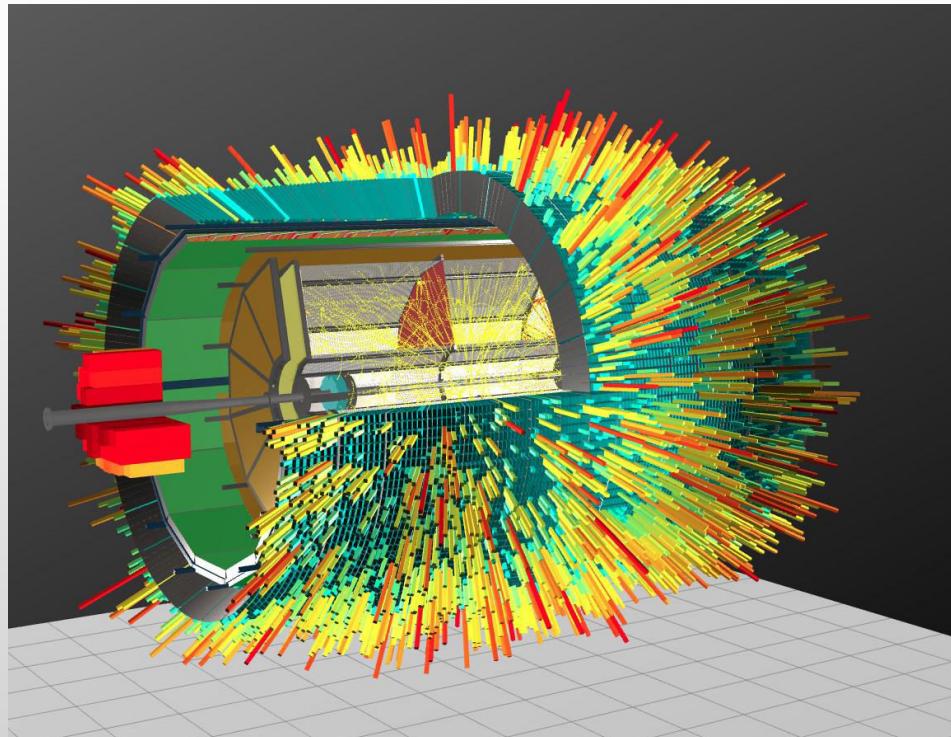


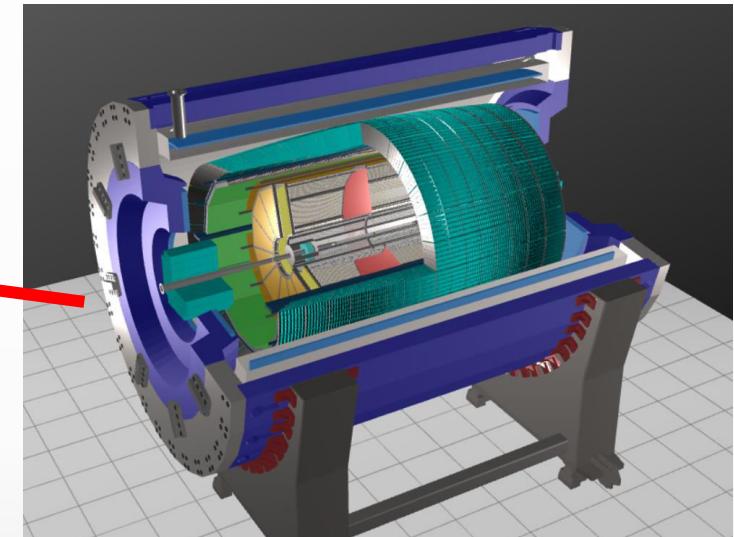
Статус эксперимента MPD и возможные задачи для ВШЭ

В.Г. Рябов (MPD Collaboration)



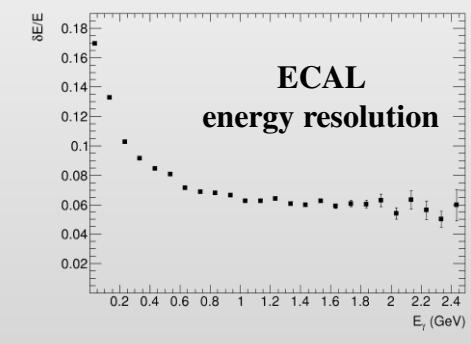
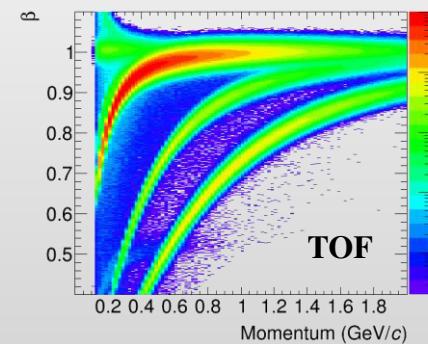
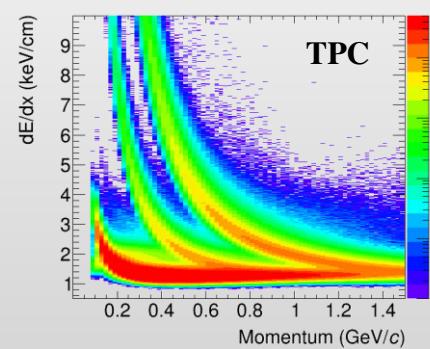
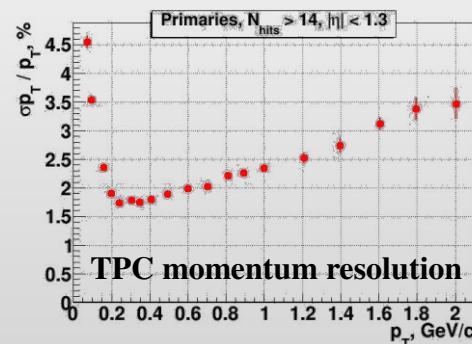
MPD @ NICA

- ❖ One of two experiments at NICA collider to study heavy-ion collisions at $\sqrt{s_{NN}} = 4\text{--}11 \text{ GeV}$



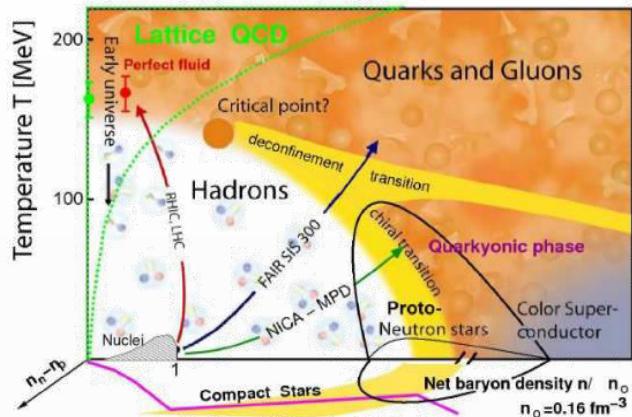
TPC: $|\Delta\phi| < 2\pi$, $|\eta| \leq 1.6$; **TOF, EMC:** $|\Delta\phi| < 2\pi$, $|\eta| \leq 1.4$; **FFD:** $|\Delta\phi| < 2\pi$, $2.9 < |\eta| < 3.3$; **FHCAL:** $|\Delta\phi| < 2\pi$, $2 < |\eta| < 5$

Au+Au @ 11 GeV (UrQMD + full chain reconstruction)

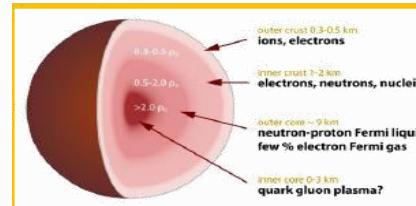


Heavy-ion collisions at NICA

- ❖ Explore the QCD phase diagram, search for the phase transition and CEP at maximum baryon density

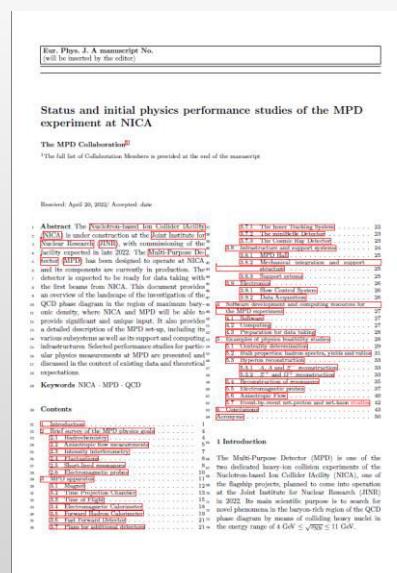
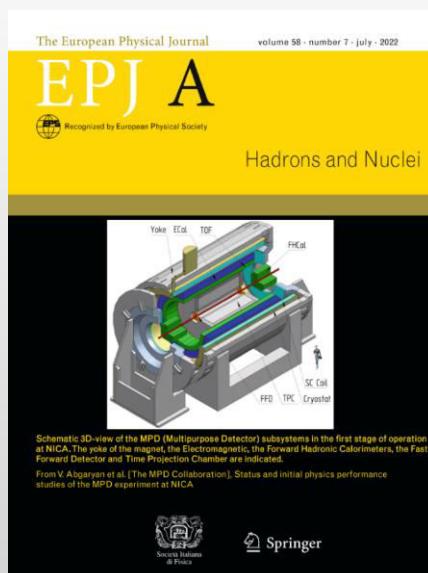


High baryon density:
Inner structure of
compact stars



Status and initial physics performance studies of the MPD experiment at NICA

Eur.Phys.J.A 58 (2022) 7, 140



Multi-Purpose Detector (MPD) Collaboration



*MPD International Collaboration was established in 2018
to construct, commission and operate the detector*

12 Countries, >500 participants, 38 Institutes and JINR

Organization

Acting Spokesperson: **Victor Riabov**
Deputy Spokespersons: **Zebo Tang, Arkadiy Taranenko**
Institutional Board Chair: **Alejandro Ayala**
Project Manager: **Slava Golovatyuk**

Joint Institute for Nuclear Research, Dubna;

A.Alikhanyan National Lab of Armenia, Yerevan, Armenia;

SSI "Joint Institute for Energy and Nuclear Research – Sosny" of the National Academy of Sciences of Belarus, Minsk, Belarus

University of Plovdiv, Bulgaria;

Tsinghua University, Beijing, China;

University of Science and Technology of China, Hefei, China;

Huzhou University, Huzhou, China;

Institute of Nuclear and Applied Physics, CAS, Shanghai, China;

Central China Normal University, China;

Shandong University, Shandong, China;

University of Chinese Academy of Sciences, Beijing, China;

University of South China, China;

Three Gorges University, China;

Institute of Modern Physics of CAS, Lanzhou, China;

Tbilisi State University, Tbilisi, Georgia;

Institute of Physics and Technology, Almaty, Kazakhstan;

Benemérita Universidad Autónoma de Puebla, Mexico;

Centro de Investigación y de Estudios Avanzados, Mexico;

Instituto de Ciencias Nucleares, UNAM, Mexico;

Universidad Autónoma de Sinaloa, Mexico;

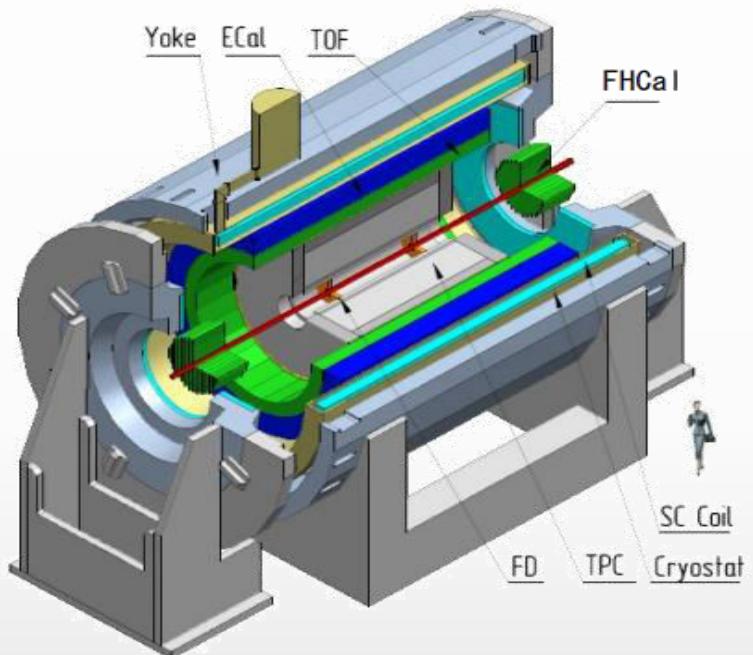
Universidad de Colima, Mexico;

Universidad de Sonora, Mexico;

Universidad Michoacana de San Nicolás de Hidalgo, Mexico

Institute of Applied Physics, Chisinev, Moldova;

Institute of Physics and Technology, Mongolia;



Belgorod National Research University, Russia;

Institute for Nuclear Research of the RAS, Moscow, Russia;

High School of Economics University, Moscow, Russia

National Research Nuclear University MEPhI, Moscow, Russia;

Moscow Institute of Science and Technology, Russia;

North Ossetian State University, Russia;

National Research Center "Kurchatov Institute", Russia;

Plekhanov Russian University of Economics, Moscow, Russia;

St.Petersburg State University, Russia;

Skobeltsyn Institute of Nuclear Physics, Moscow, Russia;

Petersburg Nuclear Physics Institute, Gatchina, Russia;

Vinča Institute of Nuclear Sciences, Serbia;

Pavol Jozef Šafárik University, Košice, Slovakia



Activities in the MPD Hall

Cryogenic platform



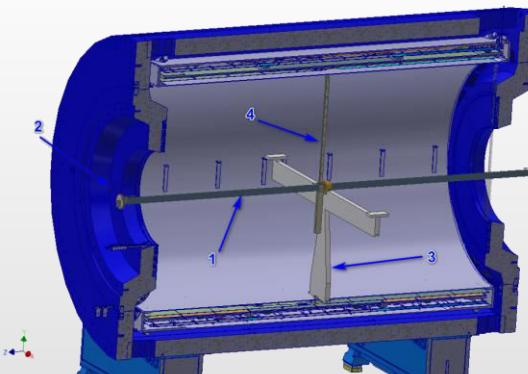
Chimney



Cryogenic pipes



Novosibirsk BINP magnetic field mapper



1. Aluminum (carbon fiber plastic) guiding rod
2. End cap fixation
3. Intermediate support
4. Carbon fiber plastic carriage

Parameter	Value
Length of movement for Z	2× 4,5 m
Length of movement for R	0.1 – 2.2 m
Rotation of measurement block	3600
Accuracy of movement for Z	50 microns
Accuracy of movement for R	50 microns
Accuracy of rotation	0.20
Hall 3D sensor	HE444, HE Hoeben Electronix,
Hall 3D sensor accuracy	0.1 Gs
Hall 3D sensor accuracy total (with accuracy of laser tracker and temperature correction)	0.3 Gs
Sag of guide line	5 mm
Weight of mapper	100 kg
Reading time per one measurement	1 sec

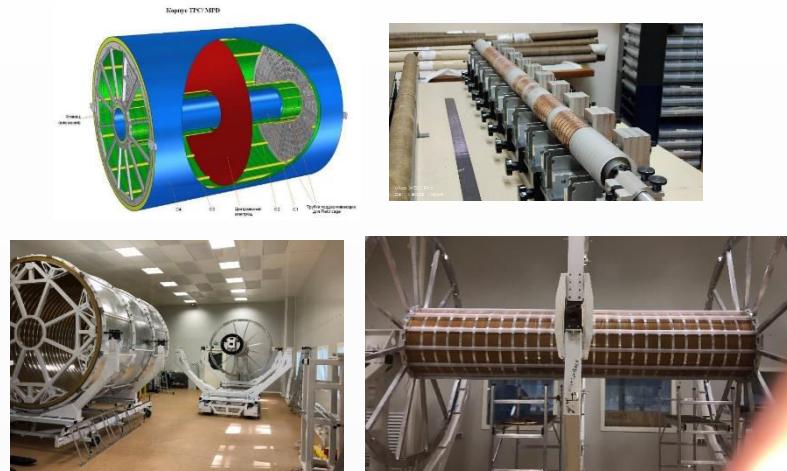
Carbon fiber support frame
sagita ~ 5 mm at full load



- ❖ Test cooling to 70° K in February-March
- ❖ Cooling to LHe → second half of 2024 → MF measurements → installation of carbon fiber support frame and subsystems

Barrel subsystems in production

TPC – central tracking detector



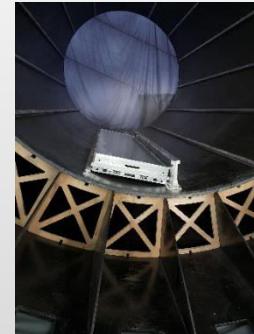
TPC cylinders, central membrane, service wheels, readout chambers,
gas system - ready - final vessel assembly by the end of year

TOF

TOF modules in storage (28 in total)



Module in the frame

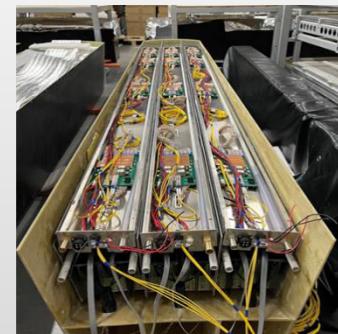


Production of MRPC detectors was completed in September 2022, (107%)

All 28 TOF modules are assembled → long-term cosmic ray tests
Electronics & cables, HV distribution modules → in stock

ECAL

Half-sectors at different stages of assembly



Production rate ~ 10 half-sectors per month
Installation procedure for electronics in half-sectors is under development

MPD physics program

G. Feofilov, P. Parfenov

Global observables

- Total event multiplicity
- Total event energy
- Centrality determination
- Total cross-section measurement
- Event plane measurement at all rapidities
- Spectator measurement

V. Kolesnikov, Xianglei Zhu

Spectra of light flavor and hypernuclei

- Light flavor spectra
- Hyperons and hypernuclei
- Total particle yields and yield ratios
- Kinematic and chemical properties of the event
- Mapping QCD Phase Diag.

K. Mikhailov, A. Taranenko

Correlations and Fluctuations

- Collective flow for hadrons
- Vorticity, Λ polarization
- E-by-E fluctuation of multiplicity, momentum and conserved quantities
- Femtoscopy
- Forward-Backward corr.
- Jet-like correlations

D. Peresunko, Chi Yang

Electromagnetic probes

- Electromagnetic calorimeter meas.
- Photons in ECAL and central barrel
- Low mass dilepton spectra in-medium modification of resonances and intermediate mass region

Wangmei Zha, A. Zinchenko

Heavy flavor

- Study of open charm production
- Charmonium with ECAL and central barrel
- Charmed meson through secondary vertices in ITS and HF electrons
- Explore production at charm threshold

TPC response using GANs

- ❖ Использование генеративно-состязательных сетей (GAN) для быстрого моделирования сигналов в детекторе TPC → отклик на прохождение через детектор заряженных частиц
- ❖ Команда ВШЭ (Ф. Ратников, А. Маевский, и др.)

Eur. Phys. J. C (2021) 81:99
https://doi.org/10.1140/epjc/s0052-021-09366-4

THE EUROPEAN
PHYSICAL JOURNAL C

Regular Article - Experimental Physics

Simulating the time projection chamber responses at the MPD detector using generative adversarial networks

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Abstract High energy physics experiments rely heavily on the detailed detector simulation models in many tasks. Running such detailed models typically requires a notable amount of the total computing capabilities of an experiment and is often the main bottleneck in the analysis of the results. In this work, we demonstrate a new approach to speed up the simulation of the Time Projection Chamber tracker of the MPD experiment at the NICA accelerator complex. Our method is based on a Generative Adversarial Network – a deep learning technique allowing for implicit estimation of the final physical result. The amount of computational resources spent on the simulation usually takes a notable amount of the total computing capabilities of an experiment and is often the main bottleneck in the analysis of the results. In this work, we demonstrate a new approach to speed up the simulation of the Time Projection Chamber tracker of the MPD experiment at the NICA accelerator complex. Our method is based on a Generative Adversarial Network – a deep learning technique allowing for implicit estimation of the final physical result.

The amount of computational resources spent on the simulation usually takes a notable amount of the total computing capabilities of an experiment and is often the main bottleneck in the analysis of the results. In this work, we demonstrate a new approach to speed up the simulation of the Time Projection Chamber tracker of the MPD experiment at the NICA accelerator complex. Our method is based on a Generative Adversarial Network – a deep learning technique allowing for implicit estimation of the final physical result.

The MPD detector is one of the two experiments at the NICA accelerator complex – a heavy ion accelerator located at the Joint Institute for Nuclear Research in Dubna, Russia [9, 10]. The complex is designed to study the properties of dense baryonic matter. For the tracking, MPD utilizes a time projection chamber (TPC) in the central barrel [11]. TPC simulation is very CPU-intensive [12], and hence a fast simulation approach for TPC is highly desirable.

A typical approach to constructing models for fast simulation of particle physics detectors is to use a simplified detector geometry and a simplified model of the interaction of particles with matter [13]. This approach is justified for subsystems with a flat sensitive volume, such as silicon trackers, that measure the two-dimensional coordinate of a passing particle. For systems with a large volume, such as calorimeters or TPC-based trackers, this approach makes it difficult to achieve a reasonable compromise between accuracy and speed.

Another fast simulation approach is an analytical parametrization of the detector response, as can be seen in shower simulation programs like GEANT4 [14]. Such approaches can significantly speed up the calculations of simulation, but it makes it difficult to achieve high quality simulated data. A common solution for calorimeters is also to use the so-called “frozen showers” [15] when detailed simulated system responses are stored as a response library for subsequent reuse.

Generative Adversarial Networks for the fast simulation of the Time Projection Chamber responses at the MPD detector

A. Maevskiy¹, F. Ratnikov^{1,2}, A. Zinchenko³, V. Riabov⁴,

Generative Surrogates for Fast Simulation: TPC Case

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^bYandex School of Data Analysis, 11-2 Timiryazev Street, Moscow, Russia

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^fPetersburg Nuclear Physics Institute, 1 mile Orlowskaya, Gatchina, Leningradskaya Oblast, Russia

arXiv:2203.16355v1 [physics.ins-det] 30 Mar 2022

arXiv:2207.04340v1 [hep-ex] 9 Jul 2022

Abstract The detailed detector simulation models are vital for the successful operation of modern high-energy physics experiments. In most cases, such detailed models require a significant amount of computing resources to run. Often this may not be justified and less resource intensive approaches are preferred. In this work, we demonstrate the application of Generative Adversarial Networks (GAN) as the basis for such fast-simulation models for the case of the Time Projection Chamber (TPC) at the MPD detector at the NICA accelerator complex. The proposed approach allows us to obtain a fast simulation model that is several times faster compared to the detailed simulation without any noticeable drop in the quality of the high-level reconstruction characteristics for the generated data. Approaches with direct and indirect quality metrics optimization are compared.

1. Introduction

Simulation of particle detectors is inevitable in the High Energy Physics (HEP) experiments. For a typical HEP experiment, the limited size of simulated data samples often contributes directly to the uncertainty in the final result. Since the number of simulated events that one can afford to produce is constrained by the computational efficiency of the simulation algorithms, faster algorithms are always desired [1].

Computational efficiency of the detailed simulation is often limited by the fine granularity of the physics simulation steps being performed. Therefore, a speed-up may be achieved by aggregating a large number of small steps into a few large ones. Another way to speed up the fast-simulation parameters, conditioned by the first step inputs. An important requirement for such a probability distribution estimate is that it should allow for efficient sampling. Generative Adversarial Networks (GANs) [2] are a good candidate for such a parametric estimate since they only require a forward pass through a neural network to generate new samples. In this work, we demonstrate an application of GANs for building a fast-simulation model of the Time Projection Chamber (TPC) detector at the MPD experiment at the NICA accelerator complex [3].

Abstract

Simulation of High Energy Physics experiments is widely used, necessary for both detector and physics studies. Detailed Monte-Carlo simulation algorithms are often limited due to the computational complexity of such methods, and therefore faster approaches are desired. Generative Adversarial Networks (GANs) are well suited for aggregating a number of detailed simulation steps into a surrogate probability density estimator readily available for fast sampling. In this work, we demonstrate the power of the GAN-based fast simulation model on the use case of simulating the response for the Time Projection Chamber (TPC) in the MPD experiment at the NICA accelerator complex. We show that our model can generate high-fidelity TPC responses, while accelerating the TPC simulation by at least an order of magnitude. We describe alternative representation approaches for this problem and also outline the roadmap for the deployment of our method into the software stack of the experiment.

Keywords: fast simulation, time projection chamber, generative adversarial network

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Preprint submitted to Nuclear Instruments and Methods in Physics Research A July 12, 2022

TPC response using GANs - performance

- ❖ Моделирование сигналов на считываемых падах:

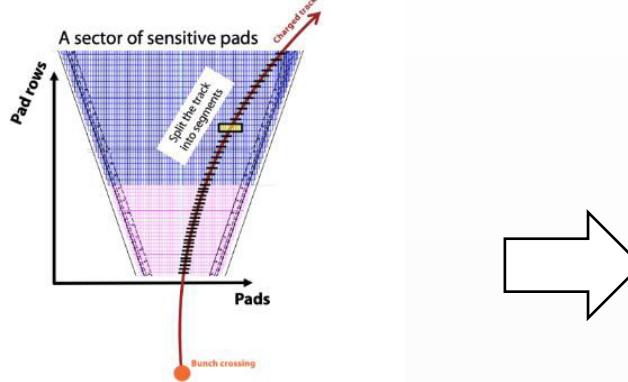


Figure 1. The transverse projection of a track on top of a sector of sensitive pads of the detector. The track is split into segments contributing to each of the rows of sensitive pads.

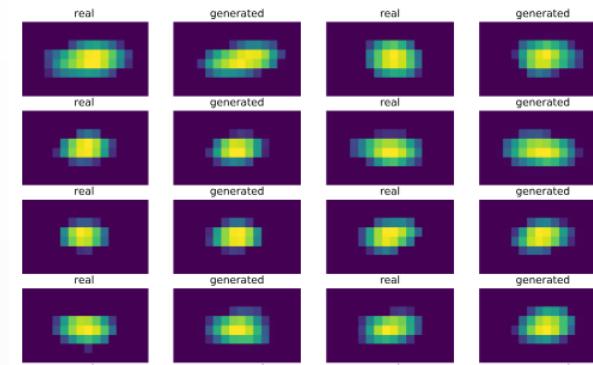
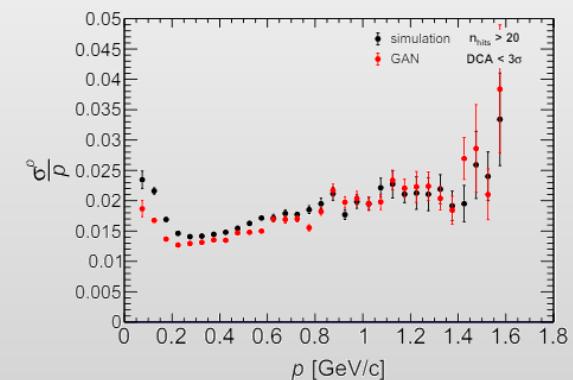
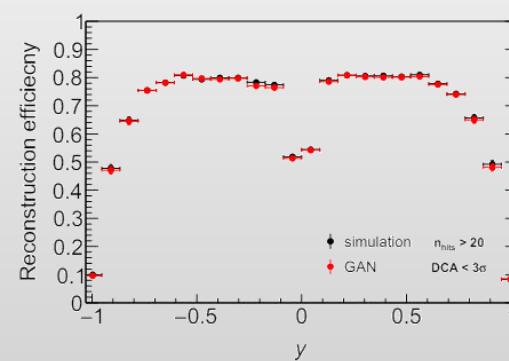
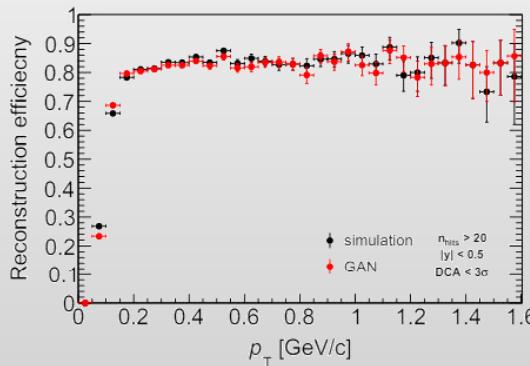


Fig. 1. Examples of the generated pad responses. Vertical and horizontal axes correspond to the pad and time bins, respectively. Each image from the validation dataset (1st and 3rd columns) is paired up with a generated image (2nd and 4th columns) obtained for the same values of the conditional variables.

- ❖ ГАН-смоделированные сигналы → сравнимые характеристики детектора (разрешение, эффективность и т.д.) :



Актуальные задачи и требуемые специалисты

- ❖ Создание, запуск и эксплуатация экспериментальной установки:
 - ✓ Электрики, монтажники, конструкторы, специалисты по криогеннике ...
 - ✓ Системы контроля и мониторинга состояния детекторов, магнитов, газовой системы (aka DCS) (LV, HV, T, утечки, состав газовой смеси ...)
 - ✓ Система аварийной индикации и реагирования на внештатные ситуации
- ❖ Разработчики программного обеспечения:
 - ✓ Система онлайн контроля качества поступающих данных (QA)
 - ✓ Онлайн и офлайн калибровка детекторных подсистем
 - ✓ Реконструкция сигналов в детекторных подсистемах, глобальные трекинг и ассоциация сигналов (включая моделирование откликов TPC и ECAL с использованием генеративных моделей)
- ❖ Обработка экспериментальных данных:
 - ✓ Физический анализ данных и интерпретация результатов → использование классических методов обработки экспериментальных данных будет наиболее уместным и приоритетным в первые годы работы экспериментальной установки
 - ✓ Внедрение продвинутых методов анализа данных, включая элементы машинного обучения (мультивариативные анализы для идентификации адронов, измерения гиперонов, нейтральных мезонов, диэлектронного континуума, D-мезонов и т.д.) → экзотика на начальном этапе, но смогут получить признание в случае демонстрации успеха

Possible application areas of machine learning techniques at MPD/NICA, Contribution to GRID 2018, 615-619
Dielectron analysis: Machine learning study, <https://indico.jinr.ru/event/4506/>

Gradient Boosted Decision Tree for Particle Identification at MPD, <https://indico.jinr.ru/event/4314/>
Photon and neutral meson reconstruction, <https://indico.jinr.ru/event/4080/>

BACKUP