1 \cdot 10^{-3}$

- Extrapolation capability evaluated with PYTHIA simulations → ALICE-equivalent energies (training/validation) → Selected energies within 0.5 – 100 TeV (test)
- Target score: Quadratic mean of validation MAE & test MAE → Best-performing architecture retrained on ALICE data

### Uncertainty estimation:

- Two different sources are added in quadrature
- Spread of Top5 performing hyperparameter configurations
- Ensemble of 20 random initializations of the top model

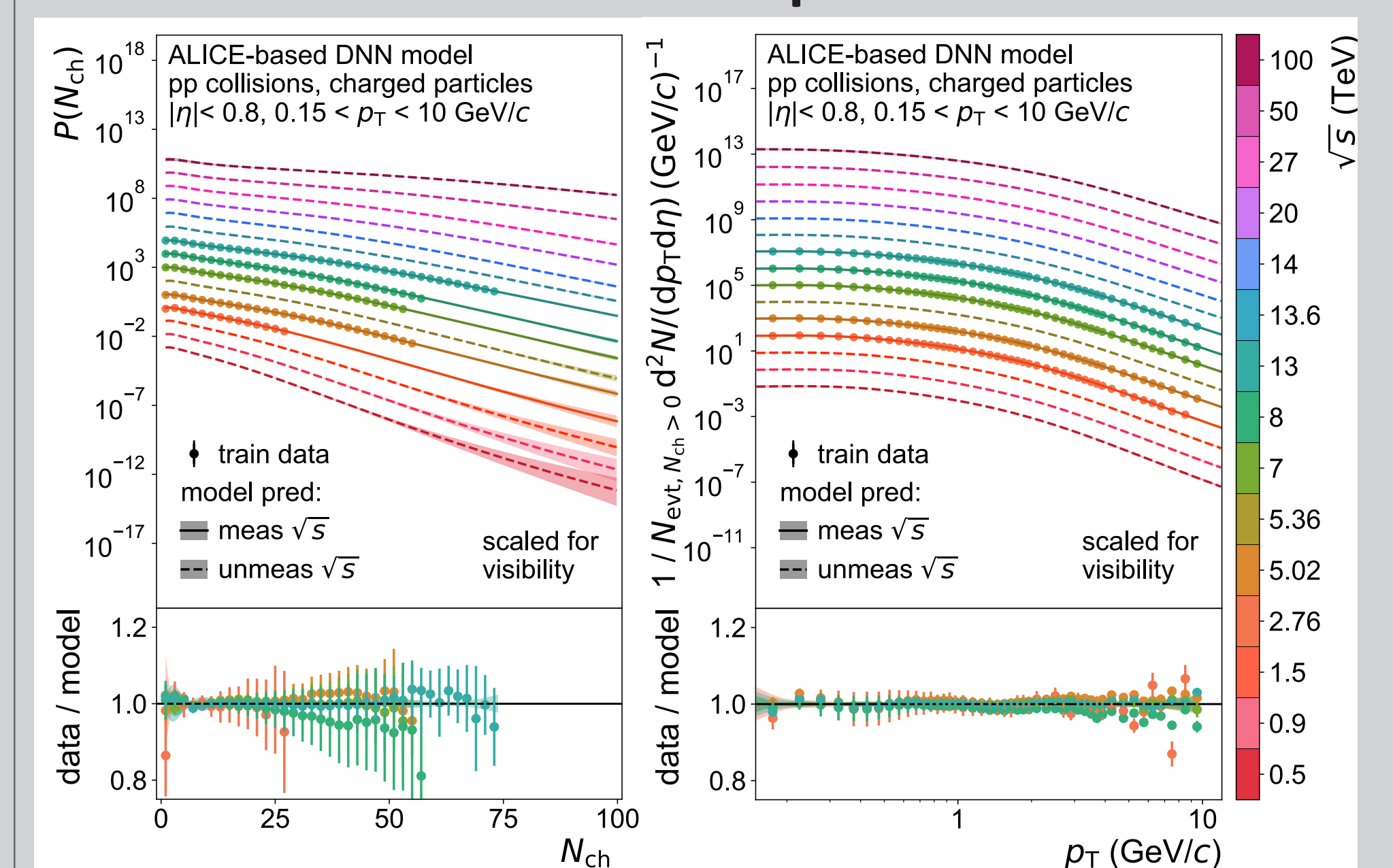
### PYTHIA-based DNN predictions



### Regression performance :

- Good description of training data with deviation < 2%
- Extrapolation for  $2.76 \leq \sqrt{s} \leq 20 \text{ TeV}$  within 5%
- Inside  $1.5 \leq \sqrt{s} \leq 27 \text{ TeV}$  accuracy drops to 10%
- For the highest and lowest energies the model fails to describe the simulation within its uncertainties

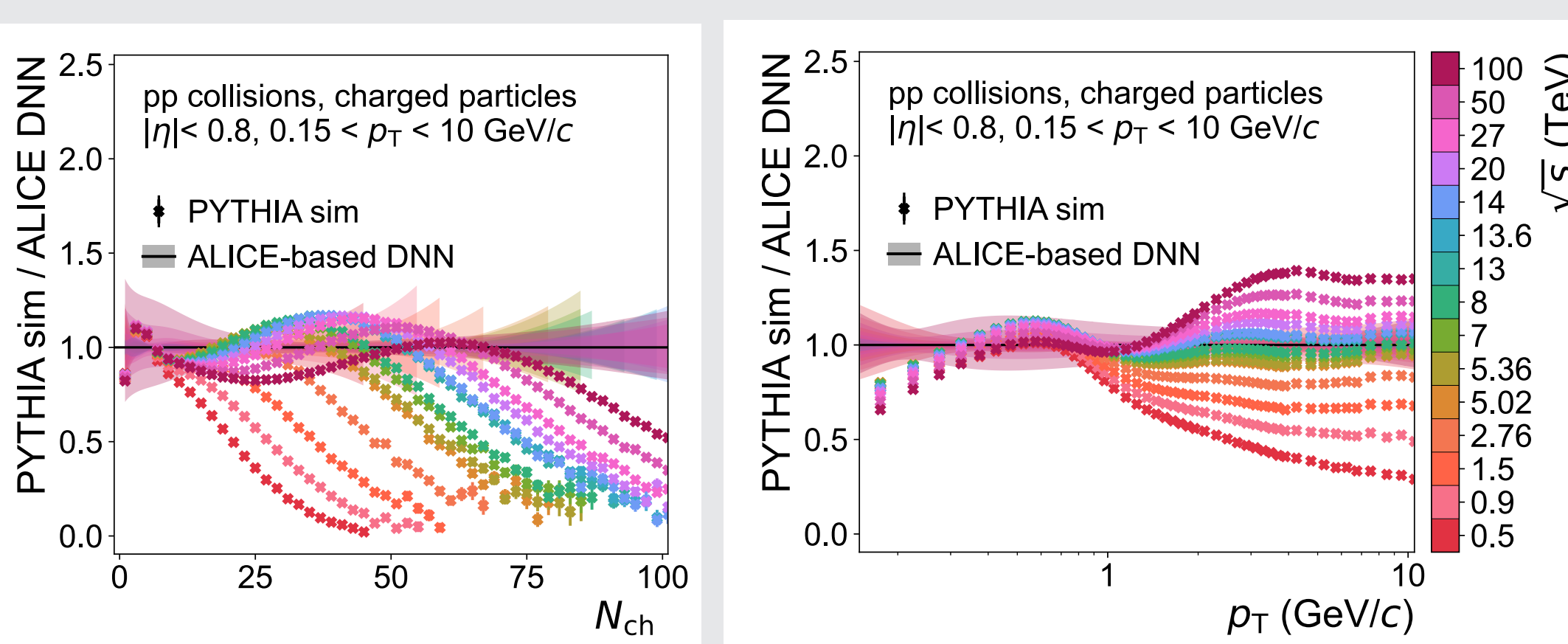
### ALICE-based DNN predictions



### Retrained on ALICE data:

- Similar performance compared to PYTHIA-based model
- All available data within their corresponding uncertainties
- Solid extrapolation in  $N_{ch}$  and  $p_T$  by about 20%
- Reliable interpolation to unmeasured energies

## PYTHIA Comparison



### Ratio of PYTHIA to DNN predictions:

- The simulations are compared to a wide range of energies:
- For lower  $N_{ch}$  ( $< 20$ ) and  $p_T$  ( $< 1 \text{ GeV}/c$ ), PYTHIA deviates from the predictions by up to 20% for all studied energies
- At higher  $N_{ch}$  and  $p_T$ , the comparison indicates an energy dependence of PYTHIA's accuracy decreasing beyond the energy range used in the tuning process
- The trend observed for the training energies is further extended to unmeasured energies
- Especially at lower energies a larger tension is observed

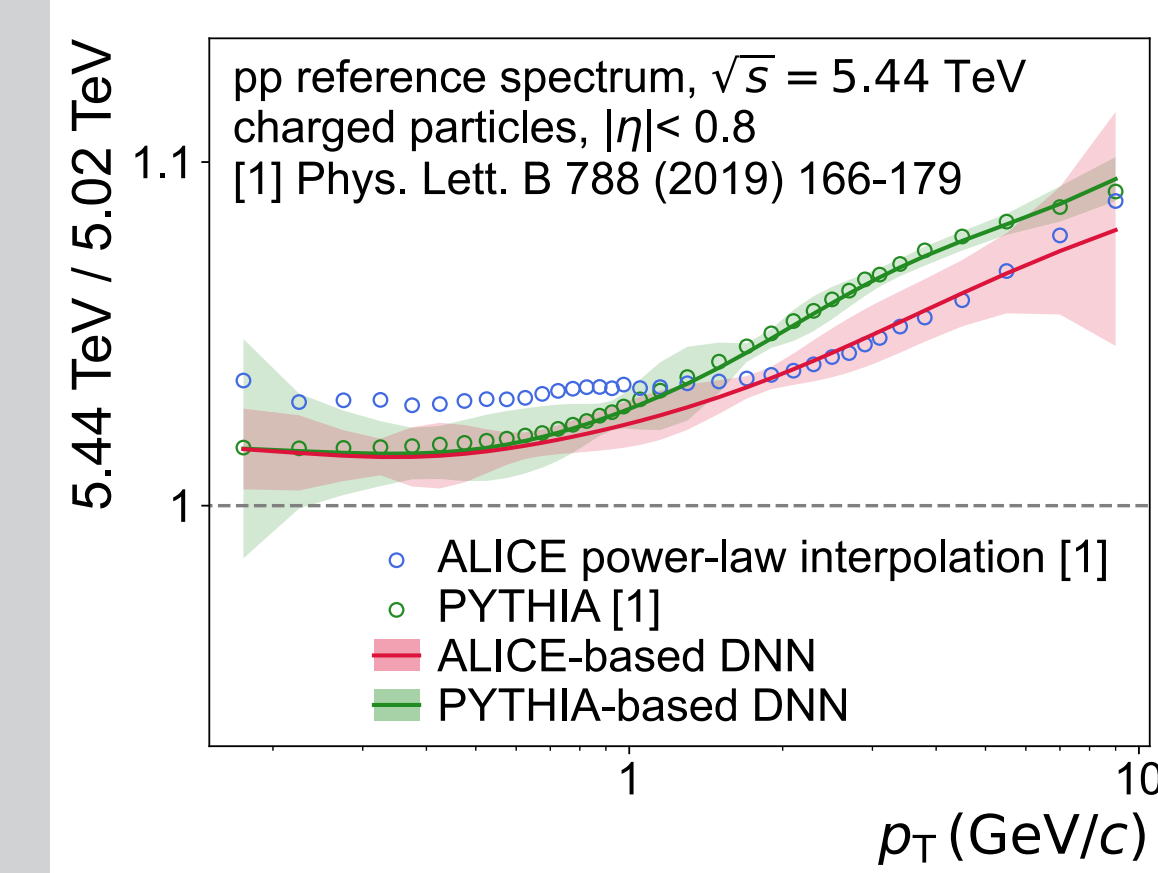
→ These deviations between the PYTHIA simulations and the data-driven predictions could provide feedback for future PYTHIA tunes

## Model Application

### Construction of pp reference spectra for the nuclear modification factor:

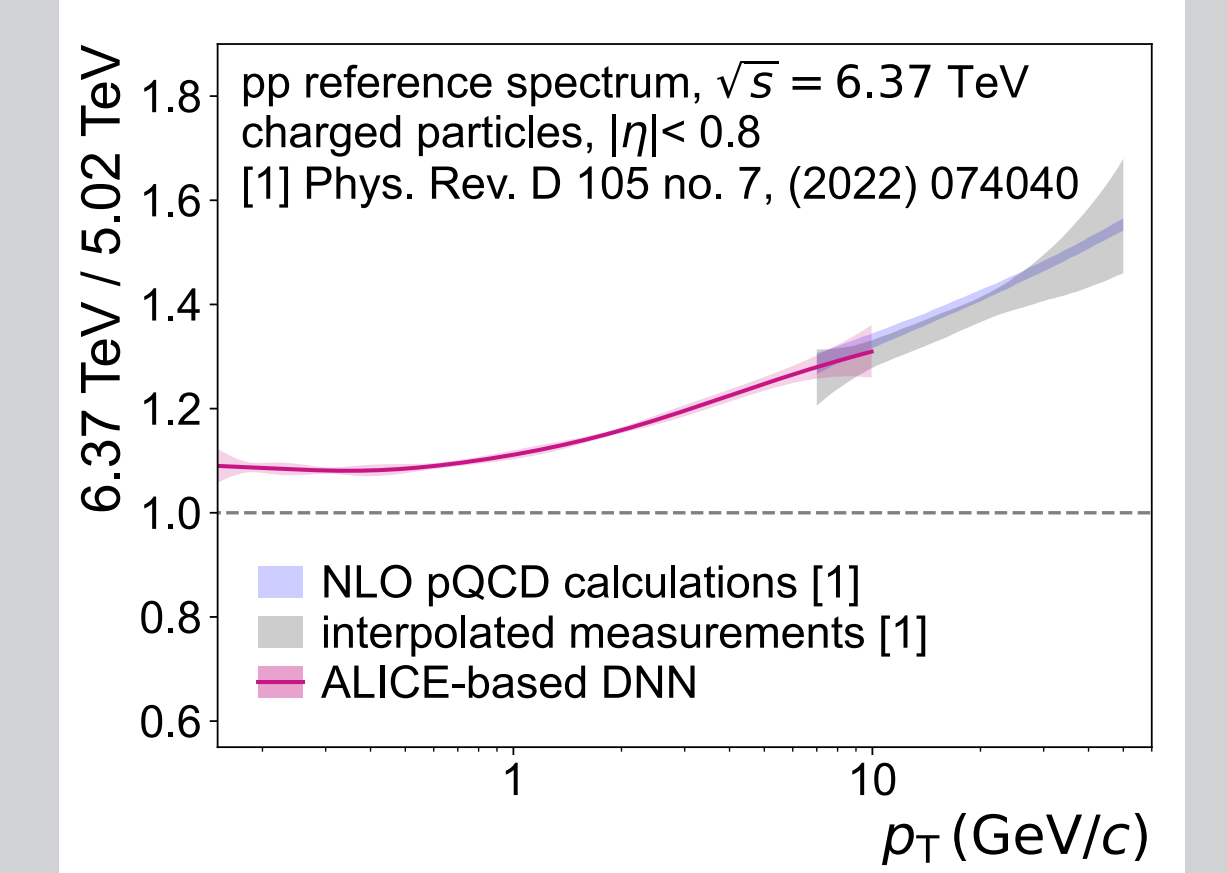
- Extract relative change of the  $p_T$  spectra at different energies
- Apply to a chosen baseline pp measurement → Allows consistent event class definition between pp and AA

A suitable baseline provided by the ALICE measurement at  $\sqrt{s} = 5.02 \text{ TeV}$  → High precision & close in energy to the interpolation targets



### Xe–Xe at $\sqrt{s} = 5.44 \text{ TeV}$ [5]:

- Consistent with established power-law interpolation at high  $p_T$
- Reduced fluctuations and matching with PYTHIA at low  $p_T$



### O–O at $\sqrt{s} = 6.37 \text{ TeV}$ [6]:

- Extending the pp reference to much lower  $p_T$
- At high  $p_T$ , good agreement with functional interpolation & theory

## Conclusion & Outlook

This approach could provide a more accurate reference than established methods or PYTHIA estimations. It could be helpful for future heavy-ion runs where no explicit pp reference measurements are foreseen. In the future, the procedure could be extended to the measured correlation of  $N_{ch}$  and  $p_T$  to further constrain the particle production or to identified particle spectra in other analyses.

[1] ALICE, "Multiplicity dependence of charged-particle production in pp, p-Pb, Xe-Xe and Pb-Pb collisions at the LHC", Phys. Lett. B 845 (2023) 138110 [5] ALICE, "Transverse momentum spectra and nuclear modification factors of charged particles in Xe-Xe collisions at  $\sqrt{s} = 5.44 \text{ TeV}$ ", Phys. Lett. B 788 (2019) 166–179 [2] P. Skands, S. Carrazza, and J. Rojo, "Tuning PYTHIA 8.1: the Monash 2013 Tune", Eur. Phys. J. C 74 no. 8, (2014) 3024, [6] J. Brewer, A. Huss, A. Mazeliauskas, and W. van der Schee, "Ratios of jet and hadron spectra at LHC energies: Measuring high- $p_T$  suppression without a pp reference", Phys. Rev. D 105 no. 7, (2022) 074040 [3] E. Shokr, A. De Roeck, and M. A. Mahmoud, "Modeling of  $N_{ch}$  and  $p_T$  distributions in pp collisions using a DNN", Sci. Rep. 12 no. 1, (2022) 8449. [4] R. Garnett, Bayesian Optimization. Cambridge University Press, 2023