## **PID Study for CEPC Drift Chamber**

Xu Gao

Jilin university

#### For the DC-PID group of the CEPC 4<sup>th</sup> conceptual detector







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#### Outline

- Introduction
- Waveform-based full simulation
- Fast simulation with Delphes

- Activities on prototype test
- Summary

## CEPC

#### • CEPC

- 240 GeV (Higgs factory),
- 91.2 GeV (Z factory or Z pole) -
- 160 GeV (WW threshold scan)

 $4 \times 10^{12}$  Z: provide diverse flavor measurements

- Particle identification (PID) is essential for flavor physics and jet study
  - Reduce combination background
  - Improve mass resolution
  - Benefit flavor tagging



### **CEPC the 4<sup>th</sup> conceptual detector**



#### Solenoid Magnet (3T / 2T ) Between HCAL & ECAL

**Advantage:** the HCAL absorbers act as part of the magnet return yoke.

**Challenges**: thin enough not to affect the jet resolution (e.g. BMR); stability.

#### Transverse Crystal bar ECAL

**Advantage:** better  $\pi^0/\gamma$  reconstruction.

**Challenges**: minimum number of readout channels; compatible with PFA calorimeter; maintain good jet resolution.

#### A Drift chamber that is optimized for PID

Advantage: Work at high luminosity Z runs Challenges: sufficient PID power; thin enough not to affect the moment resolution.

- Tracker with silicon tracker and a drift chamber
- The chamber optimized for PID with cluster counting technique
- Up to 20 GeV/c K/π separation power required

## dE/dx vs dN/dx



- dE/dx: Energy loss per unit length, Landau distribution, large fluctuation
- *dN/dx*: Number of primary ionization clusters per unit length, Poisson distribution, small fluctuation → cluster counting technique

In theory, dN/dx has a significant advantage over dE/dx.

### workflow and DC preliminary design





Preliminary	DC	parameters
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Inner radius	800 mm	
Outer radius	1800 mm	
Cell size	18 mm × 18 mm	
Gas mixture	He/iC4H10=90:10	

### Waveform-based full simulation

#### **Simulation process**



### **Reconstruction algorithm**

#### Step1. Peak Finding

Discriminate peaks (both primary and secondary) from the noises



#### ➤Two methods under study

Classical method (developed): Derivative-based peak finding + clusterization with peak merge Deep learning based algorithm (ongoing): Peak finding with LSTM + clusterization with DGCNN

Step2. Clusterization:

Determine the number of clusters  $(N_{cls})$  from the

## $K/\pi$ separation power with Classical method

K/ $\pi$  separation power vs P (1m track length, cos $\theta$ =0)

K/ $\pi$  separation power vs cos( $\theta$ )



 $2\sigma K/\pi$  separation power is reached up to 20 GeV/c

Deep learning based algorithm (under development) is expected to provide better performance

### **Fast simulation with Delphes**

- Delphes is a modular framework that simulates the response of a multipurpose detector
  - $10^2 \sim 10^3$  faster than the fully GEANT based simulations
  - Sufficient and widely used for phenomenological studies
- For simulations of the CEPC 4<sup>th</sup> concept detector :
  - Detector layout based on preliminary optimization

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- A dedicated PID module(dN/dx and TOF) developed
- · Consistent workflow for lepton/photon isolation and jet-clustering
- More details in github repository: <a href="https://github.com/oiunun/Delphes\_CEPC.git">https://github.com/oiunun/Delphes\_CEPC.git</a>



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### **Detector configuration**



#### Calorimeter system:

• Preliminary implementation, reasonable resolution achieved. Needs more tuning

### dN/dx model in Delphes



Parameterized simulation of  $dN/dx_{meas}$ 

#### The calculation of the probability

dN/dx + TOF combined chi-square:

 $(\chi^i)^2 = (\chi_1^i)^2 + (\chi_2^i)^2$  (It follows a Chi-square distribution of 2 degrees of freedom)

$$\chi_1^i = \frac{(dN/dx)_{meas} - (dN/dx)_{exp}^i}{(\sigma)_{dN/dx}^i} \qquad \qquad \chi_2^i = \frac{(tof)_{meas} - (tof)_{exp}^i}{(\sigma)_{tof}^i}$$

PID selection with probability calculated by chi-square:

• e.g. identified as  $\pi$ : Prob( $\pi$ )>Prob(K) & Prob( $\pi$ )>Prob(p)



### **PID efficiency**



efficiency : $\varepsilon_j^i = \frac{n_j^i}{n_{tot}^j}$ 

- $n_i^i$ :number of j being identified as i.
- $n_{tot}^j$ :number of j

Good PID performance up to 20 GeV/c

## PID performance with $B_s^0/B^0$ decays

- $B_s^0 \to \phi \phi, \phi \to K^+ K^-$
- $B^0/B_s^0 \rightarrow hh, h = \pi, K$
- Background:  $Z \rightarrow b\overline{b} \ (7 \times 10^8)$

channel	Sample size	Tera-Z yield	
$B_S^0 \to \phi \phi, \phi \to K^+ K^-$	630	561,600	
$B^0 \to \pi^+ \pi^-$	2,900	2,585,142	
$B^0 \to K^+ K^-$	44	39,222	
$B_s^0 \to \pi^+ \pi^-$	98	87,360	
$B_s^0 \to K^+ K^-$	3,739	3,333,051	

## Demonstration of the significance of PID: $B_s^0 o \phi \phi$



Improved signal sensitivity with PID

## Demonstration of the significance of PID: $B^0/B_s^0 \rightarrow hh$



Improved signal sensitivity with PID

## Activities on prototype test

- Prototype test at IHEP
  - A preamplifier is designed and tested with a drift tube using Sr-90 source
  - Preliminary tests show a promising future
- Further tests and optimization are on going





- Beam test organized by INFN group
- Cooperation between IHEP and INFN
  - Data taking
  - Data analysis
  - Optimizing DC simulation
  - Plan to apply ML algorithm on online FPGA





### Summary

- A drift chamber with cluster counting technique for PID is proposed for CEPC the 4<sup>th</sup> conceptual detector
- $2\sigma K/\pi$  separation power is reached up to 20 GeV/c with waveform-based full simulation
- Physics sensitivity is improved significantly with PID in flavor physics with Delphes fast simulation
- Prototype test is ongoing

# Thanks!

Backup

## Deep learning based algorithm

#### **Peak finding with LSTM**



- With Long short-term memory (LSTM) model
- Labels: Signal or Noise.
- Features: Slide windows of peak candidates, with a shape of (15, 1)

#### $\Rightarrow$ A binary classification problem

#### **Clusterization with DGCNN**



- GNN-based architecture: DGCNN
- Massage passing through neighbor nodes ⇔ Clusterization of electron timings from the same primary cluster

#### Comparison between LSTM and derivative model



Better AUC for LSTM, due to the better pile-up recovery ability of the LSTM model



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### Performance with deep learning based algorithm



Method		μ	σ	$\sigma/\mu$
Input		16.53	3.93	23.8%
Output	Classical algorithm	18.67	4.60	24.6%
	ML	16.65	4.06	24.4%

## Tracking resolution



## CDR K/ $\pi$ K/p S



## Event selection for $B_s^0 \rightarrow \phi \phi$

- $Z \rightarrow b\overline{b} \rightarrow di jet$ , so the following selections is done in each jet
- And the  $M_{\phi\phi}$  in [5.1,5.6] is retained.
- Final state:  $K^+K^-K^+K^-$
- Kaon PID(dN/dx +TOF)
  - $Prob_K > Prob_{\pi}$  &&  $Prob_K > Prob_p$
- $\phi$  reconstruction
  - $\left| M_{K^+K^-} m_{\phi} \right| < 0.02 \; GeV/c^2$
  - $0.6 \times leading E_{\phi} + subleading E_{\phi} > 15 \text{ GeV}$





# Event selection for $B_s^0/B^0 \rightarrow hh$

- $Z \rightarrow b\overline{b} \rightarrow di jet$ , so the following selections is done in each jet
- And the  $M_{hh}$  in [5.2,5.5] is retained.
- Final state:  $K^+K^-/\pi^+\pi^-$
- PID(dN/dx +TOF)
  - K:  $Prob_K > Prob_{\pi}$  &&  $Prob_K > Prob_p$
  - $\pi$ :  $Prob_{\pi} > Prob_{K}$  &&  $Prob_{\pi} > Prob_{p}$
- K/ $\pi$  criteria
  - Pt > 5 GeV
- Reconstruct  $B^0 \& B_s^0$  in  $M_{hh} \in [5.2, 5.5]$  GeV
  - $\theta_{hh} < 0.6$



### Signal samples



