Neural Network Application for Proton Kinetic Energy Reconstruction in ANKE STT*

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In this note the procedure of proton/deuteron separation and proton kinetic energy reconstruction in the ANKE silicon detectors using the Neural Network (NN) method, as well as the preliminary results are presented. For this aim we have used the simulated proton tracks (100000) from the pd-elastic and deuteron breakup process at $T_p = 49.3$ MeV, detected in the first (I) and second (II) silicon layers with thickness of 300 μm (ANKE type STT). The process was simulated using the GENBOD event generator and the GEANT3 framework (MC) for the ANKE Feb'08 setup. During the simulation, all GEANT flags for the secondary interaction was set to 0 (switched OFF).

As an input variables for the NN method we have chosen the energy deposit in each silicon layer (smeared by Gaussian with $\sigma = 100$ KeV as an intrinsic resolution) and the track path length, wich was estimated using layer thickness and track polar (θ) and azimuthal (ϕ) angles. In our opinion superior of choosing the path length is, since the energy deposit in the layers directly depends on this variable. On the other hand, in case of different layer (I and II) thicknesses, track angles θ and ϕ are the same while the estimated path lengths are different and it is extra information for NN input.

In case proton/deuteron separation the output variable for the NN was *Particle type*, which is equal to 1 for deuterons, and to 0 for protons. The results from the NN procedure (the back-propagation learning method with $E_{poch} = 500$ and *hyperbolic tangent* function has been used) are presented on Fig. 1. Half of the whole statistics was used for the training (learning) procedure and half - for the testing procedure. From the lower panel distributions it is clear, that using the NN method we can separate with high (99%) accuracy deuterons and protons.

In case of proton kinetic energy reconstruction the task has been performed in two steps. At first, we have determined over them if the protons was stopped in second (II) layer or not. As an input for the NN method, we have chosen the same variables as was described above. The output variable for NN method was the *status* of protons, which is equal to 0 for stopped protons, and to 1 for passed ones. The results from the NN procedure with $E_{poch} = 500$ are presented on Fig. 2. From the lower panel distributions we see, that using the NN method we can distinguish with high accuracy whether, a proton was stopped ($NNstatus < 0.3$) or passed ($NNstatus > 0.6$) the second layer. Efficiency (contamination) of each cut is 95.6% (3.4%) and 98.0% (0.6%) respectively. The same procedure, but using a *sigmoid* instead of the *hyperbolic tangent* function also was tested, but no significant improvement has observed.

For stopped protons the kinetic energy equals the sum of energy deposits in I and II layer. For passed protons the kinetic energy reconstruction is necessary. For this task special simulations were performed: single proton tracks were simulated with uniformly θ and ϕ inside I and II layer acceptance and uniform momentum in the range of 20-240 MeV/c. For track transporting GEANT4 framework was used.

For NN input the same variables as described above where used, while as output variable the proton kinetic energy has been taken. The results from NN procedure with $E_{poch} = 500$ are presented in Fig. 3. From lower left panel we see, that using this method we can reconstruct the proton kinetic energy in a wide energy range with less than 5% accuracy. For $T_p = 40$ MeV NN results are practically the same.

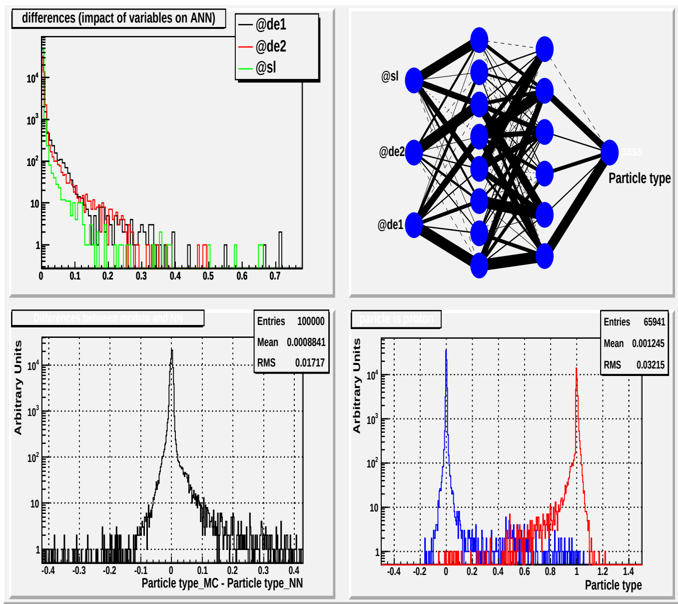

Fig. 1: Neural Network method application for the particle type determination: *upper left panel:* Impact of the input variables on NN method; *upper right panel:* NN structure; *lower left panel:* The differences in 'Particle type' variable between input (MC data) and output (NN data); *lower right panel:* Particle type NN output, blue line corresponds to protons, red line - deuterons.

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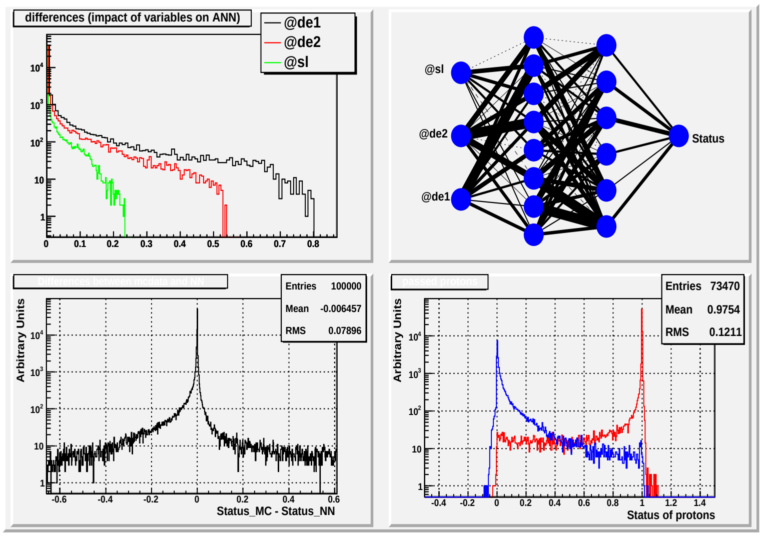

Fig. 2: Neural Network method application for the proton status determination: *upper left panel:* Impact of the input variables on NN method; *upper right panel:* NN structure; *lower left panel:* The differences in 'Status' variable between input (MC data) and output (NN data); *lower right panel:* Status of NN output, blue line corresponds to stopped protons, red line - passed ones.

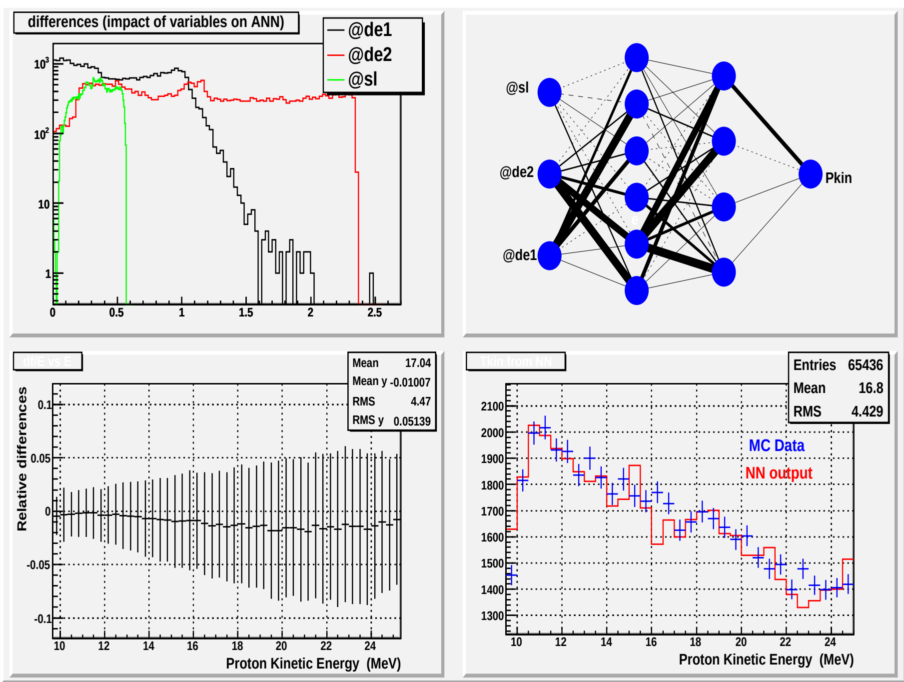

Fig. 3: Neural Network method application for proton kinetic energy determination: *upper left panel:* Impact of the input variables on NN method; *upper right panel:* NN structure; *lower left panel:* The profile histogram for relative differences between proton kinetic energy and reconstructed one; *lower right panel:* The proton kinetic energy, blue line corresponds for MC input, red line - NN output.