Machine Learning based KNO-scaling of charged hadron multiplicities with HIJING++

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Abstract. The scaling properties of the final state charged hadron and mean jet multiplicity distributions, calculated by deep residual neural network architectures with different complexities are presented. The parton-level input of the neural networks are generated by the HIJING++ Monte Carlo event generator. Hadronization neural networks, trained with $\sqrt{s}$ = 7 TeV events are utilized to perform predictions for various LHC energies from $\sqrt{s}$ = 0.9 TeV to 13 TeV. KNO-scaling properties were adopted by the networks at hadronic level.

1. Introduction

Modern developments in Machine Learning methods led us to use these techniques in the field of high-energy physics (HEP) with great benefits [1–5]. Applications of the artificial intelligence hopefully not only provide a solution for so far unsolved questions, but may help to improve physical models by recognizing and investigating the inner correlations from these new approaches. In our recent works, Deep Neural Networks (DNN) were proposed to calculate the hadron-level statistical properties of collision events from the parton-level input, which was pre-calculated and trained by the widely used PYTHIA 8 Monte Carlo (MC) event generator [6–10]. We showed that the application of relatively simple neural network models preserve the strong KNO-scaling of the hadronic final-state production yields and their multiplicity distributions at energies available at the Large Hadron Collider (LHC). Another observation was that, despite the models were trained exclusively at one fixed center-of-mass energy of $\sqrt{s}$ = 7 TeV [10–13], the acquired scaling properties result in the application of the same network in more general kinematical ranges.

The HIJING++ (Heavy Ion Jet INteraction Generator, C++ version) is the new generation of the popular HIJING Monte Carlo event generator for heavy-ion physics. This program code is under final tests in the development timeline, and the latest, tuned version already performs well with data [14–16]. In the current study, the previously proposed and PYTHIA 8-trained, ML-based hadronization models were used to investigate KNO-like scaling. In order to more inclusively test the neural network (NN) model, the parton-level input of the ML-based hadronization model was generated by the HIJING++ in this study. Replacing the Lund hadronization model with a DNN-based one can provide a cross-check and valuable input for the validation of the hadronization model, as its schematic layout is presented in Fig. 1.

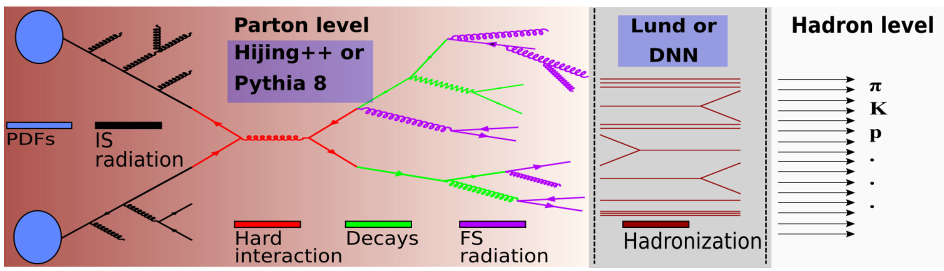

Figure 1. The schematic overview of the investigated processes and cross-checks.

2. The applied models

One of the focuses of our interest is to investigate, whether a neural network is able to represent the properties of the hadronization, especially at the non-perturbative regime of quantum chromodynamics. Within this kinematical regime the physical description lacks first principle calculations, therefore only complex phenomenological models exist with large sets of inner parameters. Since it has been proven that a complex deep neural network can pick up the properties of the jet evolution [5], indeed presenting QCD-like scaling properties [6, 10], a machine learning-based hadronization model is well motivated. On the other hand, the universality of our hadronization network module is the key idea for further development, therefore we investigated the ML-based model by inserting it into another Monte Carlo generator framework for cross-check tests.

The DNN hadronization models were developed based on the popular RESNET architecture, implemented in Python, using Keras v2.7 with Tensorflow v.2.7 backend [2, 3, 9]. Two models with different complexities were proposed, designated as 'Model S' and 'Model L', with 1.7×10^6 and 2×10^7 trainable parameters respectively. The schematic layout of the models are shown on Figure 2.

The models have been trained on PYTHIA 8 events that contained at least 2 jets (with $p_{T_J} \geq 40$ GeV/c and $R = 0.4$ in the $|y| < 3$ rapidity region) at $\sqrt{s} = 7$ TeV c.m. energy [6, 10]. By applying these DNN-based hadronization models on PYTHIA 8 generated partonic initial states, we were able to reproduce the measured charged hadron multiplicity distribution, jet-multiplicity distribution, and observables *vs.* event activity classifiers within a wide range of LHC energies. These correlated well with the physical expectations.

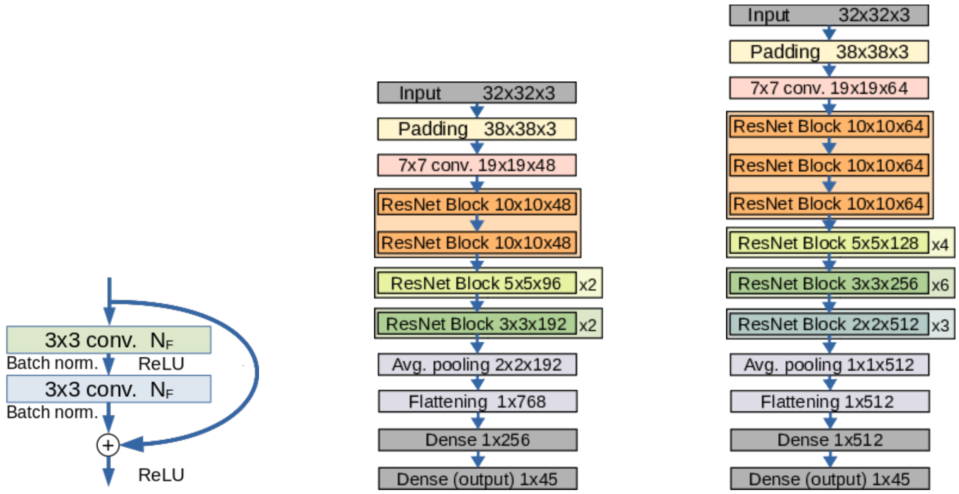

Figure 2. The basic RESNET building block (*left panel*), and the schematic layout of the applied Model S (*middle panel*) and Model L (*right panel*) variations.

The HIJING++ model is the successor of the original FORTRAN HIJING, completely rewritten in modern C++ programming language [15–17]. The core concepts of its physics engine are the well-known wounded nucleon model with energy-dependent minijet production [18], with the Lund string fragmentation model of PYTHIA 8, taking care of the hadronization [7, 8, 19]. It has new, modern built-in features such as modularity and CPU multithreading, whereas the underlying physics has been revamped and tuned for the RHIC-LHC energy era.

In this current study, our concept follows the idea presented in Fig. 1: the partonic initial state events, that are the inputs of the DNN-hadronization models, are now pre-calculated with HIJING++ with the same event criteria that has been mentioned above. The predicted observables are then presented and compared to the original Monte Carlo generated events.

3. Results

The multiplicity distributions of charged hadrons stemming from proton-proton collision events (with the same event selection criteria detailed above) are presented on the *left panel* of Fig. 3, where the HIJING++-calculated values (orange markers) are compared with the NN-predicted results (blue and green lines) for various c.m. energies in mid-rapidity, $|y| < 0.5$. The PYTHIA 8-generated Monte Carlo results are also shown with red markers for reference. Each curve has 300k generated events. The *right panel* of Fig. 3 shows the corresponding $P_n = \frac{1}{\langle n \rangle}\Psi\left(\frac{n}{\langle n \rangle}\right)$ scaling functions, with the joint curves presenting the effect of KNO-like scaling.

The primer observation on the multiplicity distribution is that, the HIJING++ results display deviation compared to PYTHIA 8 ones. A significant excess contribution appears at higher multiplicity classes against the low-multiplicity region. This difference is not surprising, since the phenomenological mechanisms of the two models are different

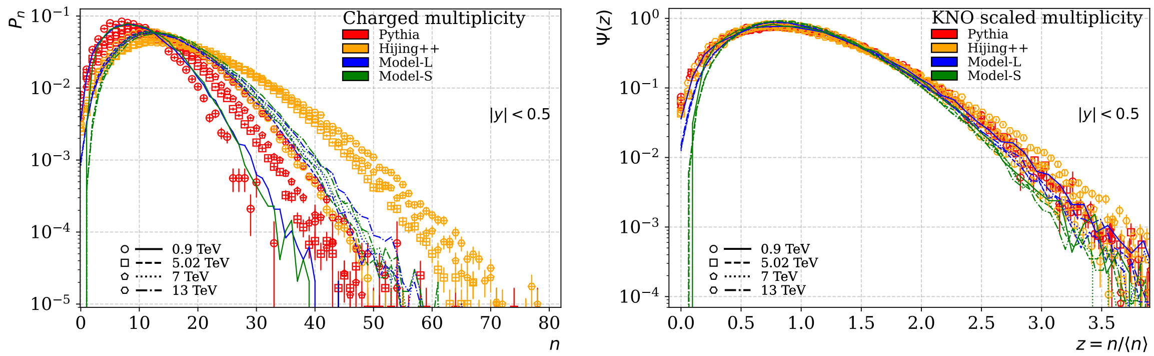

Figure 3. Mid-rapidity multiplicity (*left panel*) and KNO-scaled distributions (*right panel*) of charged hadrons in proton-proton collisions at LHC energies.

in the non-perturbative regime. Minijet production in HIJING++ generates more hadrons in the mid-multiplicity range. The predictions from the NN-based Model L and Model S lie between the two Monte Carlo models. Recalling that the NN-based models were trained with the fixed 7 TeV c.m. energy on PYTHIA 8 data only, the presented multiplicity distributions of these networks convoluted with HIJING++ is closer to the original PYTHIA 8-calculated curves at all energies. Indeed, the trends are more PYTHIA 8-like. This supports the idea, that hadronization plays a more significant role in the multiplicity production, than the parton shower evolution—the latter differs in the two Monte Carlo generators.

We investigated whether KNO-scaling of the multiplicities is preserved. One can observe on the *right panel* of Fig. 3 that good agreement were found among all the models up to the highest multiplicities after applying the KNO-transformation. It is also true for all datasets, that the larger the multiplicity, the stronger the violation of the KNO-scaling is, which has been shown experimentally as well [20]. This scaling violation here was found to be more remarkable for the original HIJING++ data. Model L and Model S scale well in parallel to these, apart from the lowest multiplicity values, where the applied cuts and statistics limit the training process.

The mean jet multiplicity distributions (the number of constituent particles in a jet) and their KNO-scaled curves are shown in the *left* and *right* panels of Figure 4, respectively. The deviation between the distribution shapes of the original Monte Carlo model results mostly vanishes. In this high-momentum fragmentation regime minor impact from the soft non-perturbative sector is present, therefore difference between the MC calculations appears only at the highest multiplicity values.

In contrary to the above agreement, the NN-based Model L and Model S present irregular, double-bump structure in the mean jet multiplicity distributions. The magnitude of this effect is independent of the hyperparameter-space volume but is getting stronger for higher $\sqrt{s}$ values. This suggests that though the global jet structure (e.g. the mean jet multiplicity) is similar among the two MC models, the sub-structure is quite different. This effect requires further investigations on a per-jet basis.

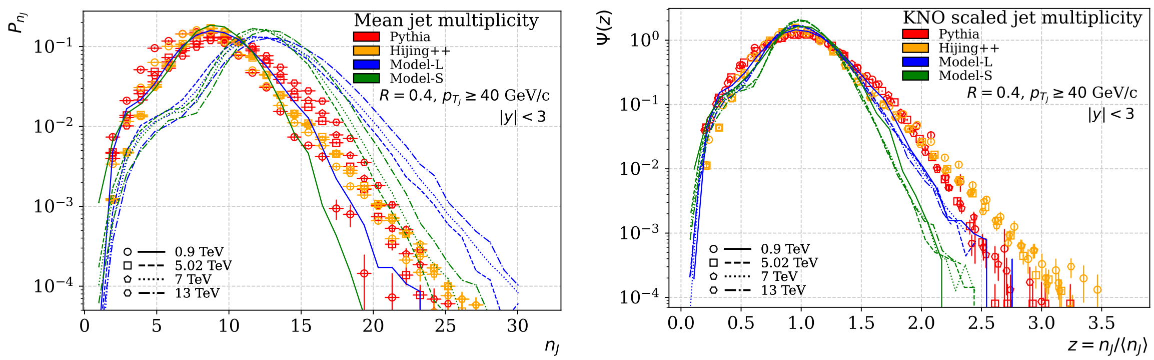

Figure 4. Jet mean multiplicity (*left panel*) and KNO-scaled jet mean multiplicity (*right panel*) in proton-proton collisions, for jets with $p_{T_J} \geq 40$ GeV/c and $R = 0.4$ in the $|y| < 3$ region.

The KNO-scaled mean jet multiplicities on the *right* panel of Fig. 4 are similar to the results that we have seen previously: the shapes of the curves are mostly universal at all energies for each investigated model—again with good agreement between the Monte Carlo models, apart from the highest multiplicity bins, which lack statistics. The shapes of the scaled distributions are different for the NN-based Model L and Model S, is separated into two branches by the size of the hyperparameter space volume.

4. Summary

In this contribution the scaling properties of charged hadron multiplicities and jets at LHC energies, stemming from proton-proton collisions were presented. The multiplicity distributions were determined by two Monte Carlo event generators and deep neural network based hadronization models. The neural network results presented a KNO-scaling of charged hadrons in jetty events at $|y| < 0.5$ rapidity, which differed from the Monte Carlo predictions. On the other hand, the mean jet multiplicity distributions on a wider rapidity region revealed diverse scaling behavior for the different models, with a better agreement between the HIJING++ and PYTHIA 8 calculations.

Acknowledgements

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