## Efficiency Studies of $H \to WW^{(*)} \to \mu^+ \nu_\mu \mu^- \bar{\nu}_\mu$ Decays with Neural Nets

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Despite its success, the Standard Model (SM) of particle physics remains incomplete without a means to explain gauge-symmetry breaking. The simplest proposed mechanism involves the introduction of a complex doublet of scalar fields that generate particle masses via their mutual interactions. This so-called Higgs mechanism also introduces a single scalar boson with an unpredicted mass  $M_H$ . Direct searches at the CERN  $e^+e^-$  collider (LEP) yield lower mass limits at  $M_H > 114.4$  GeV and the SM Higgs boson search is ongoing at the Fermilab Tevatron collider.

Searches for Higgs bosons use different methods to obtain best possible signal efficiencies and signal-tobackground ratios. In this analysis, a search for the Higgs Boson in the decay channel  $H \to WW^{(*)} \to \mu^+ \nu_\mu \mu^- \bar{\nu}_\mu$ with Artificial Neural Nets (ANN) in DØ data of an integrated luminosity of 775  $pb^{-1}$  is presented [1]. Background contributions from  $Z/\gamma^*$ , WW, WZ, ZZ and  $t\bar{t}$ events have similar topological and kinematic properties like events from  $H \to WW^{(*)}$  decays. However, correlations between those properties can be exploited by ANN to efficiently reject these backgrounds. For each of the background processes a separate neural net is built, to gain the best signal efficiency among the rejection of the background. Studies for a single neural net combining all background processes revealed a much lower performance. Figure 1 shows the composition of the neural net to reject events from WW production. The ANN is trained to classify Higgs signal events by an output value of 1 and background like events by 0. Applying the trained ANN to a test sample of signal and background events shows the discriminating power of the ANN (Figure 1 lower right)



Fig. 1: ANN composition against WW production events. Kinematic Variables and their weight (upper left), structure of the ANN and variable weights (upper right), distributions for background and signal in training sample (lower left) and training together with test sample (lower right).

To use these different ANN in an event selection, an optimal cut value on the output variable of all ANN has to be determined. In addition, the cut values need to be optimized with all ANN applied subsequently. An iterative optimization is pursued, by including all ANN step by step into the event selection. Figure 2 shows the distributions of the WW ANN output variable for Higgs signal and all backgrounds events. Output variable distributions of the ANN against other backgrounds have similar shapes.



Fig. 2: Distributions of the ANN output variable for Higgs signal and all backgrounds for the WW ANN before applying a combination of all cuts.

The ANN based selection is compared to a cut-based procedure [2]. Results from the comparison of both method assuming  $M_H = 160$  GeV are summarized in Table 1. The ANN based method yields a 5% lower signal efficiencies, but a 25% better signal-to-background ratio and less remaining background.

	ANN selection	cut-based selection
$\sum_{background}$	$3.17 \pm 1.04$	$8.24 \pm 1.05$
signal	$0.235\pm0.004$	$0.303\pm0.004$
signal efficiency	17%	22%
$S/\sqrt{B}$	0.133	0.103

Table 1: Comparison of the ANN and cut based selection methods for  $M_{H}$  = 160 GeV.

Further Higgs boson masses  $M_H = 120$  GeV, 140 GeV and 180 GeV have been studied with the ANN based method. The results are given in Table 2.

Higgs mass	signal efficiency	$S/\sqrt{B}$
$120 { m GeV}$	2%	0.004
$140 { m GeV}$	24%	0.074
$180 { m GeV}$	19%	0.078

Table 2: Results of the ANN based selection for Higgs boson masses of 120 GeV, 140 GeV and 180 GeV.

In conclusion, the application of an ANN based method yields a better signal to background ratio compared to a cut based analysis for correlated selection variables.

## References

- [1] D. Görisch, diploma thesis, LMU München, March 2006
- [2] DØ Collaboration, V.M. Abazov et al., Phys. Rev. Lett. 96 (2006) 011801, [arXiv:hep-ex/0508054].