Reactor Neutrino Energy Reconstruction with Machine Learning Techniques for the JUNO Experiment

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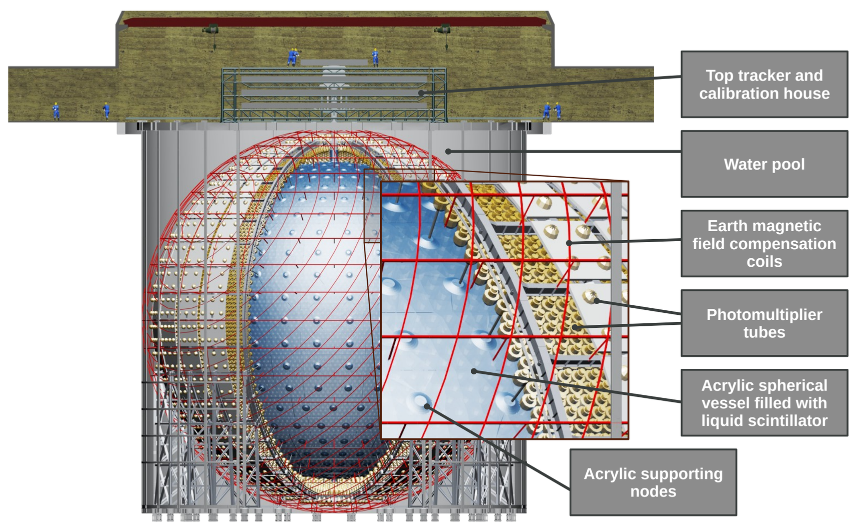
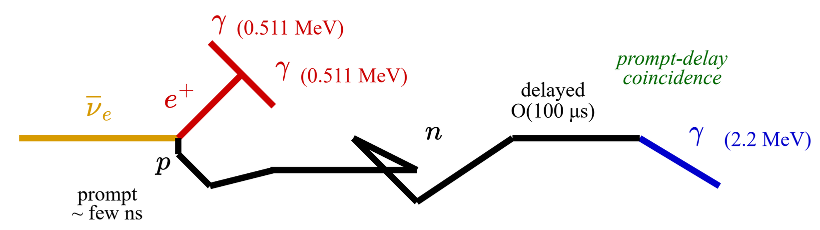
Introduction

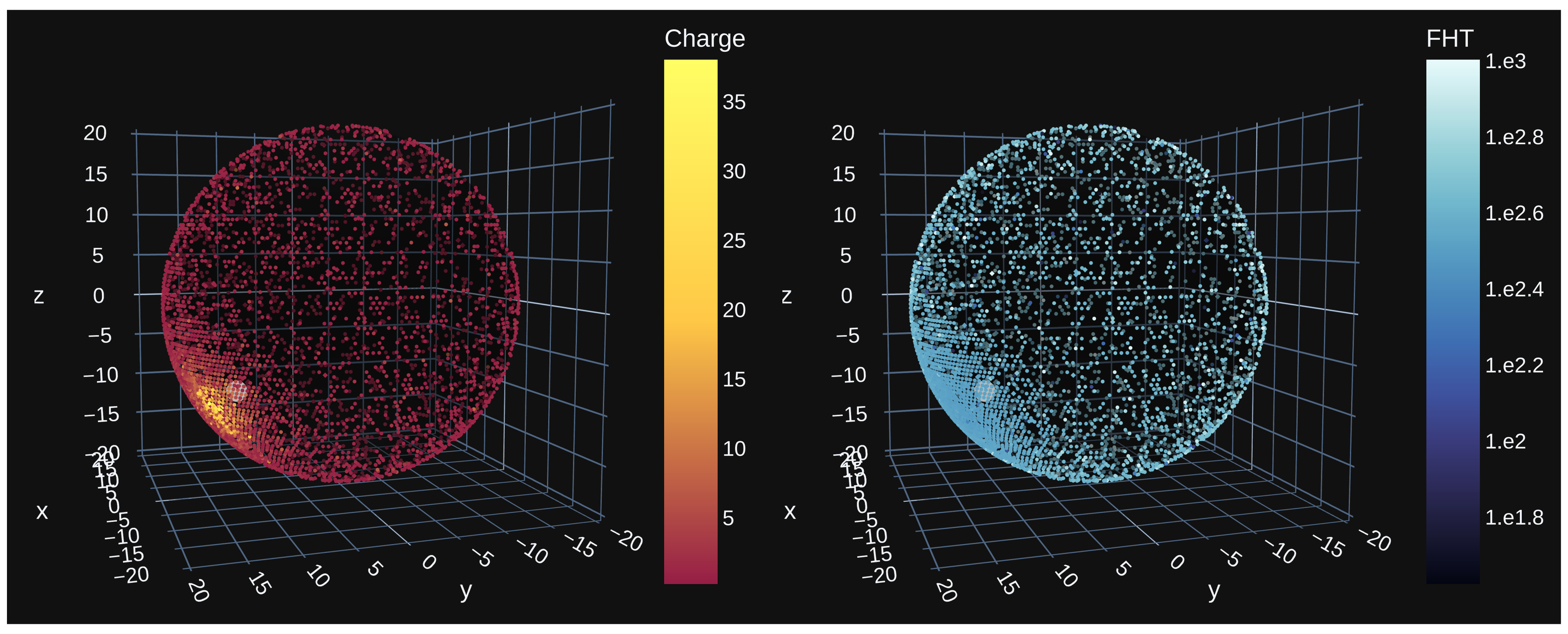
1. Jiangmen Underground Neutrino Observatory (JUNO):
   - **multipurpose** experiment;
   - 53 km away from **8 reactor cores** in China
   - ∼650-meter deep underground
   - data taking expected in ∼2024
2. The main goals of JUNO:
   - neutrino mass ordering (**3σ in 6 years**)
   - †precise measure of oscillation parameters $\sin^2\theta_{12}, \Delta m^2_{21}, \Delta m^2_{31}$
3. The Central Detector:
   - detection channel: $\overline{\nu}_e + p \to e^+ + n$
   - **deposited energy** converts to *optical light*
   - **the largest** liquid scintillator detector: 20 kt
   - **77.9% photo-coverage** by photo-multiplier tubes (PMTs): ∼18k 20" (**LPMT**), ∼26k 3" (**SPMT**)





†see poster by **V. Cerrone**: *Prospects for Oscillation Physics in the JUNO Experiment*

Problem statement



An example of a positron event with deposited energy ∼**4 MeV**. The grey sphere — the primary vertex.

Input information:

Charge at PMT   First Hit Time (FHT) at PMT   PMT position

We want to reconstruct:

Deposited energy E_{dep} with resolution < 3% @ 1 MeV

Data description

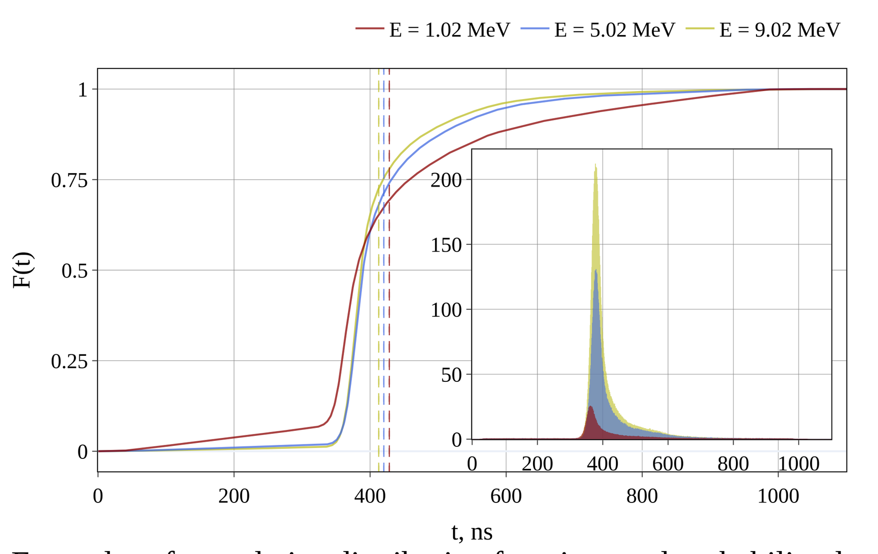
To train a model and **to evaluate** model performance we prepared **two datasets** generated by the full detector Monte Carlo method using *the official JUNO software*:

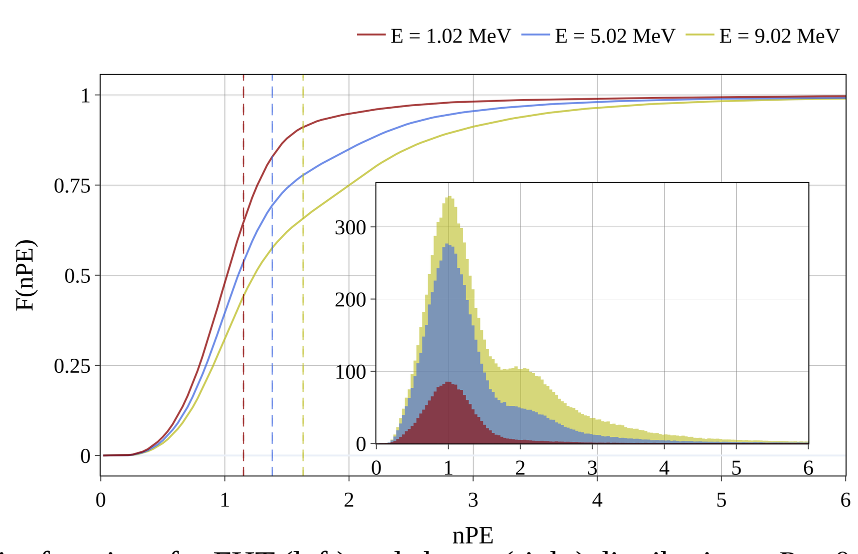
1. **Training dataset:**
   - **2.25 million** *positron* events
   - uniformly distributed in kinetic energy E_{kin}
   - uniformly spread in the volume of the central detector
   - $E_{\text{kin}} \in [0, 10]$ MeV. $E_{\text{dep}} = E_{\text{kin}} + 1.022$ MeV
2. **Testing dataset:**
   - subsets with discrete kinetic energies
   - 0, 0.1, 0.3, 0.6, 1, 2, ..., 10 [MeV]
   - uniform spatial distribution
   - each subset contains **50 thousand** events

Aggregated features

For energy reconstruction, we use **aggregated information** from the whole array of PMTs **as features** for models. Their *full* set is as follows:

1. `AccumCharge` — the accumulated charge on fired PMTs
2. `nPMTs` — the total number of fired PMTs
3. Coordinates of the center of charge:
$$(x_{\text{cc}}, y_{\text{cc}}, z_{\text{cc}}) = \vec{r}_{\text{cc}} = \frac{\sum_{i=1}^{N_{\text{LPMTs}}} \vec{r}_{\text{LPMT}_i} \cdot n_{\text{p.e.},i} + \sum_{i=1}^{N_{\text{SPMTs}}} \vec{r}_{\text{SPMT}_i} \cdot n_{\text{p.e.},i}}{\sum_{i=1}^{N_{\text{LPMTs}}} n_{\text{p.e.},i} + \sum_{i=1}^{N_{\text{SPMTs}}} n_{\text{p.e.},i}}$$
and its radial component: $R_{\text{cc}} = |\vec{r}_{\text{cc}}|$
4. Coordinates of the center of FHT:
$$(x_{\text{cht}}, y_{\text{cht}}, z_{\text{cht}}) = \vec{r}_{\text{cht}} = \frac{\sum_{i=1}^{N_{\text{LPMTs}}} \frac{\vec{r}_{\text{LPMT}_i}}{t_{\text{fht},i}+c} + \sum_{i=1}^{N_{\text{SPMTs}}} \frac{\vec{r}_{\text{SPMT}_i}}{t_{\text{fht},i}+c}}{\sum_{i=1}^{N_{\text{LPMTs}}} \frac{1}{t_{\text{fht},i}+c} + \sum_{i=1}^{N_{\text{SPMTs}}} \frac{1}{t_{\text{fht},i}+c}}$$
and its radial component: $R_{\text{cht}} = |\vec{r}_{\text{cht}}|$
5. $\gamma_x^{\text{cc}} = \frac{x_{\text{cc}}}{\sqrt{x_{\text{cc}}^2+y_{\text{cc}}^2}}$
6. $\gamma_y^{\text{cc}} = \frac{y_{\text{cc}}}{\sqrt{x_{\text{cc}}^2+z_{\text{cc}}^2}}$
7. $\gamma_z^{\text{cc}} = \frac{z_{\text{cc}}}{\sqrt{x_{\text{cc}}^2+y_{\text{cc}}^2}}$
8. $\theta_{\text{cc}} = \arctan\frac{\sqrt{x_{\text{cc}}^2+y_{\text{cc}}^2}}{z_{\text{cc}}}$
9. $\phi_{\text{cc}} = \arctan\frac{y_{\text{cc}}}{x_{\text{cc}}}$
10. $J_{\text{cc}} = R_{\text{cc}}^2 \cdot \sin\theta_{\text{cc}}$
11. $\rho_{\text{cc}} = \sqrt{x_{\text{cc}}^2+y_{\text{cc}}^2}$
12. with *7 similar features* for the components of the center of FHT
13. Percentiles of FHT and charge distributions:
    - $\{\text{ht}_{2\%}, \text{ht}_{5\%}, \text{ht}_{10\%}, \text{ht}_{15\%}, ..., \text{ht}_{90\%}, \text{ht}_{95\%}\}$
    - $\{\text{pe}_{2\%}, \text{pe}_{5\%}, \text{pe}_{10\%}, \text{pe}_{15\%}, ..., \text{pe}_{90\%}, \text{pe}_{95\%}\}$
14. Differences between percentiles for FHT:
    - $\{\text{ht}_{5\%-2\%}, \text{ht}_{10\%-5\%}, ..., \text{ht}_{95\%-90\%}\}$
15. Moments for FHT and charge distributions:
    - $\{\text{ht}_{\text{mean}}, \text{ht}_{\text{std}}, \text{ht}_{\text{skew}}, \text{ht}_{\text{kurtosis}}\}$
    - $\{\text{pe}_{\text{mean}}, \text{pe}_{\text{std}}, \text{pe}_{\text{skew}}, \text{pe}_{\text{kurtosis}}\}$





Examples of cumulative distribution functions and probability density functions for FHT (left) and charge (right) distributions. $R \simeq 0$ m, E_{dep} varied. Dashes lines illustrate mean values.

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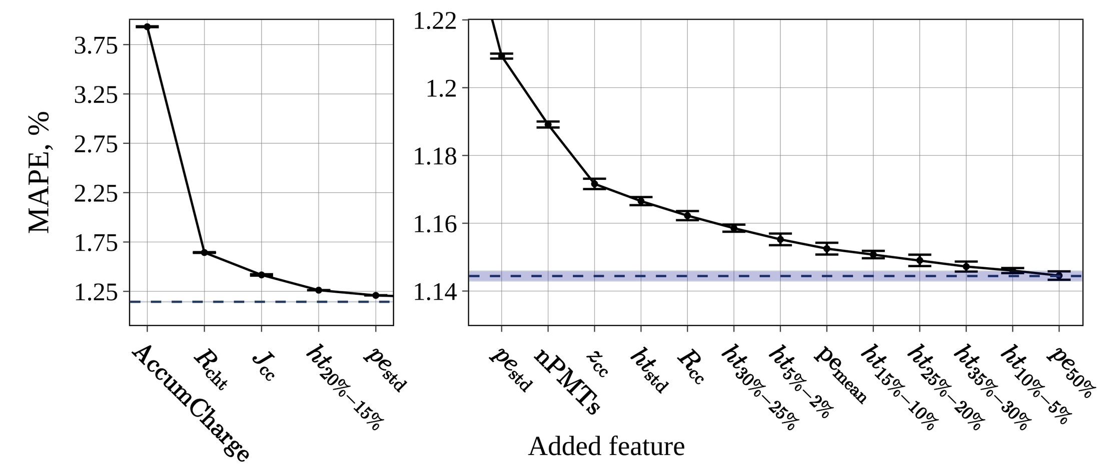
Feature selection

- **Feature selection** procedure is performed with *a greedy algorithm* using Boosted Decision Trees
- Optimized **set of features** (sorted by *importance*):

1. `AccumCharge`
2. R_{cht}
3. J_{cc}
4. $\text{ht}_{20\%-15\%}$
5. pe_{std}
6. nPMTs
7. z_{cc}
8. ht_{std}
9. R_{cc}
10. $\text{ht}_{30\%-25\%}$
11. $\text{ht}_{5\%-2\%}$
12. pe_{mean}
13. $\text{ht}_{15\%-10\%}$
14. $\text{ht}_{25\%-20\%}$
15. $\text{ht}_{35\%-30\%}$
16. $\text{ht}_{10\%-5\%}$
17. $\text{pe}_{50\%}$

charge-related features   time-related features

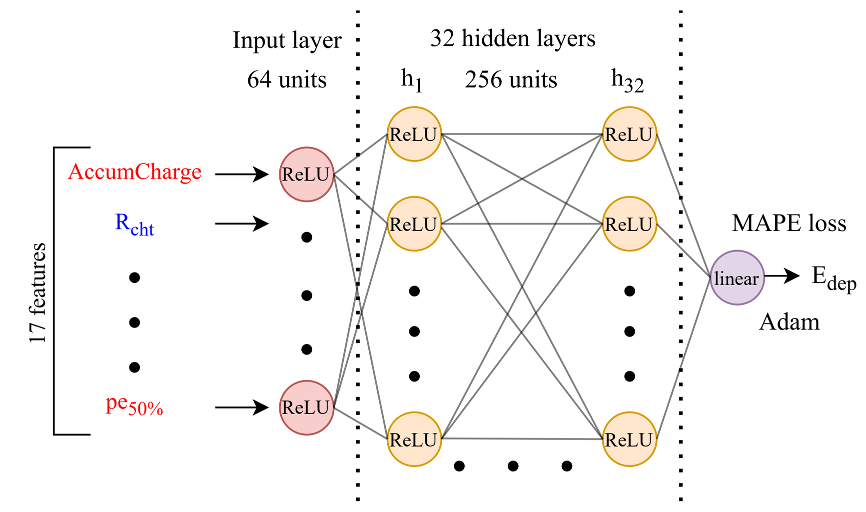


Dashed line — average †MAPE for BDT trained on all features with its standard deviation

$^\dagger\text{MAPE} = \frac{100\%}{N}\sum_{i=1}^{N}\left|\frac{E_{\text{true},i}-E_{\text{pred},i}}{E_{\text{true},i}}\right|$, where N - number of events

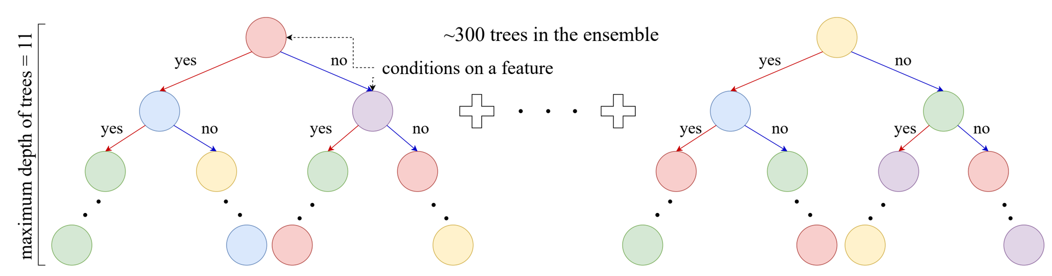
Models description

Fully Connected Deep Neural Network (**FCDNN**):



- Optimization of the hyperparameters using BayesianOptimization
- Training with early stopping
- Validation dataset: 200k events
- The optimized set of features

Boosted Decision Trees (**BDT**) from XGBoost:



- The optimized set of features
- Optimized hyperparameters (using Grid Search):
  1. The maximum depth of the tree: 11
  2. Number of trees in the ensemble: ≃300
  3. Learning rate: 0.08

Results

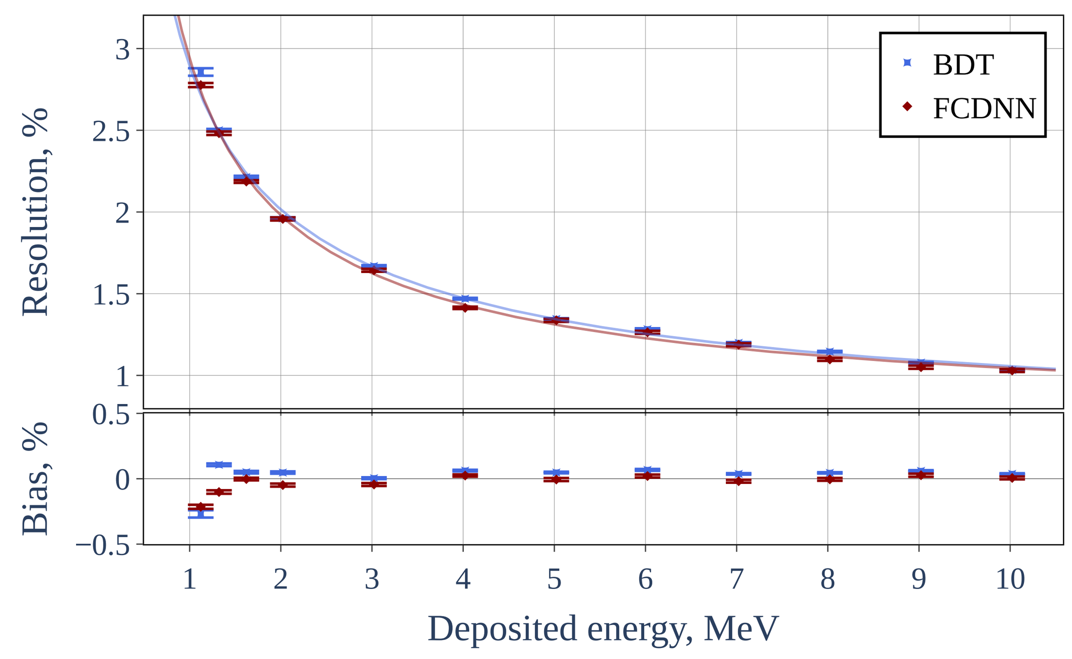
Metrics:

1. Defined by a Gaussian fit of the $E_{\text{predicted}} - E_{\text{dep}}$ distributions
2. *Resolution*: σ/E_{dep}, where σ — standard deviation of the fit
3. *Bias* μ/E_{dep}, where μ — mean of the fit

Parameterization:

$$\frac{\sigma}{E_{\text{dep}}} = \sqrt{\left(\frac{a}{\sqrt{E_{\text{dep}}}}\right)^2 + b^2 + \left(\frac{c}{E_{\text{dep}}}\right)^2}$$

Model	$a \pm \Delta a$	$b \pm \Delta b$	$c \pm \Delta c$
BDT	2.56 ± 0.11	0.67 ± 0.05	1.18 ± 0.32
FCDNN	2.35 ± 0.11	0.72 ± 0.05	1.62 ± 0.20



Summary

Machine learning approaches (FCDNN and BDT) using aggregated features:

- energy reconstruction
- required energy resolution < 3% @ 1 MeV achieved
- great computation speed

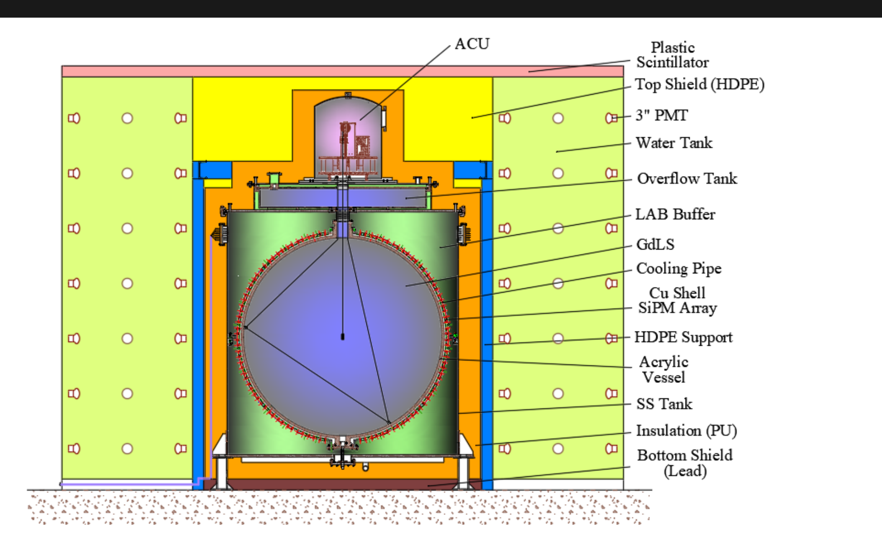
References

[1] F. An *et al.*, *Neutrino Physics with JUNO*, J. Phys. G **43** (2016) no.3, 030401.

[2] A. Gavrikov et al., *Energy reconstruction for large liquid scintillator detectors with machine learning techniques: aggregated features approach*, EPJ C **82** (2022), 1021.

Transferability of the approach: TAO

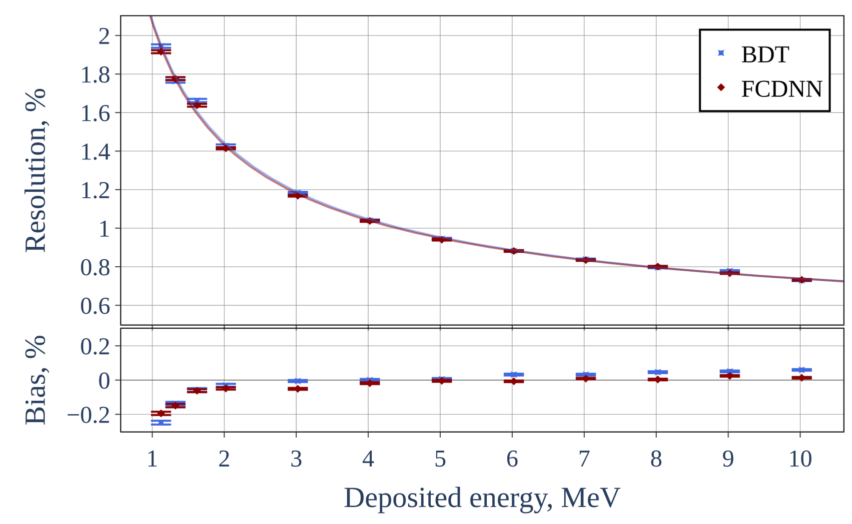
1. †Taishan Antineutrino Observatory (TAO):
   - **JUNO's satellite** near detector
   - 30 m from Taishan core
   - diameter of **1.8 meters**
2. The main goals of TAO:
   - **reference spectrum** for JUNO
   - search for sterile neutrinos
   - isotopic yields and spectra
3. The detector:
   - the liquid scintillator detector of **2.8 tons**
   - ∼**94% photo-coverage**: 4k 5x5 cm^2 SiPMs
   - required **energy resolution of 2% @ 1 MeV**



- **Analogues datasets** for training and testing
- BDT & FCDNN trained on an *optimized set* of features:

1. `AccumCharge`
2. ρ_{cc}
3. $\text{ht}_{35\%}$
4. $\text{pe}_{90\%}$
5. pe_{mean}
6. nSiPMs
7. $\text{ht}_{5\%}$
8. R_{cc}
9. pe_{std}
10. $\text{ht}_{75\%}$
11. $\text{pe}_{\text{kurtosis}}$
12. $\text{ht}_{15\%}$

- ∼2% at 1 MeV *achieved*



†more details about TAO detector in poster by **C. Lombardo**: *JUNO-TAO design, prototype and its impact for JUNO physics*