A neural network based algorithm for MRPC time reconstruction

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Motivation

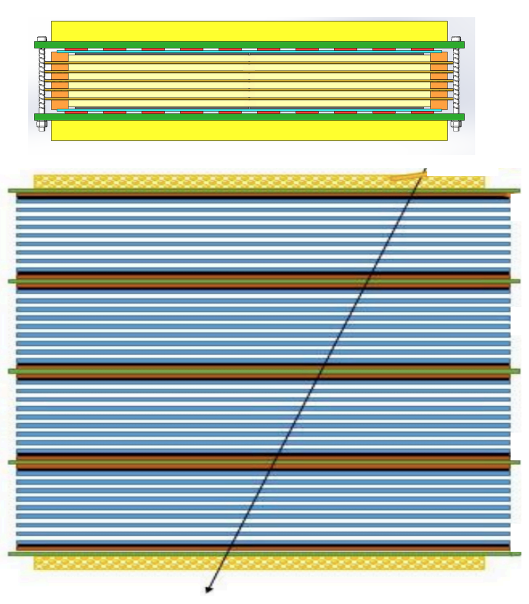
- The 3rd generation of Time of Flight(ToF) system is aimed to have even better time resolution —— 20ps. Multi-gap resistive plate chamber(MRPC) is designed to have thinner gaps and the signal is read out with high speed waveform sampling electronics instead of ToT technique.
- A comprehensive study of improving the time resolution with the entire signal waveform is in need.
- We study a new algorithm to reconstruct the MRPC time with the waveform based on the Artificial Neural Network(NN) and deep learning.

Simulation framework

- The simulation is based on Geant4 and ROOT package

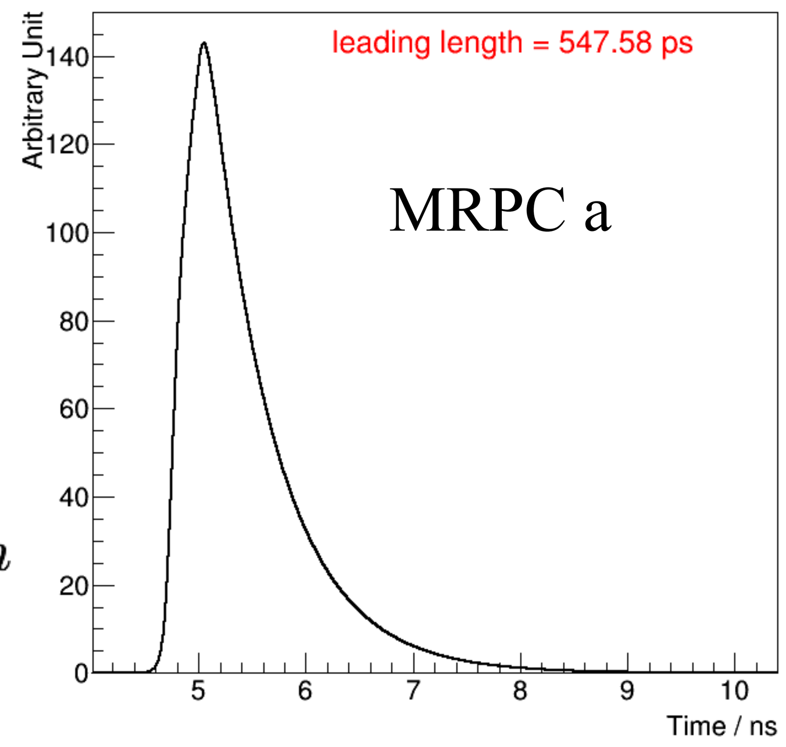
Creating a event → Simulating the primary energy deposition with PAI model → Charge Digitization → Original current signal → Electronics → Waveform

- 4 GeV mu- (cosmic) 30 MeV e- (HZDR beam)
- Photo Absorption Ionization (PAI) model is more accurate for thin absorbers *
- Avalanche gain $N(t) \sim e^{\alpha x}$ Ramo theory $I(t) = \frac{E_w}{V_w} N(t) e_0 v$
- $f(t) = A\left(e^{-t/\tau_1} - e^{-t/\tau_2}\right)$



MRPC a: $5 \times 0.25\ mm$

MRPC b: $32 \times 0.104\ mm$



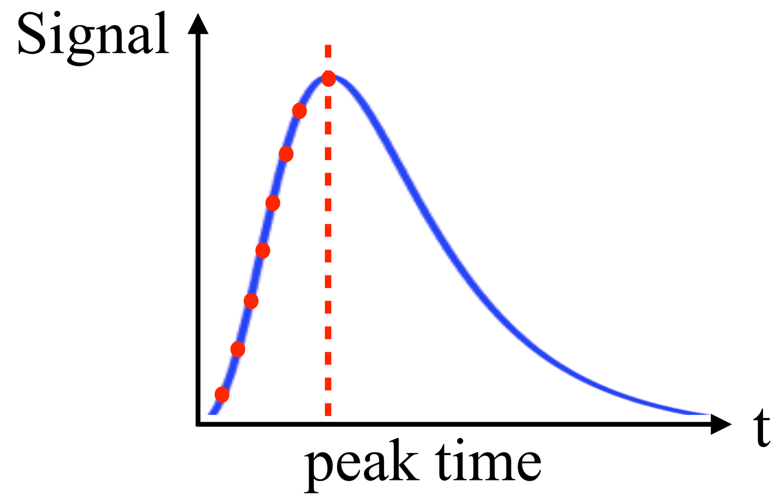
The neural network structure and time resolution

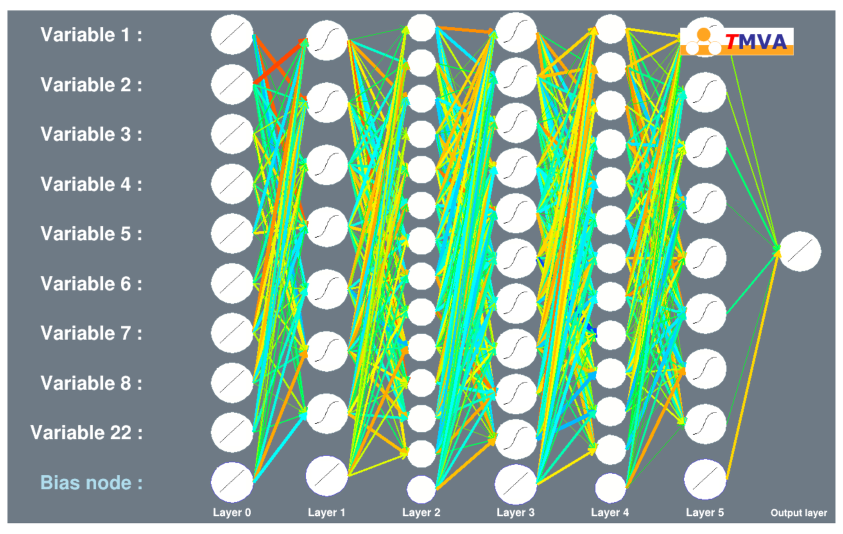
- A fully-connected neural network is used in this study.
- Take 2 hidden layers as an example:

Input layer dim: l —g(x), ω_{kl}→ Hidden layer 1 dim: k —g(x), ω_{jk}→ Hidden layer 2 dim: j —h(x), ω_{ij}→ Output layer dim: i

$$F_i(\vec{x}) = h\left(\sum_j \omega_{ij}^2 g\left(\sum_k \omega_{jk}^1 g\left(\sum_l \omega_{kl}^0 x_l + \chi_l^0\right) + \chi_j^1\right) + \chi_i^2\right)$$

- g(x) and h(x) are activation functions: sigmoid $g(x) = \frac{1}{1+e^{-2x}}$





- Network: 5~6 hidden layers, about 10 nodes in every layer
- Input: 8~9 points along the leading edge
- Output: peak time - particle arriving time

Before the waveform start

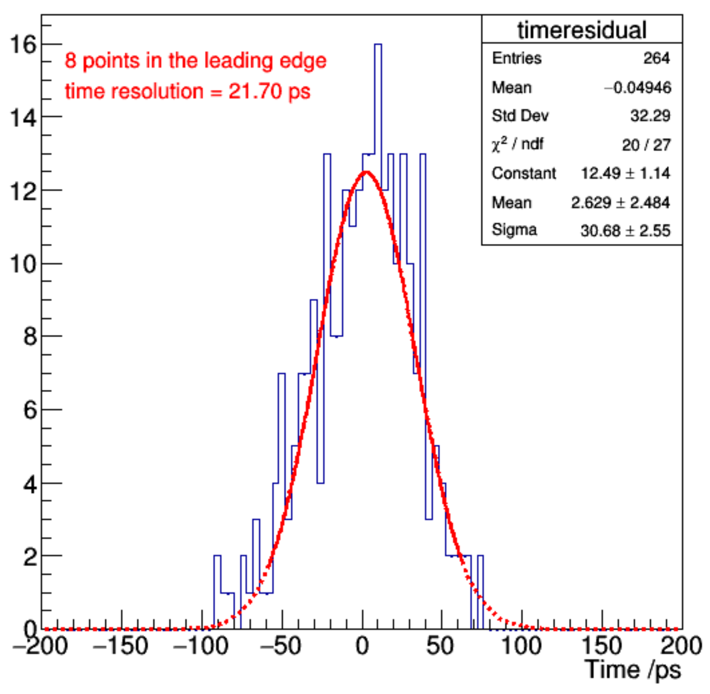
Result of experiment data — MRPC b

- Test system: 2 MRPC b:

$$\sigma(\Delta t) = \sigma(t_{res1} - t_{res2}) = \sqrt{\sigma^2(t_{resi1}) + \sigma^2(t_{resi2})} = \sqrt{2\sigma_{MRPC}^2}$$
$$= \sigma(t_{true2} - t_{est2} - t_{true1} + t_{est1}) = \sigma(t_{est1} - t_{est2})$$
$$= \sigma\left(\frac{t_{est1l} + t_{est1r}}{2} - \frac{t_{est2l} + t_{est2r}}{2}\right)$$

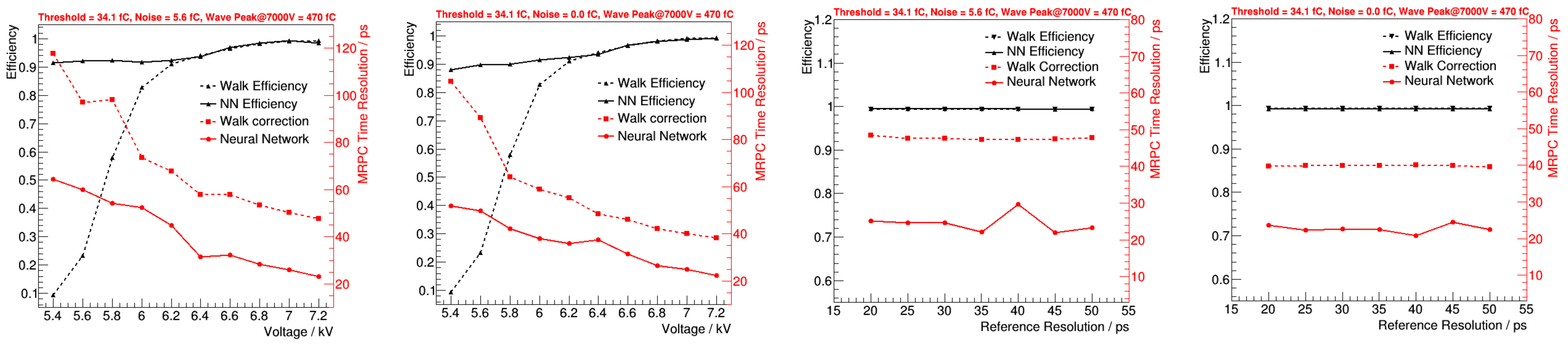
$$\sigma_{MRPC} = \frac{\sigma(\Delta t)}{\sqrt{2}}$$

- SCA+ADC waveform sampling
- Train with simulation data, test with experiment data
- Plot $Time = \frac{t_{est1l} + t_{est1r}}{2} - \frac{t_{est2l} + t_{est2r}}{2}$
- The time resolution can reach 20 ps



Result of Simulation data — MRPC a

- Result of MRPC a, train with simulation data, test with simulation data $\sigma_{MRPC} = \sigma(estimated\ time - truth\ time)$



- Both the two algorithms provide a stable result with respect to the uncertainty of the particle arriving time.
- Neural network improves the time resolution of MRPC by 20 ps or more through the voltage scan.

*H. Bichsel, Straggling in Thin Silicon Detectors, Rev. Mod. Phys. 60 (1988) 663–699

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$$=\sigma(\frac{t_{est1l}+t_{est1r}}{2}-\frac{t_{est2l}+t_{est2r}}{2})$$

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

$$Time=\frac{t_{est1l}+t_{est1r}}{2}-\frac{t_{est2l}+t_{est2r}}{2}$$