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# The study of MRPC with a high resolution

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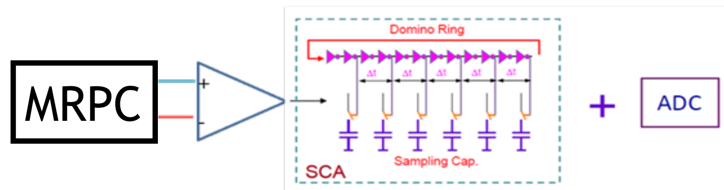
# Outline

- Motivation
- The framework of analysis
- MRPC simulation
- The neural network
- Data analysis and result
- Experiment and result
- Conclusions
- Future plan

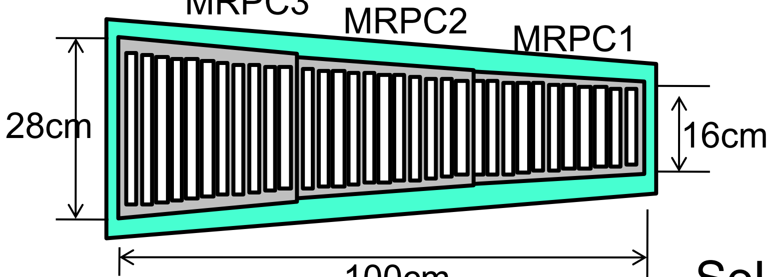
# Motivation

- Particle identification(PID) is very important in the study of hadronic physics
- In SoLID experiment, the requirements for the Time-of-Flight(ToF) system are:
  - pi/k separation up to 7GeV/c
  - Time resolution < 20ps
  - Rate capability > 10kHz/cm²
- Challenge for both MRPC and electronics.
- Electronics: Fast amplifier + waveform digitizer
- A new MRPC is under development

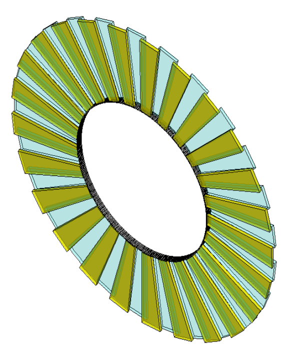



Fast amplifier

Pulse sampling



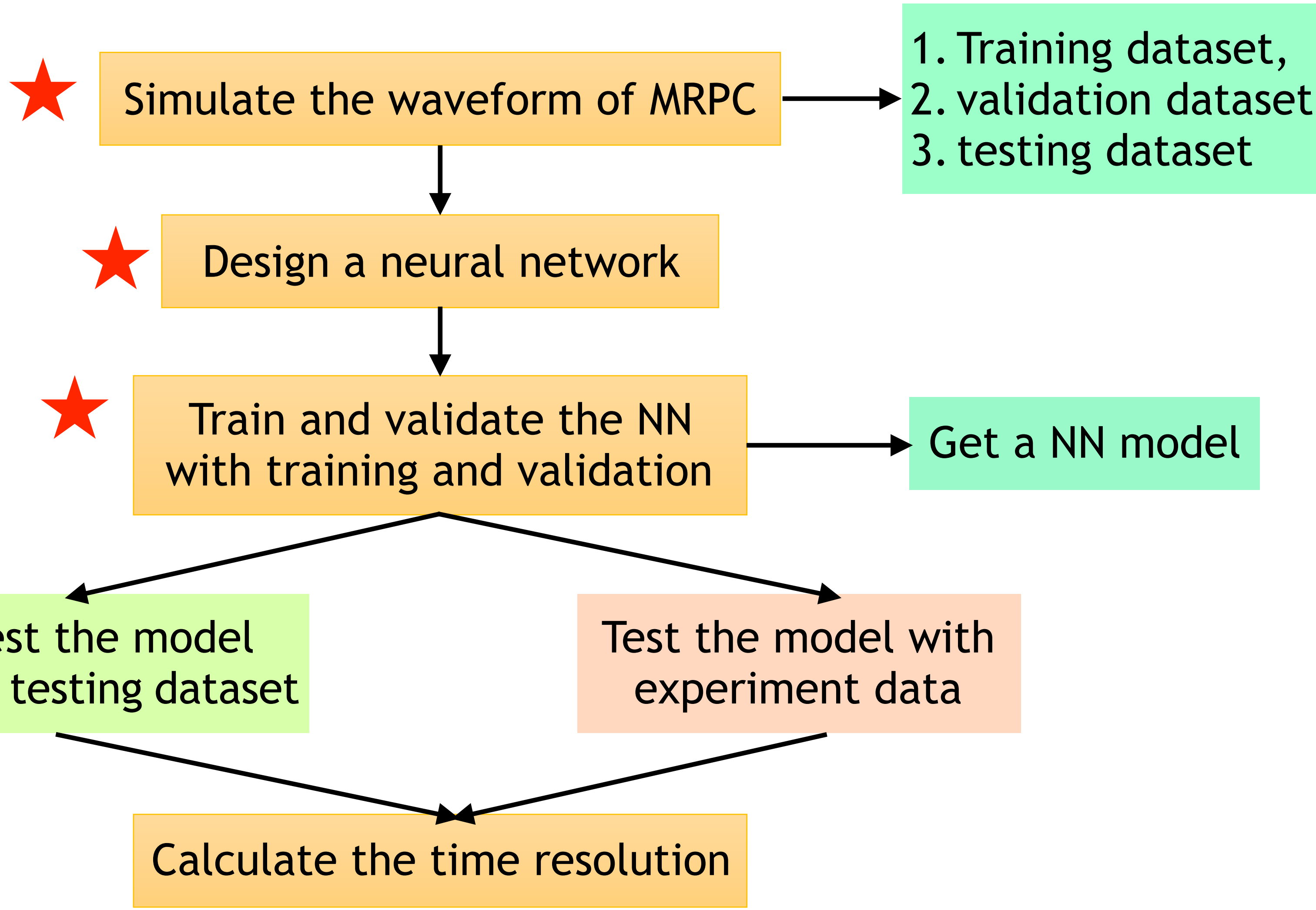

SoLID-ToF



Analysis framework that takes the advantage of the entire waveform

# The framework of analysis



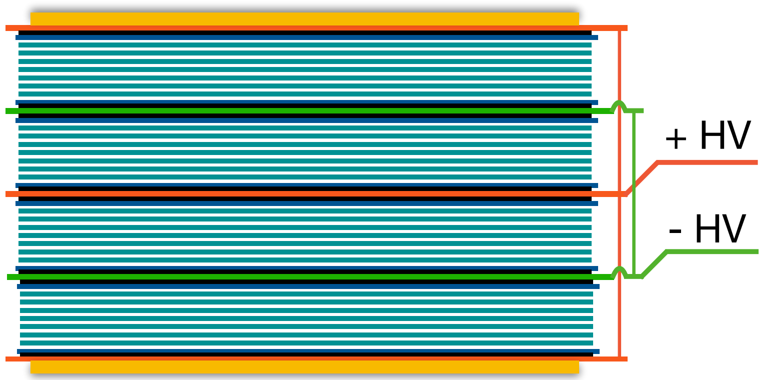


# MRPC Simulation



Design a MRPC
↓
Shoot a particle
↓
Simulate the primary energy deposition with PAI model
↓
Digitize the charge of the avalanche
↓
Original current signal
↓
Electronics

- MRPC structure




4 stack, 8 gas gaps/stack

Gap/glass thickness: 0.104/0.5 mm

Gas: 90% $C_2H_2F_4$, 5% $C_4H_{10}$ and 5% $SF_6$

- Particle source: 4GeV mu-, perpendicular to the MRPC
- **PAI** model is used to simulating the primary energy deposition*, rather than **Emstardard**

*W. Allison, J. Cobb, Relativistic Charged Particle Identification by Energy Loss, Ann. Rev. Nucl. Part. Sci. 30 (1980) 253–298.

# Charge Digitization



- Primary energy loss —— ionize electron-ion pairs. W = 30 eV
- Avalanche multiplication —— Townsend effect:

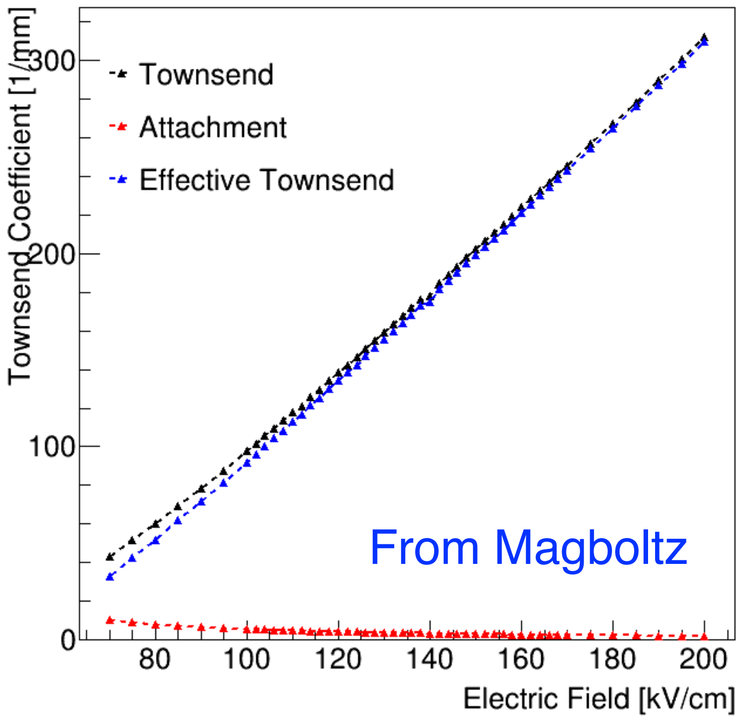
Assumptions:

1. Every step of the multiplication is independent
2. Uniform electric field

$$\frac{d\bar{n}}{dx} = (\alpha - \eta)\bar{n}$$

$\alpha$ : Townsend coefficient

$\eta$ : Attachment coefficient



# Charge Digitization



## Multiplication in a small step:

- P(n,x): Prob(one electron $\xrightarrow{x}$ n electrons)

$$P(n, x+dx) = P(n-1,x)(n-1)\alpha\,\mathrm{d}x(1-(n-1))\eta\,\mathrm{d}x$$
$$+ P(n,x)(1-n\alpha\,\mathrm{d}x)(1-n\eta\,\mathrm{d}x)$$
$$+ P(n,x)n\alpha\,\mathrm{d}x\,n\eta\,\mathrm{d}x$$
$$+ P(n+1,x)(1-(n+1)\alpha\,\mathrm{d}x)(n+1)\eta\,\mathrm{d}x$$

- Divide the gap into ~300 steps, and simulate the multiplication in every step
- Generate a random number according to P(n,x)*:

$$n\begin{cases} 0, & s < k\frac{\bar{n}(x)-1}{\bar{n}(x)-k} \\ 1 + \mathrm{Trunc}[\frac{1}{\ln(1-\frac{1-k}{\bar{n}(x)-k})}\ln(\frac{(\bar{n}(x)-k)(1-s)}{\bar{n}(x)(1-k)})], & s > k\frac{\bar{n}(x)-1}{\bar{n}(x)-k} \end{cases}$$

$$k = \frac{\eta}{\alpha}$$

s: uniform random number from (0,1)

- Finally, avalanche growth like: $e^{(\alpha-\eta)x}$

*W. Riegler, et al. NIMA 500 (1-3) (2003) 144–162.

# Original signal current

- Electrons drifting in the electric field: induce a signal on the read out strips
- Ramo theory:

$$i(t) = \frac{E_W \cdot v}{V_W} e_0 N(t)$$

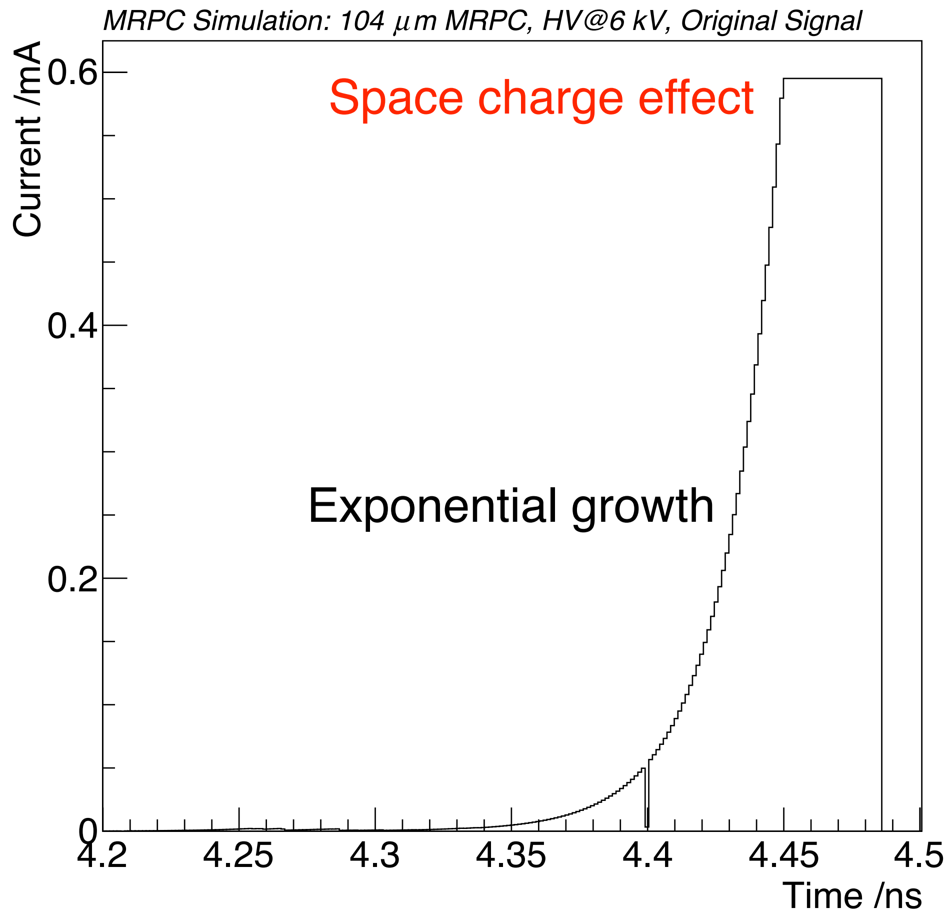
- Weighting field:

$$\frac{E_W}{V_W} = \frac{\varepsilon}{ng\varepsilon + (n+1)d}$$

0.71 $mm^{-1}$

- Space charge effect:

~$10^5$ electrons

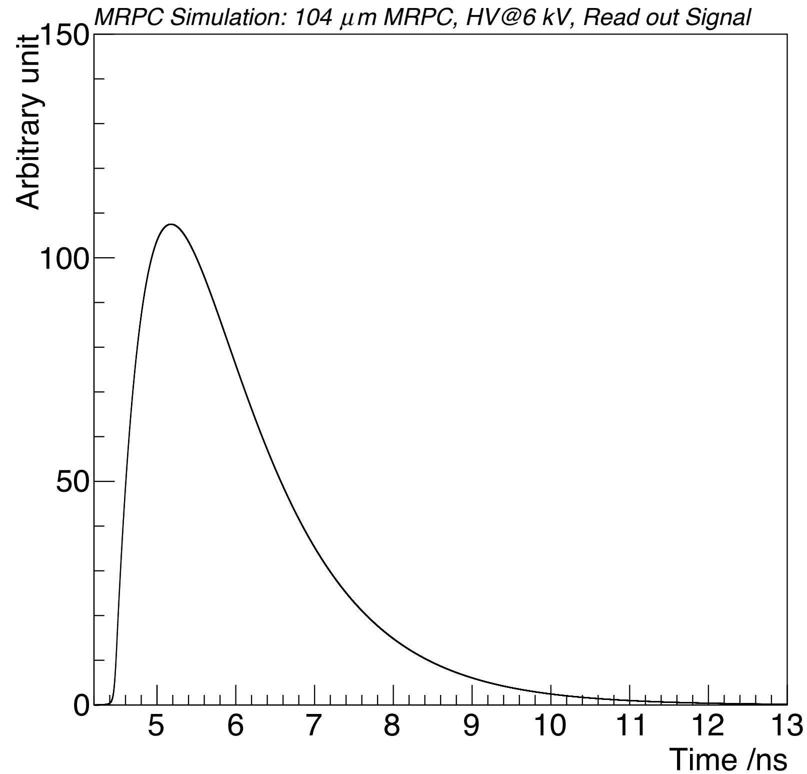


# Electronics

- Include the Front-end electronics response by convolving the original current with a simplified FEE response function:

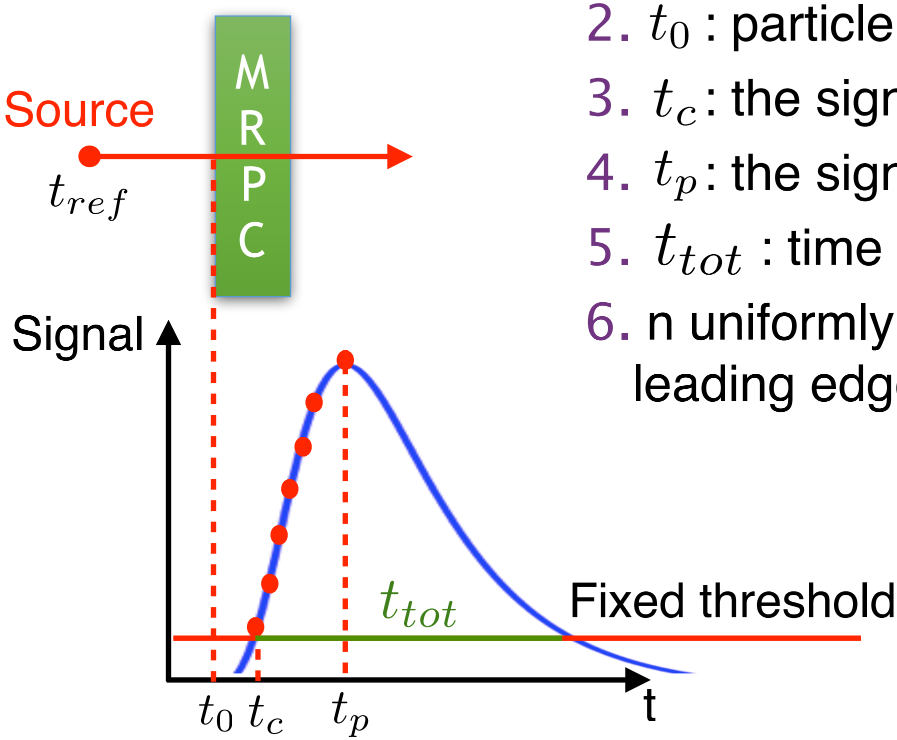
$$f(t) = A(e^{-t/\tau_1} - e^{-t/\tau_2})$$

- $\tau_1$ : corresponds to the length of the leading edge
- $\tau_2$ : corresponds to the length of the trailing edge
- Noise is introduced by adding a random number sampled from Gauss(0, $\sigma$) to every time bin
- The signal without noise



# What is in the data

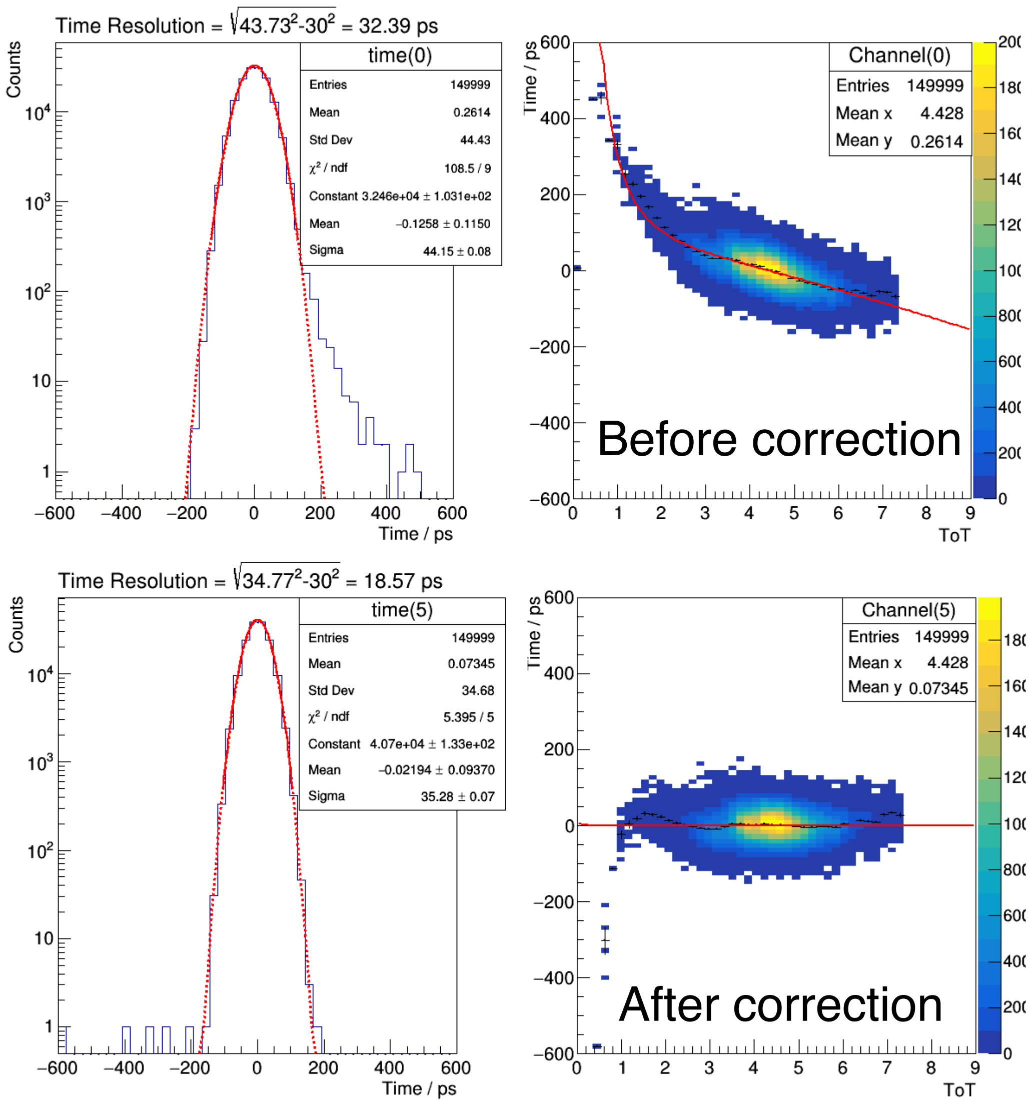





Record the information!

1. $t_{ref}$ : particle is shot from the source, with a known uncertainty
2. $t_0$ : particle arrives at MRPC
3. $t_c$ : the signal is above the fixed threshold
4. $t_p$ : the signal reach the peak
5. $t_{tot}$ : time over threshold
6. n uniformly distributed points along the leading edge

# ToT Readout



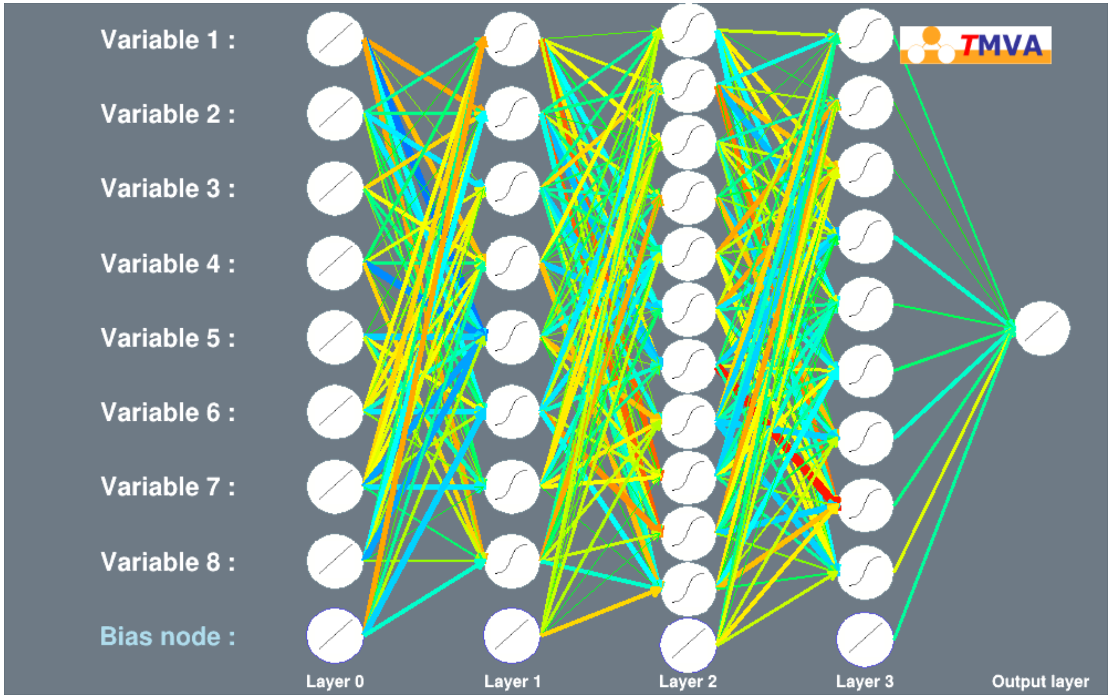

- The “walk correction”
- Due to the fixed threshold, the difference of the amplitude will generate a time walk to $t_c$ , this should be corrected by $t_{tot}$ .
- In the simulation $\sigma(t_{ref}) = 30\,ps$ should be subtracted from $\sigma(t_c)$

$$\sigma_{sim} = \sqrt{\sigma^2_{t_c,corrected} - \sigma^2_{ref}}$$

- Left plot: an example of the analysis @Voltage = ±7 kV

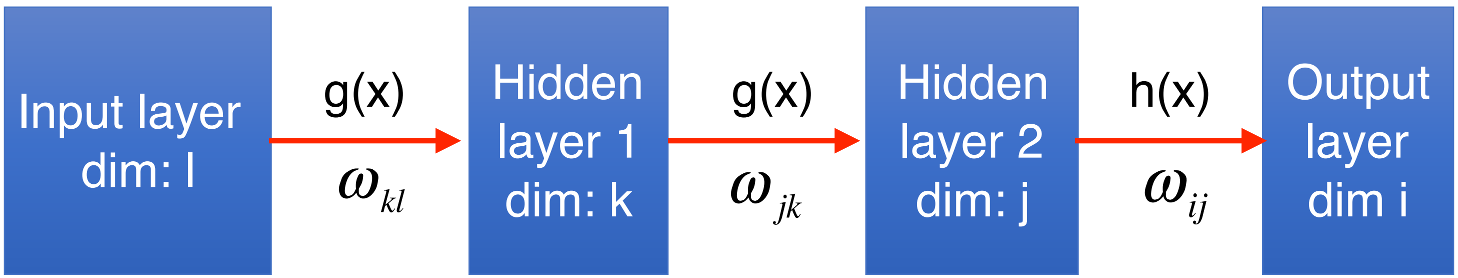
# Neural network

- Artificial neural network(NN) is a powerful tool for solving complex pattern recognition problems characterized by significant non–linearities.
- Widely used in high energy physics
- Introduce NN to MRPC data analysis:
  —— Find out the patterns from the MRPC signal and calculate the particle arriving time.
- Training and testing are based on the TMVA package in ROOT.
- An example of a NN used in our work



# Neural network

- A fully connected network
- An example: NN with 2 hidden layers




$$F_i(\vec{x}) = h(\sum_j \omega^2_{ij} g(\sum_k \omega^1_{jk} g(\sum_l \omega^0_{kl} x_l + \chi^0_k) + \chi^1_j) + \chi^2_i)$$

Output: $F_i(\vec{x})$ Input: $x_l$

- g(x) and h(x) are activation functions: sigmoid and tanh are widely used
- tanh is used in this work: converge faster.
- Train several sets of the networks with the simulation data and validate them to select the best hyper-parameters.

# Neural network

- Training is always based on the simulation data.
- Test on simulation: explore the optimal time resolution from NN.

  Fast electronics: leading edge 1ns
- Test on experiment: prove that NN is practical and can be used in the future

  Leading edge: 1.7 ns
- 2 different networks are trained for simulation and experiment data separately

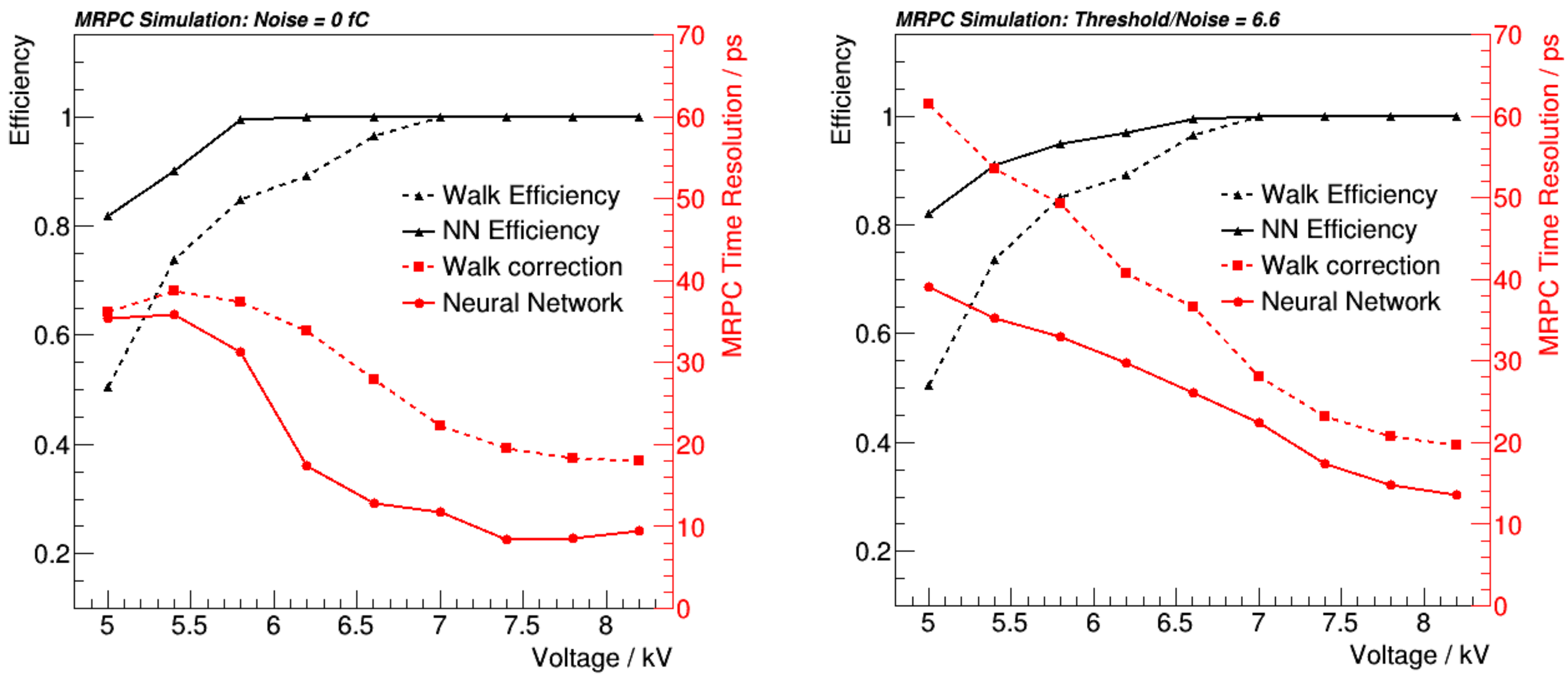
| | Simulation NN | Experiment NN |
|---|---|---|
| Input | 13 uniformly distributed points | 8 uniformly distributed points |
| Output | Length of the leading edge $t_p - t_0$ | |

- Hidden layers: 5~6
- Number of nodes in every layer: ~15
- Training data: over 120,000 events
- Simulation testing data: 80,000 events

After the training, a NN model is created

# NN on simulation

- From the network ⟶ the estimated length of the leading edge $t_{l,est}$
- The estimated arriving time: $t_{0,est} = t_p - t_{l,est}$
- The time resolution: $\sigma_{sim} = \sigma(t_{0,est} - t_{0,true})$




- Efficiency: NN has higher efficiency than walk correction.

  All the waveform can be leaned by NN, no electronics threshold!

  Signal is tremendously large or small, resolution can be very large. Excluded!

# NN on simulation

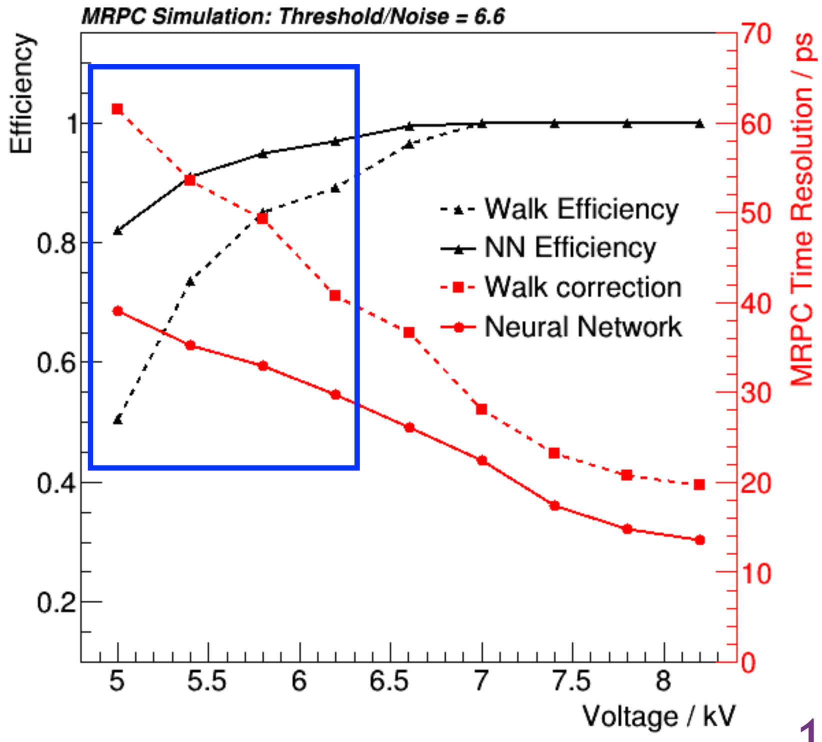
- The optimal time resolution for walk and NN is 20 ps and 10 ps

  NN is always better then walk correction!

- Noise degrades the time resolution when voltage is lower than 6.5kV, due to the small avalanche size

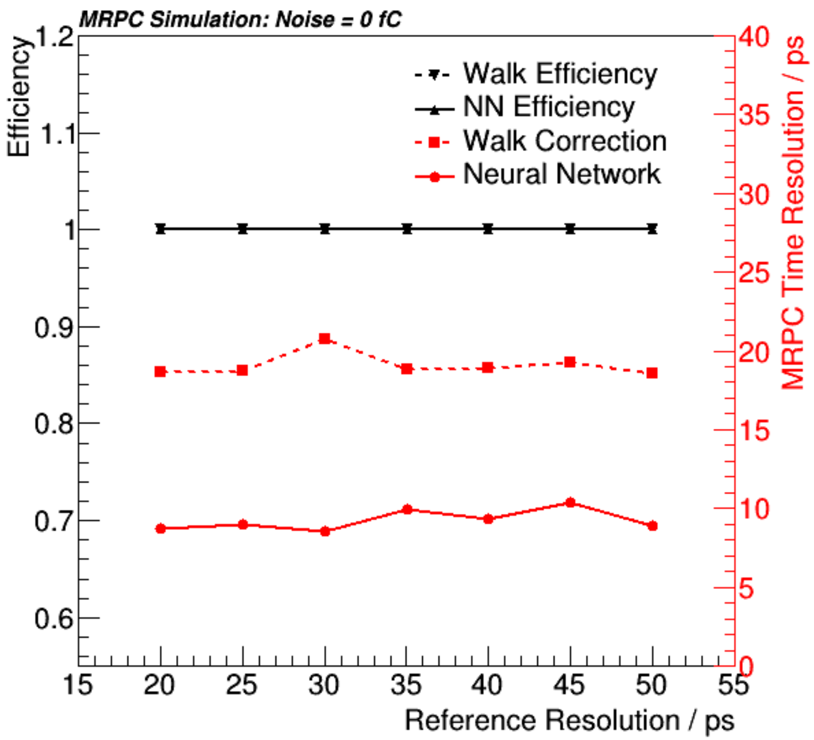
  NN algorithm is more robust with noise !

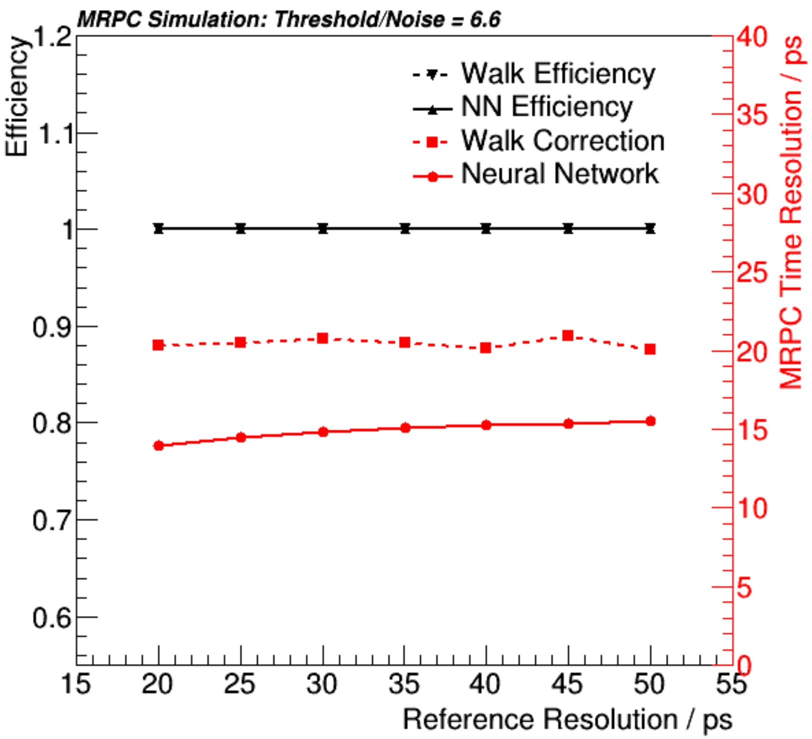
Utilizes the information of the entire leading edge



# NN on simulation

- Performance VS $\sigma(t_{ref})$ , @voltage = ± 7.8 kV
- These two methods are stable with respect to $\sigma(t_{ref})$

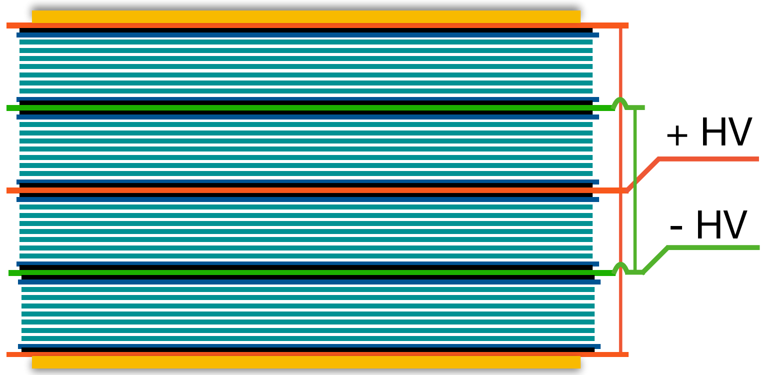


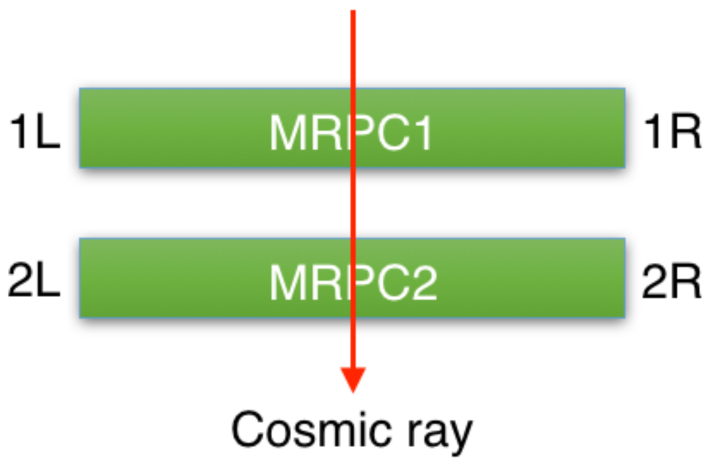



# The experiment

- MRPC in the experiment is exactly the same as the simulation

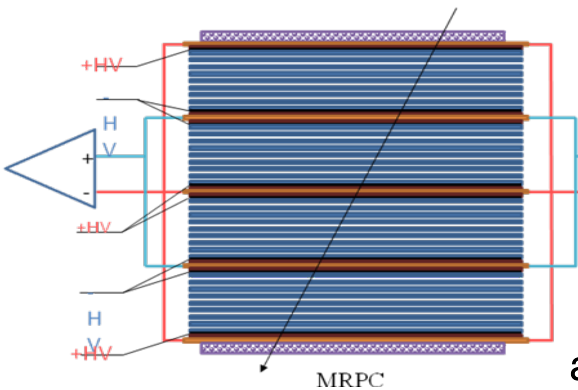
| Item | dimension/mm |
|---|---|
| Honeycomb | 90×265×7.5 |
| Outer PCB | 120×298×0.6 |
| Middle PCB1 | 120×298×1.2 |
| Middle PCB2 | 120×328×1.2 |
| Strip length | 268 |
| Strip width | 7 |
| Mylar | 90×268×0.25 |
| Glass | 80×258×0.5 |
| Carbon | 72×250 |
| Gas gap width | 0.104 |
| Number of gaps | 32 |



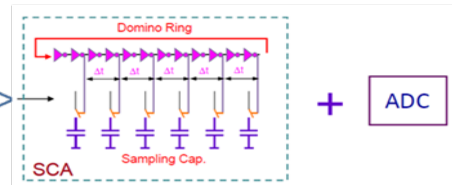



# The experiment

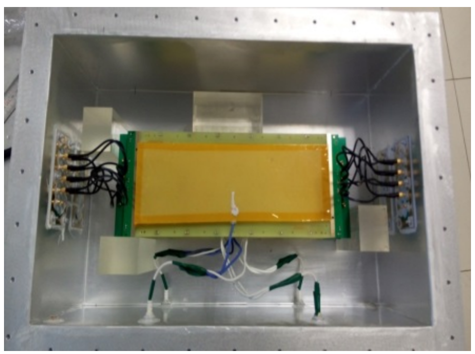


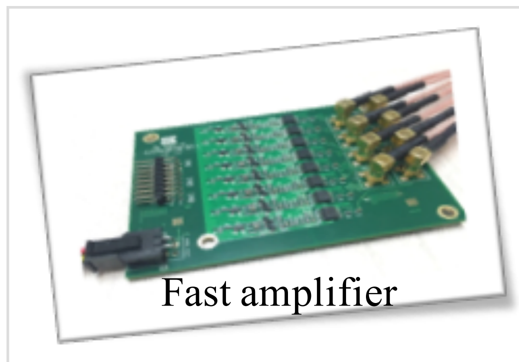


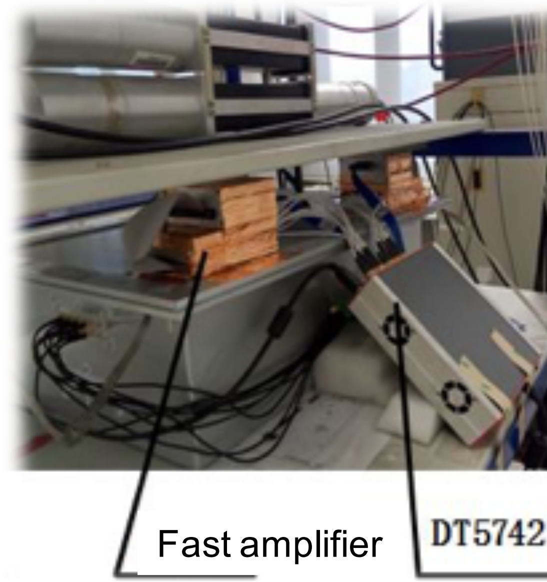

Fast amplifier




Pulse sampling






**Waveform Digitizer DT5742**


- DRS4-V5 chip
- 16 channels
- 12bit 5GS/s
- ~ 8 points along the leading edge of MRPC

# Time resolution



- Since both of the MRPCs are read out at double end —— 4 waveforms for every signal: 1L, 1R, 2L, 2R.
- The estimate time $t_{est1,2}$ of each MRPC is the average of the left and right
- To eliminate the influence of the trigger, we calculate the difference of the two MRPC time:

$$\Delta t = t_{est2} - t_{est1}$$

- The difference of the 2 MRPC's truth time is a constant:

$$\sigma(\Delta t) = \sigma(t_{est2} \boxed{- t_{true2} + t_{true1}} - t_{est1}) = \sigma(t_{res1} - t_{res2})$$

- Then:

$$\sigma(\Delta t) = \sigma(t_{res1} - t_{res2}) = \sqrt{\sigma^2(t_{resi1}) + \sigma^2(t_{resi2})} = \sqrt{2\sigma^2_{MRPC}}$$

- Therefore:

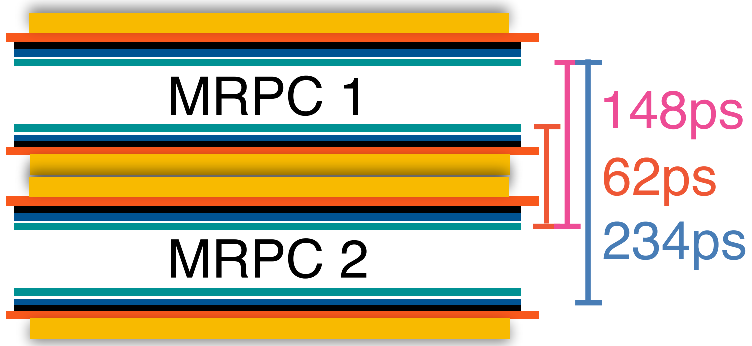
$$\sigma_{MRPC} = \frac{\sigma(\Delta t)}{\sqrt{2}}$$

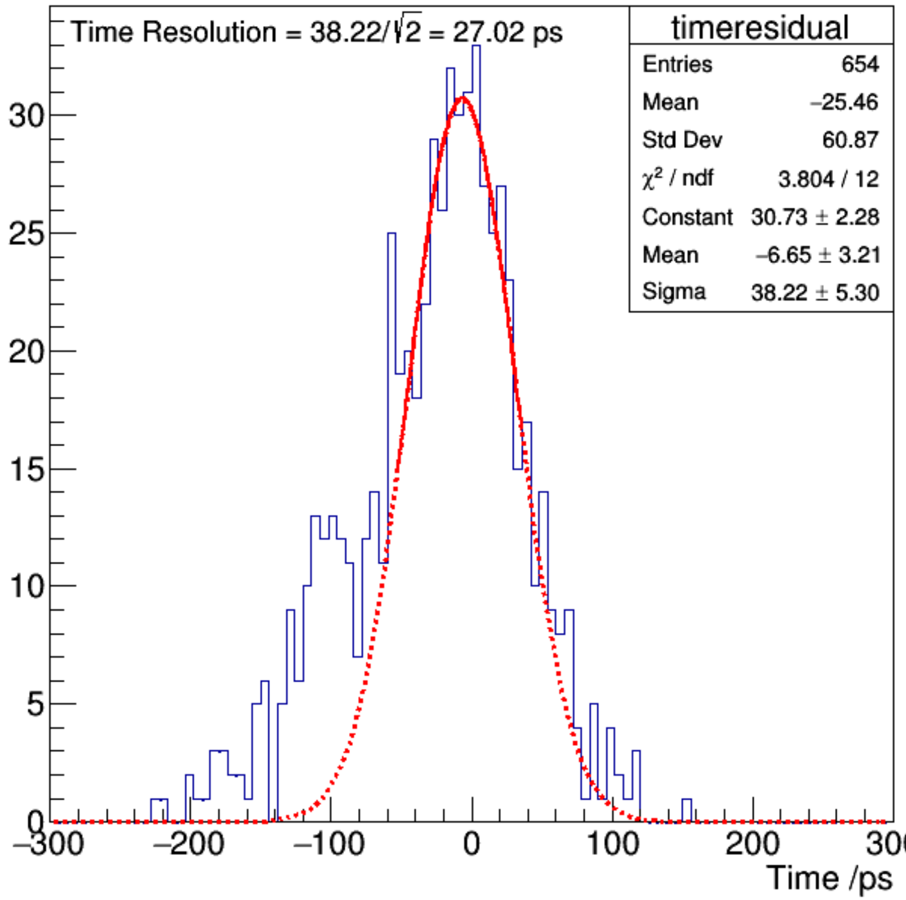
# NN on experiment



- The distribution of $\Delta t = t_{est2} - t_{est1}$ @voltage = ± 5.5 kV
- Considering the angle of the experiment data, we cut:

$$100\, ps < t_{p1} - t_{p2} < 250\, ps$$



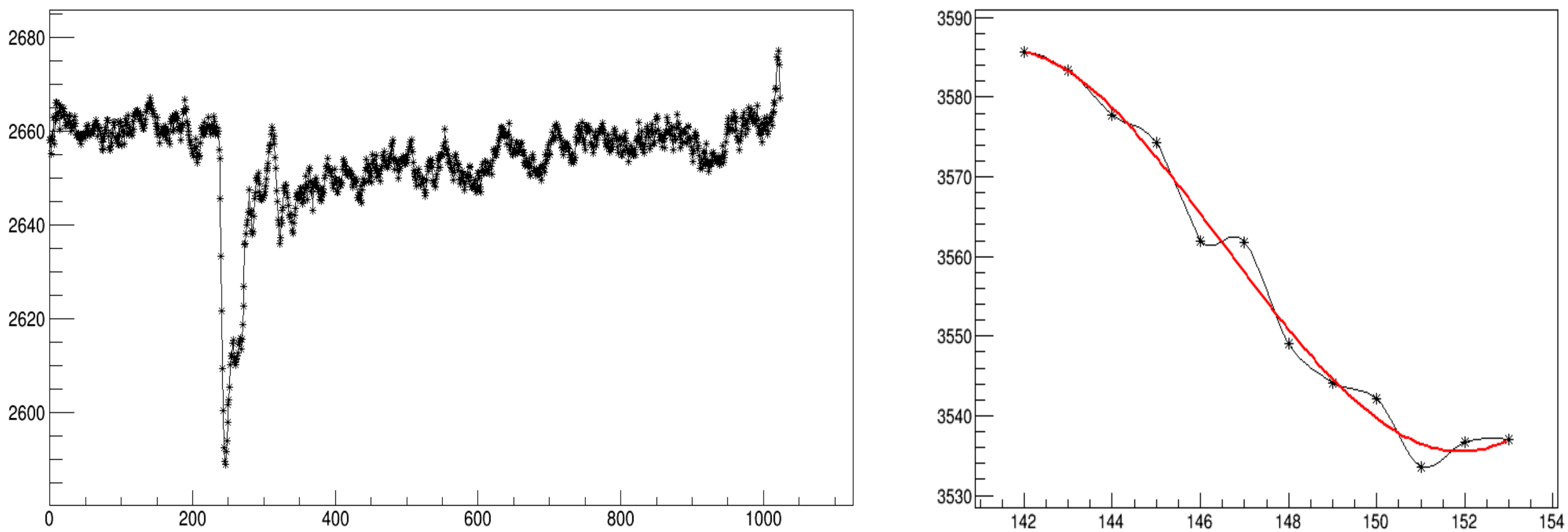




- The time resolution:

$$\sigma(\Delta t) = 27\, ps$$

# The experiment

- The waveform from the experiment




- Fit the waveform with six polynomials $y = a_0 + a_1 x + a_2 x^2 + a_3 x^3 + a_4 x^4 + a_5 x^5$
- Set a fixed threshold and obtain the threshold crossing time $t_c$ and tot $t_{tot}$
- Make some cut:

1. Noise RMS<4
2. Leading edge<1.6ns
3. Amplitude>40
4. Hit on the middle of strip

# Walk correction

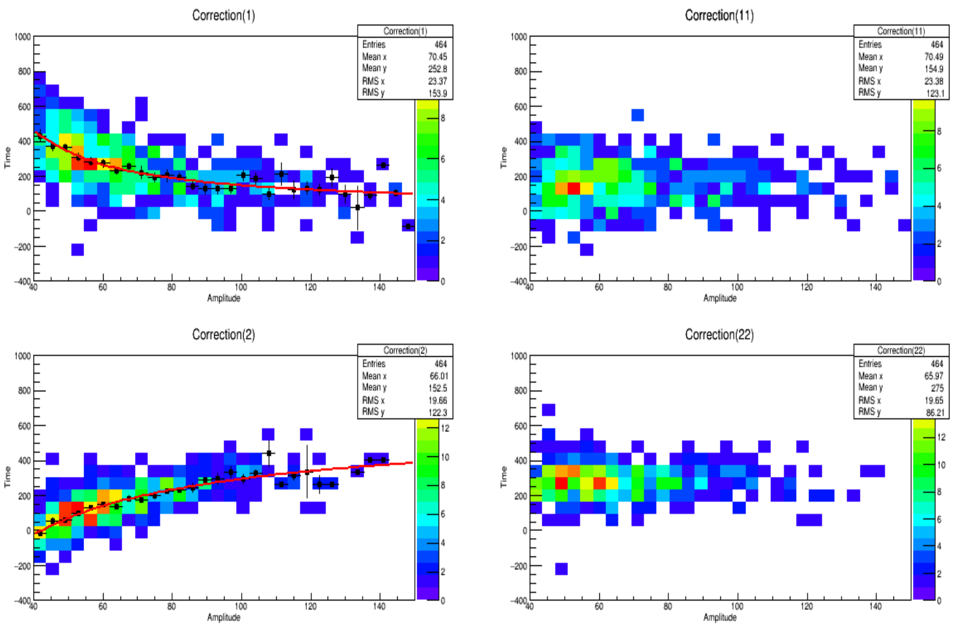
- The walk correction of $t_c$ —— with the amplitude of MRPC1,2

$$\Delta t = t_{c2,corrected} - t_{c1,corrected}$$

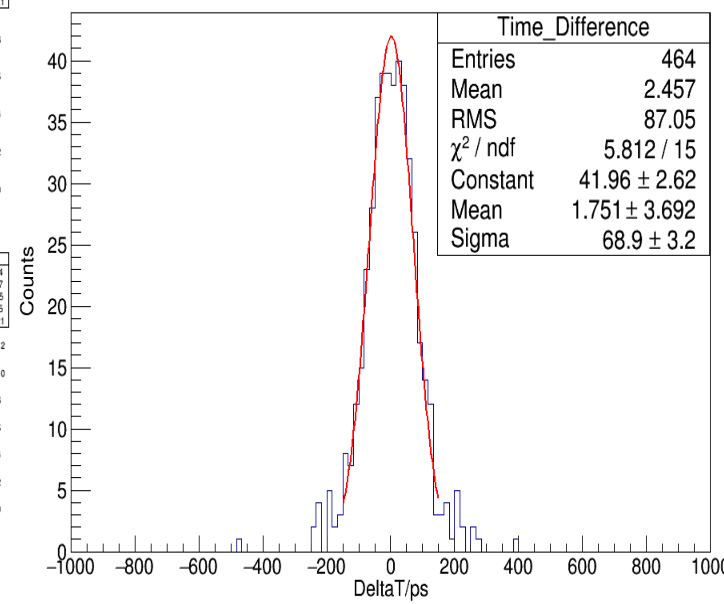
Average of left and right

MRPC1

MRPC2



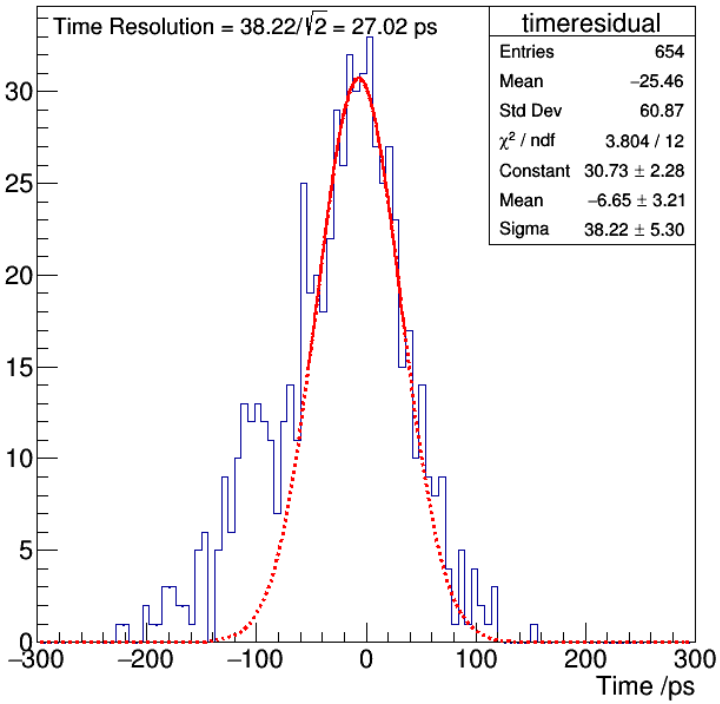

@voltage = ± 5.5 kV

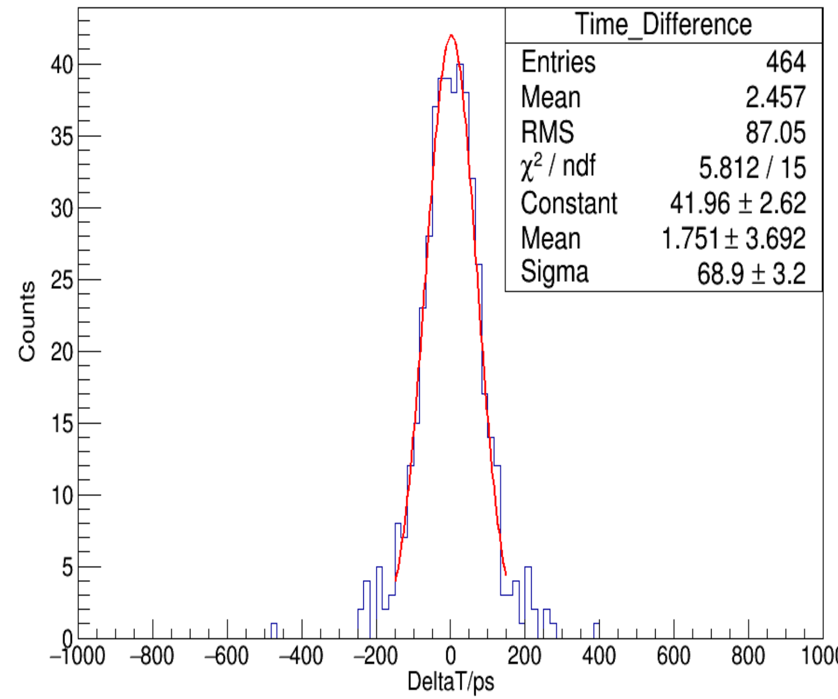



- The best time resolution

$$\sigma_{MRPC} = {\sigma_t}/{\sqrt{2}} = {68.9}/{\sqrt{2}} = 48.72ps$$

# Comparison




- The voltage (= ± 5.5 kV) is low —— noise!
- The neural network takes the advantage of the entire waveform —— the result is better
- Can be improved!

# Conclusions



- MRPC with higher time resolution —— fast amplifier and pulse sampling system is needed.
- New analysis method —— introducing neural network to reconstruct the MRPC time.
- The best time resolution got from the simulation data is less than 10 ps
- The best time resolution got from the experiment data is 27 ps
- Build a standalone MRPC simulation framework —— make it public

# Future Plan

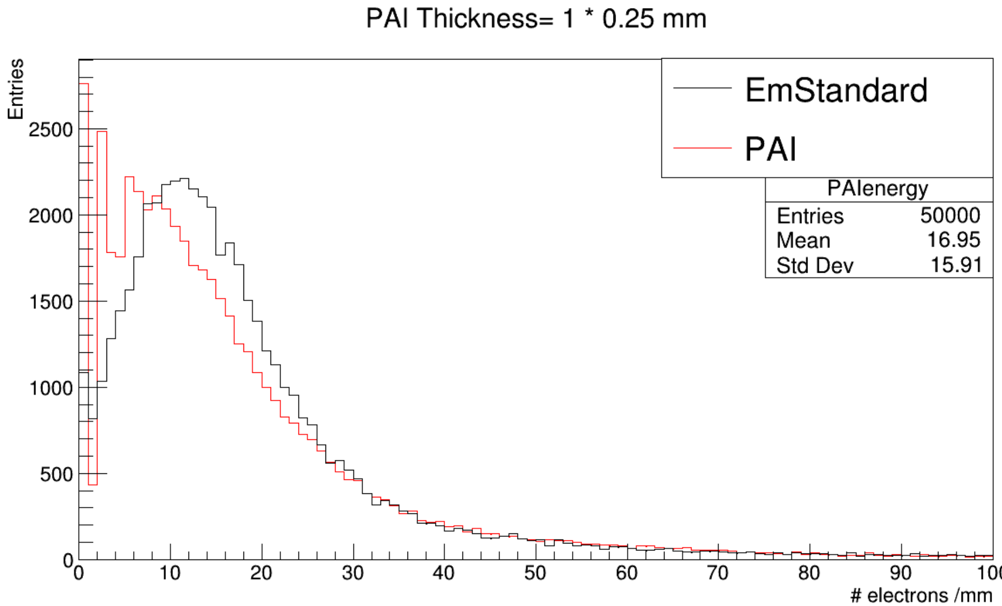
- Carefully study the pattern of the MRPC waveform
- Carefully study the consistency of the waveform between simulation and experiment data
- Build more efficient neural network. Fully-connected to LSTM(RNN)
- Thick detector: ~250um thick

# Thank you

Fuyue Wang

# Physics List

- EMstandard: is most commonly used in LHC simulation,
- However, does not include shell electron effect —— only excellent for thick sensors.
- Photo Absorption Ionization (PAI) model: based on a corrected table of photo-absorption cross section coefficients and works for various elements.
- PAI: The simulated energy loss is in good agreement with the experiment data for moderately thin sensors*.




*W. Allison, J. Cobb, Relativistic Charged Particle Identification by Energy Loss, Ann. Rev. Nucl. Part. Sci. 30 (1980) 253–298.