Improvements in prompt and delay event selection in ISMRAN using artificial neural networks

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Introduction

Reactor anti-neutrinos ($\bar{\nu}_e$) are detected using the inverse beta decay (IBD) reaction wherein a $\bar{\nu}_e$ interacts with a proton, to produce a positron and a neutron. The delayed time coincidence of the positron annihilation and neutron capture forms the signature of a $\bar{\nu}_e$ event. The Indian scintillator matrix for Reactor AntiNeutrinos (ISMRAN) is one such reactor $\bar{\nu}_e$ detection experiment proposed for reactor core monitoring and sterile neutrino searches at Dhruva reactor facility, BARC, India. The detector comprises of 100 plastic scintillator (PS) bars (10×10) each of dimensions 100cm × 10cm × 10cm and with Gd wrapping to capture neutrons. Setup is shielded with 10 cm Pb and 10 cm borated polyethylene (BP) to suppress background. The segmented geometry of the setup allows for event selection based on signal multplicity and deposition profile. But using such simplified cuts leads to drastic reduction in detection efficiency. In this work, we discuss the use of multivariate analysis techniques such as artificial neural networks (ANN) to address this issue.

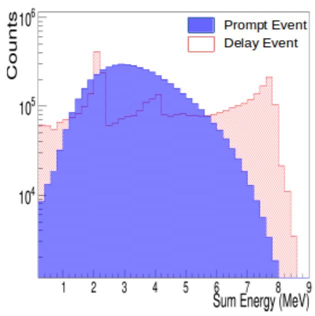

Fig 1: Overlapped sum energy (E_{sum}) distribution for prompt and delayed events in ISMRAN

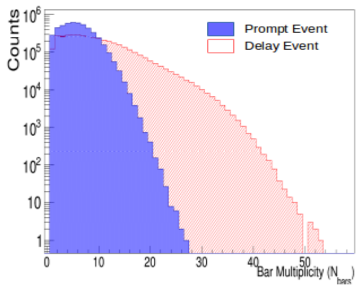

Fig 2: Overlapped N_{bars} distribution for prompt and delayed events in ISMRAN

Prompt and delayed selection and associated efficiency in ISMRAN

Monte carlo based GEANT4 simulation is performed in the 100 PS bar ISMRAN setup to simulate prompt-delay signature of pure IBD events and consequently determine the $\bar{\nu}_e$ detection efficiency. A threshold : $E^{Th}_{bar} >$ 0.2 MeV on each bar, as applied in the data for matching bar responses, is also replicated in simulations along with the upper threshold of 7.5 MeV to reject high energy background. Figure 1 and 2 show the simulated sum energy :E_{sum}, and the number of bars with energy deposit:N_{bars} distributions superimposed for both prompt and delayed events. As can be observed, there is complete overlap in both the variable distributions for prompt and delayed events. In order to define a $\bar{\nu}_e$ event inside ISMRAN a selection of $2.2 < E_{sum}$ (MeV) < 8.0 and $1 < N_{bars} < 4$ for prompt, accompanied with a selection of $3.0 < E_{sum}$ (MeV) < 8.0 and $N_{bars} > 3$ for delayed event, and additional time coincidence selection of $8.0 <$

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ΔT (μs) < 200.0 is chosen to eliminate most of the background contamination. This leads to a meager efficiency of ∼16% [1] and provides insufficient statistics over a relatively short period of time expected for real-time monitoring. Further, since the $\bar{\nu}_e$ energy spectrum is obtained from the prompt spectrum, the prompt-delay overlap will lead to huge uncertainties during reconstruction.

Application of MLP in ISMRAN event selection

The multilayer perceptron (MLP), a machine learning algorithm, is the traditional form of ANN [2]. Its purpose is to approximate a function mapping 'n' inputs to the desired classifier output, discriminating signal and background. The architecture of MLP has one input layer, one output layer and one or more hidden layers with multiple interconnected nodes called 'neurons'. Each node takes the weighted inputs from previous layer plus a bias term. It then operates upon this input using a non-linear function, preferably a sigmoid. The weights and biases are derived through a supervised learning mechanism which basically trains the network using a simulated sample to minimize the difference between the network output and the so-called 'ground truth' to acceptable levels. Using the simulations performed for ISMRAN IBD events, a signal(prompt) and background(delay) dataset is generated as input to the MLP for training and testing. The major advantage of the multivariate analysis (MVA) method is that the selection on variables can be kept relaxed, so that most of the event space is available for filtering signal events. In view of this, both the prompt and delayed selection cuts were loosened to: 0.2 < E_{sum} (MeV) < 8.0 and 1 < N_{bars} in training the network. Further, methods like MLP give better classification with variables tuned to enhance signal characteristics over background and allows formulating combinations of the raw inputs as new variables. So, another variable D_k is formulated; which is basically a weighted sum of, individual energy deposits raised to suitable power (here 2.5) and normalized accordingly. Once the training and testing is done the MVA framework provides the evaluation of the MLP classifier in terms of various quantities such as signal efficiency, background rejection and purity etc. for various cuts on classifier output. The chosen

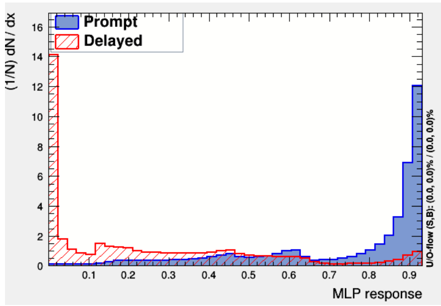

Fig 3: MLP classifier output for prompt(signal) and delayed(background) events

MLP architecture is observed to have reasonable performnace with one hidden layer having n+3 nodes where n is number of inputs including bias node. Further enhancements are being tested. The output of the trained MLP classifier (figure 3) shows improved separation of signal and background for most of the classifier range as compared to the simple cuts. A value of ∼0.4 for the MLP classifier provides the best signal efficiency and purity combination, but if the working point is chosen close to 0.7 almost 20% better purity is obtained at the cost of similar reduction in efficiency. The MLP classifier is, therefore, ready for application on the unknown datasets generated from experiment.

Conclusion and Outlook

The performance of the MLP ANN is tested for possible discrimination power amongst prompt and delayed events in ISMRAN simulated events. It is observed that, the MLP classifier clearly outperforms the selection cuts and provides a significant separation. The trained network is to be tested on experimental data. It is expected to boost the prompt signal purity and enhance the sensitivity to $\bar{\nu}_e$ energies.

References

[1] D. Mulmule et. al. Nuclear Inst. and Methods in Physics Research, A 911 (2018) 104V114.

[2] `https://root.cern.ch/tmva`